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Redefining and Adapting Feedback for Mental-Imagery based Brain-Computer Interface User Training to the Learners' Traits and States

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Redéfinition et adaptation du feedback donné à l'utilisateur lors de l'entraînement à l'utilisation des interfaces cerveau-ordinateur en fonction du profil de l'apprenant

Résumé

Les interfaces cerveau-ordinateur basées sur l'imagerie mentale (MI-BCIs) offrent de nouvelles possibilités d'interaction avec les technologies numériques, telles que les neuroprothèses ou les jeux vidéo, uniquement en effectuant des tâches d'imagerie mentale, telles qu'imaginer d'un objet en rotation.

La reconnaissance de la commande envoyée au système par l'utilisateur repose sur l'analyse de l'activité cérébrale de ce dernier. Les utilisateurs doivent apprendre à produire des patterns d'activité cérébrale reconnaissables par le système afin de contrôler les MI-BCIs. Cependant, les protocoles de formation actuels ne permettent pas à 10 à 30 % des personnes d'acquérir les compétences nécessaires pour utiliser les MI-BCIs. Ce manque de fiabilité des BCIs limite le développement de la technologie en dehors des laboratoires de recherche.

Cette thèse a pour objectif d'examiner comment le feedback fourni tout au long de la formation peut être amélioré et adapté aux traits et aux états des utilisateurs. Dans un premier temps, nous examinons le rôle qui est actuellement donné au feedback dans les applications et les protocoles d'entraînement à l'utilisation des MI-BCIs. Nous analysons également les théories et les contributions expérimentales discutant de son rôle et de son utilité dans le processus d'apprentissage de contrôle de correlats neurophysiologiques. Ensuite, nous fournissons une analyse de l'utilité de différents feedback pour l'entraînement à l'utilisation des MI-BCIs. Nous nous concentrons sur trois caractéristiques principales du feedback, i.e., son contenu, sa modalité de présentation et enfin sa dimension temporelle.

Pour chacune de ces caractéristiques, nous avons examiné la littérature afin d'évaluer quels types de feedback ont été testés et quel impact ils semblent avoir sur l'entraînement. Nous avons également analysé quels traits ou états des apprenants influaient sur les résultats de cet entraînement. En nous basant sur ces analyses de la littérature, nous avons émis l'hypothèse que différentes caractéristiques du feedback pourraient être exploitées afin d'améliorer l'entraînement en fonction des traits ou états des apprenants. Nous rapportons les résultats de nos contributions expérimentales pour chacune des caractéristiques du feedback. Enfin, nous présentons différentes recommandations et défis concernant chaque caractéristique du feedback. Des solutions potentielles sont proposées pour à l'avenir surmonter ces défis et répondre à ces recommandations.

Mots-clés:

Interface Cerveau-Ordinateur, Imagerie mentale, Feedback, Feedback émotionnel et présence sociale, Modalité de feedback, Réhabilitation motrice post-AVC, Attention

Discipline:

Informatique

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Redefining and Adapting Feedback for Mental-Imagery based Brain-Computer Interface User Training to the Learners' Traits and States

Abstract

Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) present new opportunities to interact with digital technologies, such as neuroprostheses or videogames, only by performing mental imagery tasks, such as imagining an object rotating.

The recognition of the command for the system is based on the analysis of the brain activity of the user. The users must learn to produce brain activity patterns that are recognizable by the system in order to control BCIs. However, current training protocols do not enable 10 to 30% of persons to acquire the skills required to use BCIs. The lack of robustness of BCIs limit the development of the technology outside of research laboratories.

This thesis aims at investigating how the feedback provided throughout the training can be improved and adapted to the traits and states of the users. First, we investigate the role that feedback is currently given in MI-BCI applications and training protocols. We also analyse the theories and experimental contributions discussing its role and usefulness. Then, we review the different feedback that have been used to train MI-BCI users. We focus on three main characteristics of feedback, i.e., its content, its modality of presentation and finally its timing.

For each of these characteristics, we reviewed the literature to assess which types of feedback have been tested and what is their impact on the training. We also analysed which traits or states of the learners were shown to influence BCI training outcome. Based on these reviews of the literature, we hypothesised that different characteristics of feedback could be leveraged to improve the training of the learners depending on either traits or states. We reported the results of our experimental contributions for each of the characteristics of feedback. Finally, we presented different recommendations and challenges regarding each characteristic of feedback. Potential solutions were proposed to meet these recommendations in the future.

Keywords:

Brain-Computer Interface, Mental imagery, Feedback, Emotional feedback and social presence, Modalities of feedback, Post-stroke motor rehabilitation, Attention

Discipline:

Computer Science

Laboratory:

Equipe-projet Potioc, Inria Bordeaux - Sud-Ouest, 33405 Talence

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Résumé en français

Les interfaces cerveau-ordinateur basées sur l'imagerie mentale (MI-BCI) sont des neurotechnologies qui permettent à leurs utilisateurs de commander des applications externes uniquement en exécutant des tâches d'imagerie mentale, comme par exemple imaginer un objet tournant dans l'espace [Clerc et al., 2016]. Lorsque que les utilisateurs des MI-BCIs exécutent des tâches d'imagerie mentale, leur activité cérébrale est enregistrée (souvent par électroencéphalographie), traitée et transformée en commandes pour le système. Pour contrôler les MI-BCIs, l'utilisateur doit d'abord s'entraîner à produire une activité cérébrale fiable et reconnaissable par le système. Un feedback, qui correspond à une information fournie à un apprenant au sujet de l'exécution ou de la compréhension de la tâche ou des compétences à apprendre, est fournie par le système BCI. C'est une composante fondamentale de l'entraînement aux MI-BCIs [Lotte et al., 2013]. Cependant, la littérature et les résultats expérimentaux suggèrent que les protocoles d'entraînement actuels de MI-BCI, y compris le feedback, sont inappropriés pour acquérir des compétences nécessaires pour contrôler un MI-BCI [Jeunet et al., 2016a, Lotte et al., 2013]. Au cours de cette thèse, nous avons exploré plusieurs axes de recherche afin d'améliorer le feedback fourni pendant l'entraînement aux MI-BCIs.

Comme un feedback ne profite pas toujours à un apprentissage, sa mise en œuvre doit être soigneusement étudiée [Hattie and Timperley, 2007]. Avant tout, il faut savoir si un feedback est nécessaire, dans quel contexte et pour qui. La théorie behavioriste du conditionnement opérant se fonde sur le fait qu'un feedback en récompensant ou en punissant un comportement permet de le renforcer ou l'inhiber. Cette théorie est couramment utilisée pour expliquer l'amélioration du contrôle des corrélats neurophysiologiques durant l'entraînement aux MI-BCIs [Neuper and Pfurtscheller, 2009, Vidal, 1973]. Les théories behavioristes ont mené à la vision générale que le feedback est nécessaire et bénéfique à l'apprentissage. Toutefois, la théorie du conditionnement opérant ne permet pas d'expliquer l'influence variable pouvant être positive, neutre et même négative du feedback que l'on peut voir dans les résultats de la littérature [Kluger and DeNisi, 1996]. Nous avons donc exploré trois dimensions du feedback, i.e., son contenu, sa modalité de présentation ainsi que sa dimension temporelle afin de savoir quelles étaient les caractéristiques du feedback qui sont actuellement utilisés pour l'entraînement à l'utilisation de MI-BCIs, au neurofeedback mais également à d'autres compétences comme l'apprentissage moteur. L'objectif est de fournir de premières pistes pour permettre un feedback adapté et adaptatif aux états et traits cognitifs des apprenants lors de l'entraînement à l'utilisation des MI-BCIs.

Tout d'abord, nous nous sommes intéressés au contenu du feedback, c'est-à-dire l'information transmise par le feedback à l'utilisateur. En étudiant la littérature, nous avons notamment trouvé que l'utilisation d'une dimension sociale et émotionnelle pour le contenu du feedback était très rare. Seules de simples formes de ce type de feedback ont été testées, comme l'utilisation d'un smiley [Kübler et al., 2001, Leeb et al., 2007, Zapała et al., 2018]. Pourtant, des études en neurophysiologie ainsi que des études théoriques du domaine montrent l'importance d'un contexte social [Izuma et al., 2008, Mathiak et al., 2015]. Nous avons fait l'hypothèse que le fait que les personnes non autonomes et anxieuses aient de moins bonnes performances MI-BCI que les autres pouvait être lié à ce manque de contexte social et de feedback émotionnel [Jeunet et al., 2015a]. Nous avons tout d'abord décidé de tester l'influence d'un compagnon d'apprentissage nommé PEANUT fournissant une présence sociale et un feedback émotionnel sur l'apprentissage aux MI-BCIs. Plusieurs études ont été menées pour concevoir soigneusement le compagnon. Une dernière étude a évalué son impact sur les performances et l'expérience utilisateur lors d'un entraînement aux MI-BCIs. Nous avons constaté qu'un tel compagnon améliore les performances MI-BCI pour les participants non autonomes. Le compagnon avait également tendance à améliorer la façon dont les participants se sentaient capable d'apprendre et de mémoriser l'utilisation du système. L'évaluation de l'efficience et de l'efficacité du système était également significativement différente selon le niveau d'autonomie des participants et la présence de PEANUT. Les participants autonomes entraînés avec PEANUT ont trouvé qu'ils étaient plus efficaces que ceux formés sans PEANUT. Cette expérience a révélé une influence de la présence sociale et du soutien émotionnel sur les performances aux MI-BCIs.

Les expérimentateurs, qui ont un rôle important dans le déroulement des expériences MI-BCI, sont la source principale de présence sociale et de feedback à caractère émotionnel. En examinant la littérature de différents domaines de recherche, telles que les études sociologiques et économiques [Rosnow and Rosenthal, 1997], nous avons constaté que l'interaction du sexe de l'expérimentateur et du sujet pouvait avoir une influence majeure sur les résultats expérimentaux. Par conséquent, nous avons réalisé une expérience pour évaluer l'influence de l'interaction du sexe des expérimentateurs et de celui des participants sur les performances aux MI-BCIs. Nous avons trouvé une interaction entre les sexes de l'expérimentateur et du participant sur l'évolution des performances. Les performances ont également été influencées par l'interaction du sexe de l'expérimentateur et le niveau d'anxiété du participant.

Ces résultats confirment qu'une présence sociale et un feedback émotionnel pourraient être utilisés pour améliorer l'entraînement à l'utilisation des MI-BCIs. Cependant, comme tout feedback, son effet peut être préjudiciable. Si l'influence des expérimentateurs n'est pas soigneusement évaluée et prise en compte dans la conception du protocole, cette dernière pourrait biaiser les résultats des expériences. Nous soutenons que les caractéristiques des apprenants, notamment leur niveau de tension et leur autonomie, devraient être évaluées et prises en compte lors de la conception des feedbacks.

Deuxièmement, nous avons exploré la modalité du feedback. Les modalités visuelles, auditives et somatosensorielles ont été explorées pour présenter un feedback unimodal ou multimodal lors de l'apprentissage aux MI-BCIs [Nijboer et al., 2008, Zapała et al., 2018]. Le choix de la modalité de feedback est souvent adapté aux capacités sensorielles de la population cible. Par exemple, le choix d'un feedback auditif a été fait pour des personnes ayant des déficiences visuelles [Young et al., 2014]. En revanche, nous faisons l'hypothèse que les capacités somatosensorielles des patients post-AVC, qui ne sont actuellement que très peu prises en compte, devraient l'être. Les thérapies motrices post-AVC basées sur l'utilisation de BCIs permettent la co-activation des réseaux efférents moteur liés à l'imagination ou la tentative d'exécution d'un mouvement, et des réseaux sensoriels liés à la perception du feedback sensoriel. Cette co-activation est supposée être à l'origine des améliorations fonctionnelles elles-mêmes associées à des changements neurophysiologiques du système sensorimoteur [Grosse-Wentrup et al., 2011a]. Toutefois, l'activation des systèmes afférents sensoriels dépend de la perception du feedback sensoriel. Or, un peu plus de la moitié des patients post-AVC ont des troubles somatosensoriels [Pumpa et al., 2015, Kessner et al., 2016]. Il est donc fort probable que ces déficits somatosensoriels limitent les bénéfices thérapeutiques des thérapies basées sur l'utilisation de BCIs. Notre revue de la littérature sur la rééducation motrice post-AVC basée sur l'utilisation de BCIs nous a mené à étudier 14 essais cliniques randomisés. Sur ces 14 études, seules 2 ont rapporté avoir utilisé les capacités somatosensorielles comme critère d'inclusion/exclusion. Toutefois, elles ne mentionnaient pas les méthodes d'évaluation de ces capacités, ce qui limite la reproductibilité de leur étude. Nous pensons que l'évaluation des capacités somatosensorielles des patients est nécessaire pour éviter tout biais et permettre une comparaison fiable entre les sujets et entre les études. L'évaluation des capacités somatosensorielles pourrait également être mise à profit pour améliorer notre compréhension des mécanismes sous-jacents de la récupération motrice et adapter la modalité de présentation du feedback aux capacités somatosensorielles du patient.

La modalité du feedback a une incidence sur les performances MI-BCIs [Neuper and Pfurtscheller, 2009]. Notamment, un feedback multimodal composé de stimulations visuelles et somatosensorielles permet de meilleures performances qu'un feedback visuel seul. Toutefois, l'influence à long terme d'un feedback somatosensoriel et l'importance du caractère intéroceptif ou extéroceptif de la stimulation restaient inconnues. D'autre part, l'influence des capacités d'imagination visuelles et kinesthésiques sur les performances MI-BCI font débat [Vuckovic and Osuagwu, 2013, Marchesotti et al., 2016, Rimbert et al., 2017]. Nous avons fait l'hypothèse que les capacités d'imagination kinesthésiques et visuelles des participants pourraient influencer la modalité de feedback à favoriser. Notre hypothèse était que, selon les capacités visuelles et kinesthésiques des participants et la modalité du feedback, l'exécution d'une tâche d'imagerie mentale pourrait solliciter des ressources cognitives sensorielles similaires à celles requises pour traiter l'information provenant du feedback. Par exemple, un participant pourrait solliciter des ressources cognitives visuelles à la fois pour réaliser une tâche d'imagerie visuelle et traiter l'information provenant d'un feedback visuel. Cela pourrait entraîner une surexploitation des ressources cognitives sensorielles et une diminution des performances MI-BCI. Par conséquent, nous avons testé l'influence des capacités visuelles et kinesthésiques sur les effets à long terme d'un feedback multimodal composé de stimulations visuelles réalistes et vibrotactiles, et d'un feedback unimodal avec uniquement des stimulations visuelles réalistes. Nous avons constaté que l'impact bénéfique d'un feedback multimodal composé d'une stimulation à la fois visuelle et somatosensorielle par rapport à un feedback visuel seul reste vrai même pour un entraînement à long terme, ce qui n'avait pas encore été testé. De plus, l'ordre de présentation des différentes modalités de feedback pourrait avoir une influence. L'utilisation d'un feedback visuel unimodal semble mieux convenir aux participants novices. Nous émettons l'hypothèse que l'intégration d'informations issues de deux modalités de feedback tout en effectuant la tâche pourrait être particulièrement difficile pour quelqu'un de novice. Nous avons également constaté une évolution différentielle des performances d'exécution motrice en fonction des capacités initiales des participants en imagerie visuelle et de la modalité de rétroaction.

Ces résultats tendent à confirmer que les traits des apprenants ne doivent pas seulement être pris en compte pour adapter le contenu du feedback, mais également la modalité de présentation de ce dernier. Plus spécifiquement, les capacités somatosensorielles des patients post-AVC et les capacités initiales d'imagerie visuelle des personnes neurotypiques devraient être évaluées lors d'expériences futures. Nous pensons que si ces caractéristiques ne sont pas soigneusement évaluées et prises en compte dans la conception du protocole, elles pourraient biaiser les résultats de l'expérience.

Enfin, nous avons étudié la dimension temporelle du feedback, c'est-à-dire le moment et la fréquence à laquelle le feedback doit être fourni aux participants. Un feedback continue, i.e., fourni lorsque la personne réalise la tâche d'imagination, est théoriquement et en pratique recommandé [McFarland et al., 1998, Neuper et al., 1999]. Toutefois, peu d'informations existent sur la fréquence de présentation que le feedback devrait avoir. Des études réalisées dans d'autres domaines révèlent que la fréquence de présentation du feedback pourrait avoir une influence sur l'état attentionnel des personnes [Magill, 1994]. Plus le feedback est fréquent et plus les ressources attentionnelles sont sollicitées pour analyser le feedback. Par conséquent, nous avons apporté une première contribution pour qu'une évaluation des états attentionnels à l'aide de signaux EEG au cours de l'entraînement aux MI-BCIs puisse être réalisée dans le futur. Nous avons constaté que chacun des états attentionnels décrit dans le modèle de van Zomeren et de Brouwer présente des patterns d'activation spécifiques pouvant être observés à l'aide de signaux EEG [Zomeren and Brouwer, 1994]. Nous avons également testé la possibilité de classifier les différents types d'attention à partir des données EEG filtrées dans la bande de fréquence alpha ou thêta. La classification fournit des résultats assez prometteurs puisqu'un peu plus des deux tiers des essais sont correctement classés. Des études ultérieures doivent être menées afin de vérifier si l'adaptation de la fréquence du feedback en fonction du niveau d'attention des participants a un impact bénéfique sur les performances.

Pour conclure, une amélioration de la fiabilité des BCIs est nécessaire avant que la technologie puisse être développée à grande échelle en dehors des laboratoires de recherche. Parallèlement à l'acquisition et au traitement du signal, l'entraînement à l'utilisation des BCIs doit être amélioré pour atteindre cet objectif. La formation des utilisateurs repose sur l'utilisation d'un feedback. La théorie du conditionnement opérant est principalement utilisée pour expliquer l'apprentissage intervenant au cours de la formation des utilisateurs BCI et le rôle de ce feedback.

Cependant, les théories comportementales ne rendent pas compte de l'effet neutre et même préjudiciable du feedback que l'on trouve dans la littérature. S'éloigner de la théorie du conditionnement opérant permettrait de prendre en compte les divers impacts qu'un feedback peut avoir sur l'entraînement aux interfaces cerveau-ordinateur. L'étude du rôle du feedback pourrait fournir des informations pertinentes sur les mécanismes sous-jacents de l'apprentissage à l'utilisation des MI-BCIs. Par exemple, cela permettrait d'étudier l'existence de feedbacks intrinsèques permettant aux apprenants de savoir si la tâche d'imagerie mentale qu'ils ont réalisée produit des patterns d'activation fiables et distincts. L'utilisation de définitions et de classifications communes des différents types de feedback, telles que celles proposées dans cette thèse, pourraient permettre une meilleure compréhension de la littérature et des défis à relever. De plus, comprendre pourquoi et comment l'impact du feedback varie selon le profil des apprenants pourrait permettre de mieux comprendre les différences de performances entre les études et entre les participants. À l'avenir, des modèles devraient être conçus pour savoir comment sélectionner un feedback en fonction de la tâche et du profil du participant. En outre, une fois que nous aurons suffisamment de connaissances sur chaque type de feedback de manière indépendante, il sera nécessaire d'adopter une vision plus systématique des différentes caractéristiques du feedback.

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Acronyms

ALS	Amyotrophic Lateral Sclerosis
BCI	Brain-Computer Interface
CA	Classification Accuracy
EEG	ElectroEncephaloGram
EMG	ElectroMyoGram
EOG	ElectroOcculoGram
ERD	Event-Related Desynchronization
ERS	Event-Related Synchronization
FMA-UE	Fugl-Meyer Assessment of Upper Extremity
fMRI	functional Magnetic Resonance Imaging
ITS	Intelligent Tutoring Systems
KVIQ	Kinaesthetic and Visual Imagery Questionnaire
MA	Motor Attempt
MI	Mental Imagery
MI-BCI	Mental-Imagery based Brain-Computer Interface
NIHSS	National Institute of Health Stroke Scale
NIRS	Near InfraRed Spectroscopy
PSD	Power Spectral Density
SCP	Slow Cortical Potentials
SMC	SensoriMotor Cortex

Introduction

Authors of science fiction have imagined and written about controlling objects and communicating without using the natural muscular channel long before scientists developed the technology that would lay the foundation of such methods of interaction. Still far from the idealistic vision depicted in the science fiction literature, Brain-Computer Interfaces (BCIs) monitor (e.g., using electroencephalography), process (using machine learning techniques) and translate patterns of brain activity into commands for different types of digital technologies [Wolpaw et al., 2002]. A famous example of BCI is a smart wheelchair that is controlled by imagining left or right hand movements, e.g., imagining waving at someone, to make the wheelchair turn respectively left or right [Carlson and Millan, 2013].

Most often, brain activity is measured using Electroencephalography (EEG), which uses electrodes placed on the scalp to record small electrical currents reflecting the activity of large populations of neurons, which are the functional units of the brain [Clerc et al., 2016]. EEG signals are continuous rhythmic sinusoidal waves characterized by their amplitude and frequency. Several EEG patterns were correlated with concurrent intentions and/or state and can therefore be interpreted by BCIs to send commands to digital devices. For instance, early research on BCIs have shown that people could learn to control their Slow Cortical Potentials (SCP), i.e., potential shifts generated in the cortex and occurring over 0.5 to 10 seconds, to control the movement of an object on a computer screen [Birbaumer et al., 2000].

Also, mu (8-12 Hz) and beta (12-30 Hz) rhythms recorded over the sensorimotor cortex are associated with movement preparation and execution. Indeed, motor preparation or execution lead to a decrease of the mu and beta rhythms in the sensorimotor cortex, particularly in the cortex contralateral to the movement. This decrease is called "Event-Related Desynchronization" (ERD) and is followed by an opposite increase of the mu and beta rhythms called "Event-Related Synchronization" (ERS), which occurs after the movement and with relaxation [Wolpaw et al., 2002]. Interestingly, the imagination of movement also produces similar characteristic ERD and ERS. As motor imagery is related to specific neural correlates, it can be used to control EEG-based BCIs. Motor imagery represents only one of the different imaginary tasks that can be associated with specific neural correlates and be used for BCIs. For instance, mental rotations are typically associated with activation of the parietal and right frontal lobes [Kosslyn et al., 2001].

In this thesis, we will mainly focus on BCIs that are controlled using mental imagery tasks, i.e., Mental Imagery based Brain-Computer Interfaces (MI-BCI). To control MI-BCIs, users have to perform mental-imagery tasks. While they do, their brain activity is recorded and processed by the system. Then, the system attempts to deduce which task the user is performing from the processed signals, often using machine learning algorithms. A feedback is then provided to the users to inform them of the MI task that the system recognized and often how confident the system is in its recognition. Figure 1 represents the standard MI-BCI processing loop. MI-BCIs represent new interaction tools and have for example been used to control video games [Lécuyer, 2016, Marshall et al., 2013]. They also enable several promising therapeutical applications. For instance, they can be used to foster brain plasticity and improve motor rehabilitation for post-stroke patients [Biasiucci et al., 2018].

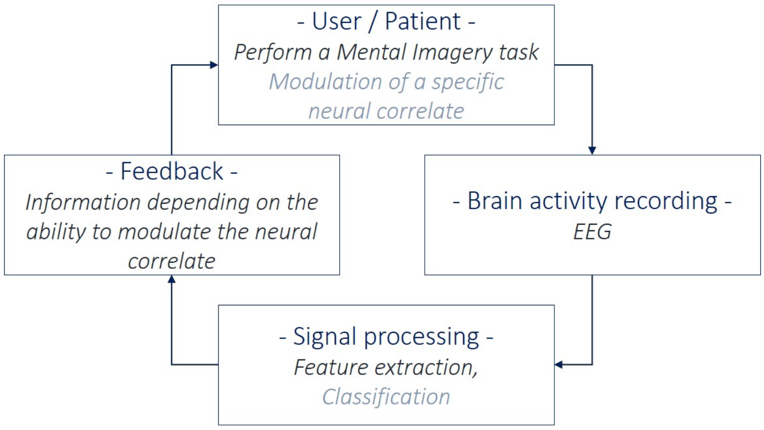

Figure 1: Standard MI-BCI processing loop.

All the MI-BCI applications rely on their ability to send the correct command to the system, i.e., the one selected by the user. However, the accuracy still has to be improved for the technology to undergo a strong growth outside of research laboratories. For example, when the system has to decide which task the user is performing between two motor imagery tasks, e.g., imagining a right versus a left hand movement, on average the system is mistaken once every four guesses [Allison and Neuper, 2010]. There are several lines of research aiming at improving the efficiency of MI-BCIs. A great deal of them focus on improving the acquisition and processing of the brain activity [McFarland and Wolpaw, 2018]. However, MI-BCI applications also rely on users themselves. Indeed, on the one hand, the computer has to learn to discriminate the different brain-activity patterns corresponding to each task performed by the user. Though on the other hand, the user has to train and learn how to produce a stable and distinguishable brain-activity pattern for each of the tasks in order for them to be recognized by the computer [McFarland and Wolpaw, 2018].

MI-BCIs share some characteristics with neurofeedback, which protocol aims to train people to self-regulate specific functional biomarkers, often associated with mental disorders [Batail et al., 2019]. However, the main goal of neurofeedback is that the changes of brain activity resulting from the training will have a therapeutical influence and the main goal of BCIs is to be able to control external devices [Batail et al., 2019]. We do refer to the literature on neurofeedback during this thesis as it provides relevant insights regarding the role of feedback for self-regulation of neurophysiological pattern training.

During BCI user training based on the imagination of hand movements, users can adopt a great variety of strategies, e.g., imagining waving at someone or playing the piano. During the training, it is assumed that users have to find their own strategies, i.e., characteristics of mental imagery, which make the system recognize these tasks as correctly as possible. However, the adequacy of the feedback provided during the training has been questioned both by the theoretical literature [Lotte et al., 2013] and by experimental results [Jeunet et al., 2016c]. The inadequacy of the training and more particularly of the feedback are probably part of the reasons why MI-BCIs remain insufficiently reliable [Lotte et al., 2013].

Indeed, while instructional design literature recommends the feedback to be, among others, explanatory/non-evaluative, supportive, multimodal and timely [Shute, 2008], the standard MI-BCI feedback (see Figure 2) is evaluative/non-explanatory, non-supportive, unimodal and very frequent. Thus, the fact that 15-30% of users cannot control an MI-BCI is most likely partly due to the fact that current feedback does not comply with recommendations from the literature [Lotte et al., 2013] and thus does not support enough users in acquiring BCI-related skills. Regardless of the method of brain activity acquisition and processing, if the users do not know how to command the BCI, we cannot expect the system to work. Therefore, their is a great need to improve the feedback in order to better comply with the recommendation in the literature. We expect that it would lead to a significant improvement of the BCI user training and thereby of the reliability of BCIs.

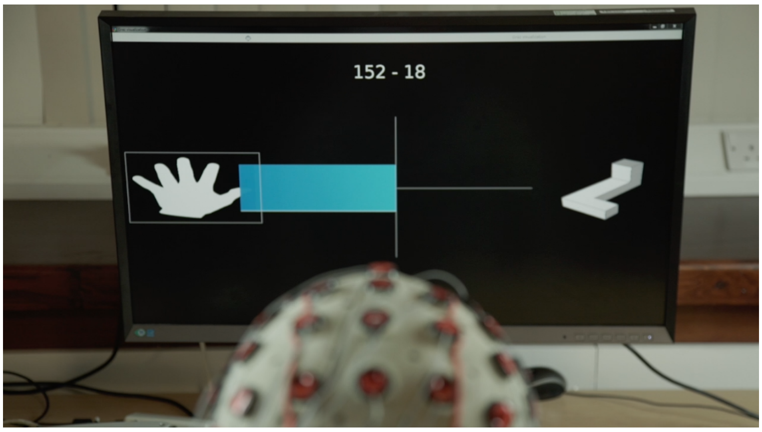

Figure 2: Example of feedback which is often provided to users during training. In this example, the user is imagining a left-hand movement, performing mental calculation tasks and imagining an object rotating. At the moment the picture was taken the user had to imagine moving his left-hand. The blue bar indicates which task has been recognized and how confident the system is in its recognition. The longer the bar and the most confident the system is. Here the system rightly recognizes the task that the user is performing and is quite confident about it.

This thesis aims at redefining the feedback for MI-BCI user training and adapting it to the users' traits and states. A comprehensive analysis of the different characteristics of feedback that have been used for BCI user training and their impact on the learning outcome is necessary. The development of standard definitions and classification of the different feedback could enable a better understanding of the current state of the literature and the challenges that remain to be overcome. Therefore, in the following paragraphs we provide several definitions of types of feedback that are important in order to understand the different contributions of this thesis.

Feedback is an information which is provided to a learner regarding aspects of the performance or understanding of the task/skills to learn [Hattie and Timperley, 2007]. Therefore, feedback is a repercussion of the learner's performance. Winne and Butler [Winne and Butler, 1994] define feedback as an "information with which a learner can confirm, add to, overwrite, tune, or restructure information in memory, whether that information is domain knowledge, meta-cognitive knowledge, beliefs about self and tasks, or cognitive tactics and strategies". Feedback has been a subject of studies in numerous fields of research such as education, sport, where it is primordial as the motor task performed might not be directly observable by the athlete [Baca, 2008] or organizational behaviour management, where it is for example used to reduce tardiness and absenteeism [Balcazar et al., 1985].

There are different types of feedback depending on where it originates. A feedback can either be *extrinsic*, i.e., when the information originates from an external source, e.g., a screen or a person, or *intrinsic*, or proprioceptive, i.e., sensations felt by the person. For example, extrinsic feedback encompasses the verbal comments of someone attending the task. Intrinsic feedback encompasses sensations such as the sense of balance or our knowledge regarding the position of our limbs in space.

Also, feedback can either be inherent to the performance of the task or artificially provided intentionally or unintentionally by an external agent, e.g., teacher, student, peer, or computer, to the learner to improve the acquisition of the skills. When the feedback is artificiality provided it is also called "augmented feedback" as it could not be elaborated without an external agent. In this thesis, the term feedback means augmented feedback. Otherwise, we explicitly refer to intrinsic feedback. The term of augmented feedback is still used when it is necessary to avoid ambiguity. Feedback can be positive and/or negative when it respectively highlights the correct or incorrect performances of the learner.

Also, the notion of feedback intermingles with the notions of instruction and reward. Depending on the amount of correctional review, i.e., explanation regarding the difference between what is expected and what as been done during training, included in the feedback, the latter can be assimilated to an instruction [Hattie and Timperley, 2007]. Feedback can also include reward, i.e., retribution provided to people depending on their performance. Though, this interrelation between feedback and reward has been questioned by Deci et al., because rewards can contain little information regarding the task [Deci et al., 1999].

Finally, we argue that a feedback can be defined using three main dimensions, i.e., its content, its modality of presentation and its timing. The first one represents the content of the feedback, i.e., the information that are conveyed by the feedback to the learner. During BCI training the feedback mostly conveys information regarding how well the system currently recognize the task performed by the learner and how confident the system is in its recognition. Feedback can also have a supportive content, e.g., emotional feedback and social presence. The second one is the modality of feedback, i.e., how the information is presented to the user. Classical feedback for MI-BCI user training are often conveyed through the visual modality and take the form of a moving object or an extending bar that the user has to train to control (see Figure 2). The third and final dimension is the temporal one. Usually, feedback is continuously presented to the BCI learners while they train.

In this thesis, the feedback is analysed using these three main dimensions. It is subdivided into five parts. An augmented feedback might not always be necessary to learn a task, and might even have a detrimental impact on the learning [Hattie and Timperley, 2007]. Therefore, in the part I Theoretical background of this thesis we review the literature and assess the role that feedback has had on MI-BCI user training. The aim is to answer three main questions: (1) Why should we use a feedback?, (2) Which feedback have been used? and (3) Who benefits from the feedback?. Based on this analysis of the literature, the different experimental contributions that we made for each of these dimensions of the feedback are presented in three respective following parts.

In part II What information should feedback convey?, we investigated the supportive dimension of the feedback. We were particularly interested in improving the MI-BCI training for non-autonomous and tensed users as they were shown to have lower MI-BCI performances than the others [Jeunet et al., 2015a]. Non-autonomous people are persons who rather learn in a social context. Yet, while educational and neurophysiological literature show the importance of a social presence [Izuma et al., 2008, Mathiak et al., 2015], this aspect of feedback, as well as emotional support, have been neglected during MI-BCI training. In chapter 4, we present the results of the studies we led to design, implement and test the first learning companion dedicated to providing social presence and emotional feedback during BCI user training. This experiment revealed a potential differential impact of social presence and emotional support on MI-BCI performance. The literature also indicates a main influence of the experimenters, who are the main sources of emotional feedback and social presence during MI-BCI training. For instance, interaction of experimenters' and participants' gender were shown to have a major influence on experimental results in other fields [Rosnow and Rosenthal, 1997]. Therefore, in chapter 5 we performed an experiment to assess the influence of the interaction of experimenters' and participants' genders on MI-BCI performances and user experience.

The part III How should the feedback be presented? presents a theoretical and an experimental contribution both aiming at adapting the modality of feedback to the users. The modality is currently adapted to the aim of the training, e.g., proprioceptive feedback for motor rehabilitation [Biasiucci et al., 2018], and to the sensory abilities of the learners, e.g., auditory feedback for visually impaired patients [Young et al., 2014]. In chapter 6 we present our theoretical contribution regarding the role of somatosensory abilities for BCI-based therapies for post-stroke motor rehabilitation. The underlying mechanism of such therapies is the co-activation of efferent motor and afferent sensory pathways. Stroke has an impact on the somatosensory abilities for more than half of the patient. Based on our review of the literature, somatosensory loss might limit the potential impact of such therapies. We argue that BCIs would benefit from the assessment of patients' somatosensory abilities. Somatosensory loss is associated with kinaesthetic and visual imagery dysfunctions.

The literature is not decisive on the impact of kinaesthetic and visual imagery abilities on neurotypical users' BCI training [Vuckovic and Osuagwu, 2013, Marchesotti et al., 2016, Rimbert et al., 2017]. It is hypothesised that displaying feedback on the same modality as the one used to perform mental imagery causes a decrease of performance related to the limited amount of cognitive resources [Wickens, 2008]. Based on this assumption, we hypothesised that depending on the kinaesthetic and visual abilities, people might benefit differentially from feedback depending on its modality of presentation. In chapter 7, we report the results from our experiment which tested if there was a differential impact between two feedback, one realistic visual and one realistic visual and vibrotactile, on long-term MI-BCI performances depending on users' neurophysiological and psychological characteristics.

In part IV When should the feedback be provided?, we made a first step toward taking into account the attentional state of the learners to adapt the timing of feedback in the future. MI-BCI performances seem to be related to both attentional traits and states, i.e., stable and unstable attentional characteristics [Hammer et al., 2012, Daum et al., 1993, Grosse-Wentrup et al., 2011b, Grosse-Wentrup and Schölkopf, 2012]. However, given the model of Zomeren and Brouwer, there are at least four types of attention. Alertness and sustained attentions refer to the intensity of attention (i.e., its strength) whereas selective and divided attentions refer to its selectivity (i.e., the amount of information that are monitored) [Zomeren and Brouwer, 1994]. The selectivity of attention might be an important indicator of the adaptability of the feedback [Kluger and DeNisi, 1996]. The assessment of the attentional states of the user during MI-BCI training might therefore be useful to adapt the training of a user. We led a study to assess the ability to distinguish the different types of attention using EEG.

Finally, in part V Discussion & Prospects, we discuss future opportunities and challenges to improve each of the three dimensions of feedback.

Part I

Theoretical background

Chapter 1

Why should we use a feedback?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - Can a physical learning companion be useful for mental-imagery based BCI user training?
	5. **Contribution 2** - Do experimenters influence MI-BCI training?
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

Before providing a feedback, the reasons justifying its use should always be considered. Indeed, to better understand how to improve the feedback, we first need to know in which contexts it is used and why it is necessary for BCIs. Therefore, in this first chapter, we analyse the role that feedback has during MI-BCI training. We start with concrete examples of different applications of BCIs in section 1.1. We argue that all these different applications rely on the reliability of the system, which partly depends on the feedback used to train the user. In section 1.2, we present two classical BCI user training protocols. We argue that feedback is at the very center of the MI-BCI definition. Though, an augmented feedback is not always necessary for learning to occur [Kulhavy, 1977]. Therefore, in the sections 1.3 and 1.4, we question the necessity of a feedback to train and produce distinct mental imagery patterns. In section 1.3 we analyse different results that are informative regarding the role that feedback is given for BCIs and neurofeedback trainings. Then, in section 1.3 we contextualize the role that feedback has by analysing the results from other fields of research. Finally, in the section 1.5, we provide a summary of the role of feedback for MI-BCI training.

1.1 Examples of applications of BCIs

The origins of EEG trace back to Hans Berger, a German psychiatrist and neurologist, who was the first to record brain activity from a human brain in 1929. The first applications of EEG were mostly oriented toward neurophysiological assessment, either for evaluation of neurological disorders or for the scientific study of brain functions [Wolpaw et al., 2002]. In such applications users did not try explicitly to control their brain activity. The first experiment that provided participants with a feedback related to their own brain activity took place in 1962 [Kamiya, 1962]. Then, in the mid 70s therapeutic applications were considered [Kuhlman, 1978]. For instance, therapies were developed for epilepsy and attention deficit disorders. They were presumably based on the training of patients to control their own spontaneous brain activity [Kuhlman, 1978]. The training was based on the presentation of a feedback regarding the brain activity of the participant. Such experiences were the first to introduce the notion of human training and learning.

In parallel, the possibility of controlling interfaces without using the brain's natural outputs, i.e., peripheral nerves and muscles, was investigated [Vidal, 1973]. Using BCIs to convey intentions and commands opened up numerous new opportunities, especially for people who have impairments of motor functions, e.g., people suffering from Amyotrophic Lateral Sclerosis (ALS), spinal cord injury, stroke or cerebral palsy [Lebedev and Nicolelis, 2006]. It enabled new means of communication and mobility, e.g., spelling devices, wheelchairs or neuroprosthesis [Wolpaw et al., 2002]. BCIs applications are not limited to medical ones. BCIs represent new interacting tools and have for example been used to control video games [Lécuyer, 2016]. Such applications rely on the possibility to associate people's intent or neuromuscular outputs and different neurophysiological measures of the brain that can be acquired. In the following sections, three examples of the main applications of BCIs are provided, i.e., post-stroke rehabilitation, communication with locked-in patients and video games. We chose therapeutical and non therapeutical applications, with different goals, such as communication and entertainment, and different method of brain activity acquisition. These choices were made to represent how diverse BCI applications can be and the different roles that feedback has in these applications. For an overview of the different applications of BCIs we recommend the book of Clerc et al. [Clerc et al., 2016].

1.1.1 Post-stroke motor rehabilitation

Upper-limb paresis is a frequent consequence of stroke [Rathore et al., 2002]. Despite spontaneous improvement of motor function, this impairment lingers at the chronic phase (~3 months post stroke onset), resulting in disabilities for around 40% of patients [Duncan et al., 2000].

Neuroplasticity, i.e., the ability of the brain to structurally adapt at the cellular, molecular and system levels in order to foster functional abilities – encompasses several mechanisms [Murphy and Corbett, 2009]. It leads to a very plastic functional cortical representation which can favour the improvement of functional outcomes. Underlying mechanisms include the functional use of pre-existing synaptic networks as well as structural changes, with the creation of new networks [Murphy and Corbett, 2009]. Hence, a crucial question for rehabilitation is how these mechanisms could be enhanced.

Post-stroke rehabilitation training procedures aim to improve recovery of deficiencies or to establish adaptive strategies in order to compensate for impaired body functions [Murphy and Corbett, 2009]. Among the different rehabilitation procedures of the upper-limb, the ones providing patients with sensory feedback (e.g., visual feedback based on mirror therapy) or somatosensory stimulation (e.g., transcutaneous electrical stimulation or neuromuscular stimulation) appear to be promising. On the one hand, mirror visual feedback[1] induces changes from molecular to anatomical and physiological levels associated with functional recovery. Indeed, it is known to increase neurons' excitability [Thieme et al., 2018], cortical reorganization in the primary motor cortex (M1) and to induce functional changes in somatosensory, premotor or higher-order visual areas [Fritzsch et al., 2014]. On the other hand, somatosensory stimulation improves motor function and the ability to perform activities for post-stroke patients [Conforto et al., 2018].

These therapies provide sensory feedback through afferent networks regardless of the voluntary activation of efferent sensorimotor networks. However, a co-occurrence of these synergistic networks seems to improve the outcome of the therapies [Pavlides et al., 1993].

Such co-occurrence is possible using BCIs [Clerc et al., 2016]. BCIs enable to provide the best time-matched sensory feedback depending on the motor cortex activity for post-stroke motor rehabilitation. Motor imagery-based BCI therapies seem to be more efficient in improving motor functions than motor imagery alone [Pichiorri et al., 2015] or proprioceptive stimulation alone [Biasiucci et al., 2018]. BCIs enable the online detection of the neuronal activity associated either with a motor imagery or attempted movement task (i.e., top-down processes) and then reward the patient by providing adapted feedback (i.e., bottom-up processes) [Grosse-Wentrup et al., 2011a]. BCI-based training promotes the activation of neural networks associated with movements and induces Hebbian plasticity, which underlies functional improve-

[1] Mirror visual feedback consists in positioning, with respect to a mirror, the arms of the patients in order for them to perceive their unimpaired limb in the position of the impaired limb, therefore providing the patients with the impression of two unimpaired arms.

ment [Grosse-Wentrup et al., 2011a]. For this application, the feedback is primordial to the therapy as it enables the co-activation of efferent motor systems and afferent sensory systems. It often represents the output of a classifier trained on EEG patterns and it is provided to post-stroke patients in controlled environments.

1.1.2 Communication with locked-in patients

The locked-in syndrome is characterised by a severe loss of voluntary muscular control, which resulted in limited or complete loss of the functional ability to communicate. However, patients retain their cognitive abilities and will to communicate [Vansteensel et al., 2016]. Often, such syndrome originates from brainstem stroke, but degenerative disorders such as Amyotrophic Lateral Sclerosis (ALS) can also lead to a similar state.

Preserving the ability of locked-in people to communicate is a priority as it correlates to their reported quality of life [Vansteensel et al., 2016]. When voluntary eye-movements are preserved, eye trackers can be used to control interfaces of communication. Such system present some limitations related to the context of use, e.g., lightning condition, and depend on remaining muscular control abilities [Vansteensel et al., 2016]. BCIs represent a new solution for locked-in patients to keep communicating. Vansteensel et al. worked with a late-stage locked-in patient with ALS who had implanted subdural electrodes placed over the motor cortex [Vansteensel et al., 2016]. When attempting to move the hand on the opposite side of the electrodes, the patient could control a spelling interface. On a spelling task, the letters were correctly spelled 89% of the time on average. The patient was able to type two letters per minute 28 weeks after having the electrodes implanted. Furthermore, the amount of cognitive load required to used the system diminished over time. Such results indicate that implanted BCIs might represent a reliable and ecological tool for home use autonomous communication. However, so far, there was no successful use of BCIs to communicate with complete locked-in patients. For this application, the feedback enables the communication of a woman with her surroundings. It depends on the amplitude of a specific feature acquired from implanted electrodes located over the sensorimotor cortex. The system is adapted on one specific user and designed for home-use, i.e., ecological context.

1.1.3 Controlling video games

Beyond the medical applications, BCIs represent a new tool for human-computer interaction [Lécuyer, 2016]. Recent technological advances enabled the development of low cost devices to acquire brain activity. These new devices do not enable the same quality of brain activity acquisition as medical devices. Though, this drop in the cost of access to the technology represents a necessary step toward its democratization. From 2009 to 2012, a large project called OpenViBE2, involving both industrial partners and research laboratories, explored the potential use of BCIs for video games [Lécuyer, 2016]. They did not consider that BCIs could replace traditional methods of interaction, e.g., joy sticks or mouse. BCIs might not be reliable enough to provide alternative interaction methods to the existing ones but they could supplement them. The game BrainArena developed by Bonnet et al. gives an example of a game relying on a mental-imagery based BCI [Bonnet et al., 2013]. This game is a simplified version of a football game. Players have to imagine right or left hand movements to move a virtual ball toward a goal located on the right or left side of the screen. Three different modes can be used: a single-user condition and collaborative or competitive condition. Passive BCIs could be used as tools to estimate the mental state, e.g., attention or workload, of the user and adapt the game accordingly [Lécuyer, 2016, Marshall et al., 2013]. For this application, the feedback has an entertaining purpose. It is most often based on the output of a classifier trained on EEG patterns.

1.2 Models of BCI training

The applications of BCIs, presented in the previous section, rely on the production of brain activity patterns that can be distinguished by the BCI system [Neuper and Pfurtscheller, 2009, Lécuyer, 2016]. However, the accuracy still has to be improved for the technology to undergo a strong growth outside of research laboratories [Lotte et al., 2013]. It is particularly true for applications dedicated to ecological environments, such as video game control or daily communication devices [Neuper and Pfurtscheller, 2009, Lécuyer, 2016]. Therapeutical applications such as post-stroke rehabilitation are often performed in a controlled environment. Though, applications such as video game or daily communication would be performed in an ecological environment where the brain activity can fluctuate unpredictably and where motor related artefacts are more frequent. The reliability of a system is one, if not the, most important acceptance factor for interactive device [Lotte et al., 2013, Lécuyer, 2016].

There are several lines of research aiming at improving the reliability of BCIs. Many of them focus on improving the acquisition and processing of the brain activity [McFarland and Wolpaw, 2018]. However, BCI applications also rely on users themselves. Indeed, on the one hand, the computer has to learn to discriminate the different brain-activity patterns for the tasks performed by a user. But on the other hand, the user has to train and learn how to produce a stable and distinguishable brain-activity pattern for each of the tasks in order for them to be recognized by the computer [McFarland and Wolpaw, 2018].

Two main approaches, that are not mutually exclusive, were explored to improve the BCI user training [Neuper and Pfurtscheller, 2009]. The first relies on operant conditioning to train the users to produce patterns of brain activity recognizable by the computer. The second relies on a machine learning approaches and provides the user with instructions of specific cognitive tasks, e.g., motor imagery, to perform. In the following subsections, two main BCI protocols for BCI user training based on either one of these approaches are presented.

1.2.1 The Wadsworth protocol

The Wadsworth protocol was used to successfully design one of the first BCIs that aimed at controlling an external device, i.e., a cursor on a screen [Wolpaw et al., 1991]. It is internally paced as users are given a specific and quite long period to learn to modulate their brain activity (asynchronous BCI). The aim of this protocol was initially to test if participants could learn to increase or decrease the amplitude of their sensorimotor rhythm μ (8-12Hz) recorded over their sensorimotor cortex [Wolpaw et al., 1991]. The users are not provided with any specific instruction on the type of mental imagery that they should perform.

During one of the first experiments, users had to control the position of a cursor [Wolpaw et al., 1991]. At the beginning of a trial, the cursor was placed at the center of the screen. A target, represented by a square, was located at the bottom or at the top of the screen. The cursor moved every 333ms toward or away from the target depending on the similitude between the current amplitude of μ and the goal amplitude determined by the experimenter. The system does not rely on the use of machine learning methods. Once the cursor had reached the target, a checkerboard pattern was displayed to indicate the success of the trial. After a little break, a new trial began with a new target appearing either at the bottom or at the top of the screen. Participants were instructed to make the cursor reach the target as fast as possible. Participants reported using diverse strategies such as motor imagery or relaxing to move the cursor up of down. However, such strategies did not seem to be necessary anymore with the progress of the training [Wolpaw et al., 1991]. A few days to several months are necessary for users to learn to control such BCI. Such types of protocol enabled participants to control a cursor in 1D [Wolpaw et al., 1991], 2D [Wolpaw et al., 2000b] and more recently in 3D [McFarland et al., 2010].

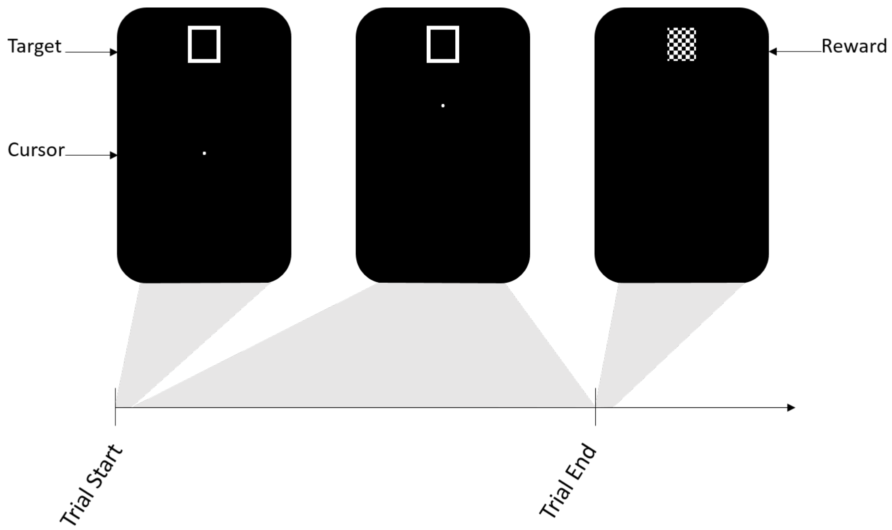

Figure 1.1: Graphical display of a trial from the "Wadsworth protocol".

1.2.2 The Graz-BCI standard protocol

The Graz-BCI standard protocol unfolds in two main phases (1) training of the system and (2) training of the user [Neuper and Pfurtscheller, 2009]. A number of tasks, often two or three, are pre-selected and explained to the user. Originally, the tasks consisted in imagining right or left hand movements [Pfurtscheller and Neuper, 2001]. First, the pre-existing modifications occurring in the brain activity of the users when they perform each mental imagery task need to be acquired to serve as reference to the BCI system. Therefore, during a first phase, the users must repetitively perform the different mental-imagery tasks in a cue-based mode while their brain activity is recorded. Using these recordings, the system extracts characteristic patterns for each of the mental tasks. These extracted features are then used to train a classifier, which has the goal of determining the class to which the signals belong to. During a second phase, the users are asked to perform the different tasks. While they perform the task, they are provided with a feedback regarding which task is recognized by the system and how confident the system is in its recognition.

The training is based on the notion of trials. Each trial is 8 seconds long. A trial starts when a cross is displayed on the center of the screen followed one seconds later by a short warning tone (beep). At 3 seconds, the users are provided with the instruction of the task that they have to train to perform. This instruction is provided in the form of an arrow pointing in the direction of the task to perform, e.g., left or right for respectively left or right hand movements. The arrow is displayed on the screen for 1.25 second and is then replaced by an horizontal feedback bar. The bar extends in the direction of the task that has been recognized. Its length represents the confidence that the system has in its recognition of the task.

The classifier can then be adjusted to adapt to (1) the modifications in the placement of the EEG cap, (2) the state of the user or (3) the modifications that resulted from the learning of the user. The user training relies on the adaptation of the activity patterns that are produced for each task so that they are better recognized by the classifier. If the patterns change, then the classifier might not be adapted anymore. However, if the classifier is changed, then the users might loose their ability to interpret the feedback. This conundrum was named the “man-machine learning dilemma” [Pfurtscheller and Neuper, 2001]. It is based on the fact that two entities that are strongly interdependent, the user and the system, must be trained independently. A compromise must be found between the adaptation of the classifier and the conservation of a feedback that users can interpret.

In this protocol, the training is externally paced (synchronous BCI). The users have to produce a specific mental state in response to an external event. Therefore, the time window containing the specific brain pattern of the command is known. Usually the training comprises several sessions. The time necessary for users to control the BCI is variable but a few sessions are usually required [Pfurtscheller and Neuper, 2001].

1.3 Is feedback necessary for BCI skills learning?

Augmented feedback is part of the very concept of mental-imagery based BCIs. The most commonly adopted definitions of BCIs include feedback as one of the main criterion. Pfurtscheller et al. provided four criteria that BCIs must fulfil, the fourth and last one is “the user must obtain feedback” [Pfurtscheller et al., 2010]. Both of the

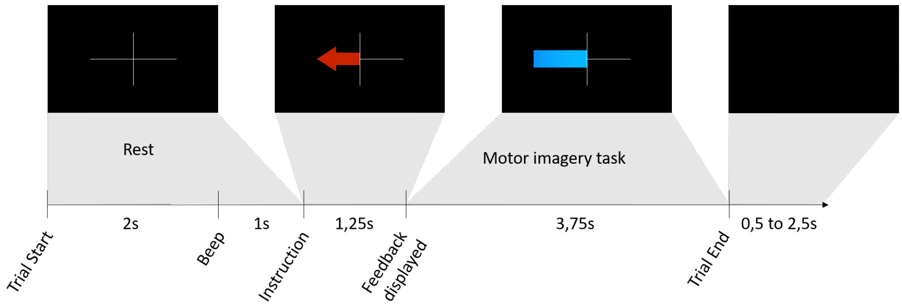

Figure 1.2: Typical graphical display of a trial from the “Graz-BCI protocol”.

training protocols presented in the previous section use feedback as an integral part of the BCI training. Sentences used in the articles of the field reflect this main role that feedback supposedly play for BCIs, such as “[...] a BCI system must provide feedback and must interact in a productive fashion with the adaptations the brain makes in response to that feedback.” [Wolpaw et al., 2002], “Learning to operate many BCI-controlled devices requires repeated practice with feedback and reward.” [Neuper and Pfurtscheller, 2009], “[Neurofeedback] has already proven successful in human subjects when used to train people to change a particular brain activity through feedback and reward (instrumental learning).” [Vaadia and Birbaumer, 2009] or “Visual feedback is the essential part of [EEG-based BCIs] training.” [Lebedev and Nicolelis, 2006].

The assumption that feedback is essential to the control of neurophysiological correlates dates back from the early days of BCIs. It might not have been founded on experimental results but it may be representative of the overall vision of the feedback, particularly the one conveyed by the behaviourist theory. This assumption that feedback is necessary probably reflects the operant learning principles that were supposed to be the foundation of BCI user training [Neuper and Pfurtscheller, 2009, Vidal, 1973]. Though, feedback may not only have beneficial impact on the user training. For instance, it can create modifications in the brain activity that might induce noise in the signal and lower the performances [Pfurtscheller and Neuper, 2001, McFarland et al., 1998], distract the learner from the task [McFarland et al., 1998], or solicit cognitive resources that are necessary for the performance of the tasks [McFarland et al., 1998]. In the current section, we assess if feedback really is necessary to learn to control ones’ own neurophysiological activity.

During a single session neurofeedback experiment, participants seem to be able to learn to up regulate their alpha band over their occipital cortex significantly better if a feedback is provided than if it is not [Plotkin, 1976, Beatty, 1972]. However, a study from Holmes et al. did find opposite results indicating that feedback has no impact on the production of alpha waves [Holmes et al., 1980]. For mental-imagery based BCIs, Roberta Carabalona trained 6 participants over a session first without feedback and then with a classical feedback of a bar continuously varying length [Carabalona, 2010]. Participants were instructed to perform mental imagery kinaesthetically. Overall, participants’ performances seemed comparable with and without feedback. When comparing the results intra-participants the feedback seemed to have a participant-dependent influence. Results were perfectly balanced: two participants add decreased performances, two had an increase of performances and two had the same performances. Further experiments with more sessions and more participants are needed to know if these results are sustained for long-term training.

The influence of the feedback was also assessed through the use of non-contingent feedback, or sham feedback, i.e., a feedback that mimics a realistic feedback but does not relate to the brain activity of the participant. The studies do not seem to reveal a placebo effect of feedback. The control gained over alpha production was found to be significantly positive with a contingent feedback and significantly negative or not significantly different with a non contingent feedback [Pressner and Savitsky, 1977, Beatty, 1972]. Ramos-Murguialday et al. compared the performances of healthy participants separated in three groups and receiving either contingent feedback regarding the desynchronization or synchronization of their sensorimotor rhythm or a sham feedback [Ramos-Murguialday et al., 2012]. They compared their BCI performances during motor imagery with and without feedback, proprioceptive stimulation, motor execution and rest. The feedback was provided using an orthosis. Participants were asked to perform kinaesthetic motor imagery tasks. They found a significant learning effect without feedback in the contingent group only indicating that feedback might not have to be provided during each trial. ERDs were higher when a proprioceptive feedback was provided than when it was not. Though, it did not lead to a higher classification accuracy. For all the tasks except the resting task, the group receiving contingent feedback had better performances.

Sham feedback was also used for control groups to assess the impact of BCI-based post-stroke motor therapies [Biasiucci et al., 2018, Mihara et al., 2013, Ramos-Murguialday et al., 2013, Wada et al., 2019]. All of the corresponding studies revealed functional motor improvements associated with significant neurophysiological changes for the experimental group receiving contingent feedback that were either not present, or significantly less important, for the control group receiving sham feedback [Biasiucci et al., 2018, Mihara et al., 2013, Ramos-Murguialday et al., 2013, Wada et al., 2019]. In neurofeedback, a feedback was found necessary to gain control over predefined neurophysiological characteristics [Caria et al., 2007]. Absence of feedback or feedback unrelated to the brain activity of the persons, e.g., feedback originating from a non targeted or another person's targeted cerebral area, did not elicit significant changes in the targeted neurophysiological data [Caria et al., 2007, DeCharms et al., 2005, Hamilton et al., 2011].

Interestingly, feedback might not be necessary once users have learned to control their brain activity [Kuhlman, 1978, Zotev et al., 2011]. In 1978, William Kuhlman trained epileptic patients over several sessions (over 4 to 10 months) to control their alpha and some beta rhythms (9-14Hz) acquired over the central area with the aim of reducing their number of seizures [Kuhlman, 1978]. Patients were not given any instruction on the type of task that they should perform. The training was divided into two or three phases depending on the responsiveness of the patients to the first phase of training. During the first phase, the patients received a non-contingent feedback based on their EEG acquired from another patient. Then, during the second phase, the patients received a contingent feedback. Finally, if the patients were responsive to the second phase, i.e., their number of seizures diminished, then the feedback was removed during a third phase. In this study, three patients out of five had a diminution of their number of seizures by 60% on average. This diminution was only observed when a contingent feedback was presented to the patients. The diminution of the number of seizures was still present during a third phase when the feedback was non-contingent. These results indicate that the patients might have learned from the feedback how to control their brain activity. Concurring results were found in neurofeedback by Zotev et al. They found that after one session of training to control hemodynamic activity of the amygdala (acquired using fMRI), the participants were still capable of modulating the target brain activity during a transfer run without feedback [Zotev et al., 2011]. Though, still in neurofeedback, Hamilton et al. found a contradictory result. After two sessions of down regulating activity in the subgenual anterior cingulate cortex (acquired using fMRI) using a contingent feedback, participants were not able to down regulate the targeted brain activity during a third session without feedback. This result indicates that the learning might be dependent on the feedback [Hamilton et al., 2011]. The results from McFarland et al. suggest that the effect of feedback vary across participants. After ten sessions of training using both a continuous feedback through a cursor movement and a feedback regarding the trial outcome (success or failure), they removed either or both of the continuous or discrete feedback intermittently and found that participants still had overall comparable performances in all conditions. The facilitatory or inhibitory effect of feedback varied across participants [McFarland et al., 1998].

The differential impact of feedback revealed in the previous studies might partly be explained by the use of instructions. Reward and instructions can be understood as part of the feedback. Instructions were shown to impact MI-BCI performances. MI-BCI performances were shown to be better when participants were asked to perform kinaesthetic motor imagery than when they were instructed to perform visual motor imagery [Neuper et al., 2005]. A prior demonstration of the task to perform might also have a beneficial impact. Kosslyn et al. asked their participants to imagine a wooden piece rotate [Kosslyn et al., 2001]. Before performing the task, all participants saw a wooden shape similar to the ones they would have to imagine rotating during the task. Participants either saw the piece of wood being rotated by an electric motor or had to rotate it themselves. They were instructed to imagine the object rotating similarly as they had seen the wooden piece rotate. Participants that had rotated the object themselves had their primary motor cortex activated but not the participants that had seen the motor rotating the object. Also, the prior visualization of 3D videos of movements from the viewer's perspective elicited significantly stronger ERDs in a following MI task without feedback than the prior visualization of a similar 2D video [Sollfrank et al., 2015]. Instructing participants to perform complex and familiar tasks may lead to more robust SMRs and increase classification accuracy [Gibson et al., 2014, Qiu et al., 2017]. If specific motor imagery instructions might be beneficial in short term, previous results from the literature tend to indicate that the learning curve could be more important when participants do not employ specific strategies [Kober et al., 2013].

Instructions are traditionally seen as necessary for BCI and neurofeedback training [Sepulveda et al., 2016]. Though, it is assumed that BCIs are based on operant conditioning based on the reports of neurofeedback on non-human animals [Neuper and Pfurtscheller, 2009, Vidal, 1973]. Based on this assumption, conscious strategies and explicit instructions may not be necessary and might even have a negative impact on the training [Kober et al., 2013, Witte et al., 2013]. The results of Sepulveda et al., assessed the impact of both reward and instructions in a neurofeedback study (based on functional Magnetic Resonance Imaging (fMRI)) with 20 participants, tend to confirm these hypotheses. They were distributed in four groups depending on if they received monetary reward and if they were given explicit instructions to perform motor imagery. All groups were able to up regulate the level of activation of the target supplementary motor area. Their results indicate that a monetary reward could have a beneficial influence on neurophysiological control. Though, explicit instructions to perform motor imagery did not seem to be necessary for neurofeedback training. This might implicate that feedback in neurofeedback and BCI training should be considered as a positive or negative reinforcer that conditions the behaviour of people through an iterative process [Sepulveda et al., 2016]. Another study from Caria et al. in neurofeedback, found that a feedback is necessary to gain control over predefined neurophysiological characteristics, even if instructions were provided [Caria et al., 2007]. However, the results Jackson Beatty and Holmes et al. for neurofeedback training of alpha rhythm tend to contradict these results. Jackson Beatty provided his participants with either prior instructions regarding the strategy to adopt during the task, a second by second neurofeedback, or both prior instructions and neurofeedback [Beatty, 1972]. The results obtained were comparable among the three different groups. Later, the results from Holmes et al. concurred with the ones of Jackson Beatty's and suggest that the control over the alpha rhythm was not dependent on the feedback but relied on the instructions given to the participants [Holmes et al., 1980].

Beyond the presence of instructions, the type of strategies that users employ might also impact feedback's efficiency [Carabalona, 2010]. Roberta Carabalona instructed her participants to perform mental imagery kinaesthetically. The two participants that had a decrease of performances with a feedback compared to when the feedback was present also had an increased of alpha power over the occipital cortex both with and without a feedback. This might indicate a higher cognitive load potentially associated with the strategies adopted by the participants or the amount of attentional process dedicated to the task.

In this section we analysed the influence of the feedback on MI-BCI training. We argue that the field would benefit from more studies comparing training with and without feedback and instructions. However, studies using non-contingent or sham feedback indicate that feedback has a beneficial impact on the training and on therapies outcome which does not seem to result from a placebo effect [Ramos-Murguialday et al., 2012, Ramos-Murguialday et al., 2013, Biasiucci et al., 2018]. Once, BCI-related skills are acquired, the feedback does not seem to be necessary anymore [Kuhlman, 1978, Zotev et al., 2011]. However, the long-term impact of feedback might vary across participants [McFarland et al., 1998]. The use of a feedback is most often rationalised by the fact that BCI learning is based on operant conditioning [Neuper and Pfurtscheller, 2009, Vidal, 1973]. Behaviourist theories have had a strong impact not only on the literature regarding neurofeedback but also feedback interventions in general [Kluger and DeNisi, 1996]. Analysing the literature on feedback intervention in other field might provide some relevant insights that could be transferred to BCIs.

1.4 What can we learn from other fields of research?

Feedback is of interest for numerous research fields such as education, industry or psychology [Kluger and DeNisi, 1996]. It is an important part of a training or teaching process. Having some feedback, intrinsic or augmented, is necessary for learning. Without any type of feedback, learners would not have any information to relate to in order to improve their performances. Bilodeau et al. wrote that feedback is “the strongest, most important variable controlling performance and learning” [Bilodeau and Bilodeau, 1961].

The most influential theory regarding the origin of feedback’s efficiency is the one developed by Thorndike in 1913 called the “Law of Effect”. Thorndike was a pioneer of behaviourism. Therefore, positive and negative feedback were assimilated to reinforcement and punishment. The theory states that both a positive or a negative feedback could have a beneficial impact on learning [Kluger and DeNisi, 1996]. A positive feedback should reinforce adequate behaviour and a negative one should limit the reproduction of an inadequate behaviour by punishing it. In other words, behaviourists consider contingent feedback as a necessary reinforcer or inhibitor for respectively desired or undesired behaviour. The parsimony of this theory is its main advantage and may explain why the theory has had a substantial impact on the research on feedback [Kluger and DeNisi, 1996].

In the beginning of the 20th century, early research on feedback were quite unanimous in suggesting that a feedback improved the learning [Kluger and DeNisi, 1996]. Though, most of these studies presented flaws. Some had methodology issues, e.g., lack of a control group. There was a lack for a standardisation of the definition of the term feedback. Others studies did not interpret or account for the negative impacts of feedback that were sometimes present in the result [Kluger and DeNisi, 1996]. Such research, as well as the review of Ammons [Ammons, 1956], contributed to the general opinion that feedback increases performances and motivation during training. This opinion was forged despite the presence of contradictory results in the literature [Kluger and DeNisi, 1996]. Indeed, if feedback is a prerequisite for learning, it does not imply that any feedback has always a beneficial influence on the learning [Kluger and DeNisi, 1996]. An augmented feedback might not be necessary or useful to improve learning. The behaviourist theory was amended by Kulhavy [Kulhavy, 1977] to take into account the fact that feedback can be accepted, modified, or rejected by the learner.

Feedback is necessary when essential intrinsic feedback is not provided during the training. It is also primordial when a new concept must be learnt and the learner does not have a reference on how to perform the task correctly, i.e., when “the learner lacks prior knowledge about the relationship between the goal of an action and the movement required” [Magill, 1994]. According to Magill [Magill, 1994], an external feedback might not be required when the task originating feedback does provide the learner with all the information needed to learn the skill. Feedback is only useful to the learners if they can interpret it into some corrections for the next trial of their training, i.e., if they can relate the new information provided by the feedback to their existing knowledge [Magill, 1994].

The relevance of an external feedback is assessed during the training. However, the performance should be evaluated with and without the external feedback to make sure that the skills were learnt and that the performances are not only the result of a dependence to the external feedback by the learner [Magill, 1994]. The development of a dependency is explained by the guidance hypothesis that states that a frequent feedback during the acquisition of a skill leads to a dependency on the feedback [Schmidt et al., 1989]. It can also be explained by the specificity of learning hypothesis. The latter states that during the training, the most relevant sources of feedback to perform the task are integrated. A dependency toward the augmented feedback occurs when the augmented feedback surpasses the relevance of the intrinsic feedback [Sigrist et al., 2013]. For instance, such dependency could occur if the informative aspects of the intrinsic feedback is not readily apparent to the learner and that the augmented feedback is easier to understand [Magill, 1994]. Because of the limited amount of cognitive resources available to process information, augmented feedback might hinder or even preclude the processing of the intrinsic feedback [Wickens, 2008]. The decrease of performances observed when feedback is withdrawn might be due to an unwanted change of task learned caused by the feedback. Instead of learning the targeted task, people learn to control the feedback, which involves different strategies.

These last paragraphs inform us that feedback can either be beneficial or detrimental to the learning [Magill, 1994]. Feedback is detrimental when it supplants the processing of intrinsic feedback, which is essential for learning [Annett, 1959]. Limiting the amount or variating the type (e.g., visual, verbal) or content (e.g., simple measure of performance) of external feedback might improve skill learning and be a solution to the dependency developed toward external feedback [Magill, 1994].

The "Law of Effect" theory does not account for the detrimental impact that feedback can have depending on the type of feedback that is used. Indeed, different types of feedback seem to have various impact on learning [Kulhavy, 1977, Hattie, 1999]. In the field of education, a meta-analysis of 74 meta-analysis papers of Hattie showed that the most effective types of feedback were cues, reinforcement, video or audio feedback, computer-assisted feedback and goal related feedback [Hattie, 1999]. Programmed instruction, praise, punishment and extrinsic rewards were the least effective to increase performances [Hattie, 1999]. The "Feedback Intervention Theory" (FIT) of Kluger and DeNisi [Kluger and DeNisi, 1996] is more extensive than the "Law of Effect" theory and is more consistent with the effects of feedback reported in the literature. It is based on the following five arguments: "(a) Behavior is regulated by comparisons of feedback to goals or standards, (b) goals or standards are organized hierarchically, (c) attention is limited and therefore only feedback-standard gaps that receive attention actively participate in behavior regulation, (d) attention is normally directed to a moderate level of the hierarchy, and (e) [feedback] change the locus of attention and therefore affect behavior" [Kluger and DeNisi, 1996].

Kluger and DeNisi [Kluger and DeNisi, 1996] propose to rely on the role of attention. It is based on the assumption that there is a hierarchy in the goals and standards associated to the task to learn. These goals can be positioned on a continuum ranging from the physical-action to the self. To quote an example of Kluger and DeNisi, a task can be both described as “reading words”, i.e., physical-action, and “investing in my scientific career”, i.e., self. Throughout a training, the level of perception of the task increases. As the realisation of the task becomes automatized, the attention of the learner can be on higher and self-related levels of action [Kluger and DeNisi, 1996].

The differential impact of feedback is also related to feedback’s interrelation with reward. Indeed, feedback can elicit extrinsic motivation, i.e., motivation to perform the task to receive a reward, e.g., money or social recognition, or avoid a punishment. Such extrinsic motivation can have a negative impact on short and long term intrinsic motivation, i.e., motivation to perform the task for one’s own sake, which has thereby a negative impact on the learning [Benabou and Tirole, 2003, Kluger and DeNisi, 1996]. The impact of a reward is limited to current performances, when withdrawn, the lack of reward may turn into a negative reinforcer. In their meta-analysis, Deci et al. found a negative correlation between extrinsic reward and task performance [Deci et al., 1999]. If the task was considered interesting or not the reward respectively undermined or improved the intrinsic motivation.

1.5 Conclusion

Brain-computer interfaces offer new medical and therapeutical applications as well as a new human-computer interaction method. The wider development of these applications mostly depend on the reliability of the system. The efficiency of BCIs relies on the independent training of the machine and the users, which are both interdependent. Improving the user training, during which the users learn to control their brain activity in order to produce patterns of brain activity that are increasingly recognizable by the BCI system, represents an opportunity to enhance the robustness of BCIs [Lotte et al., 2013]. Different traditional models of training exist. Both models that we presented concur on the aim of the users during the training. Usually, users have to learn how to move an element on a screen. This element is most of the time an extending bar or a moving cursor. Even though the feedback was central in the BCI user training from the beginning of the field, the fact that its characteristics could influence the efficiency of the training was not immediately investigated. One of the first to speculate the differential impact that neurofeedback has was Paul Tyson in 1982 who stated “the medium interacts with the message and may interfere with or enhance alpha training” [Tyson, 1982]. The assumption that feedback has a beneficial impact on learning might arise from the behaviourist theory, which was mainly used to explain the underlying mechanism of BCIs [Neuper and Pfurtscheller, 2009, Vidal, 1973]. Results from the literature indicate that a contingent feedback is necessary for acquiring control over a specific feature of the brain activity if no instructions are provided. Once, BCI skills are acquired, the feedback does not seem necessary anymore. The effect of instructions on BCI performances remains unclear. Long-term studies indicate that participants that learnt the most reported not using specific strategies in the end of the training. Further studies are needed to have a better understanding of the short and long term effects of feedback and instructions on the acquisition of MI-BCI skills. If providing instructions to the learners without any feedback is sufficient for a learning to occur, then we could assume that an intrinsic feedback related to the task exist, can be interpreted by novices and account for the improvement. If a feedback is necessary for a learning to occur regardless of the presence of instructions, two options seem possible. First, if experienced users do not need the feedback anymore to regulate their brain activity, then their might be an intrinsic feedback though it might not be interpretable by novice users. Second, if experienced users still need the feedback to regulate their brain activity, then their might not be any intrinsic feedback. The operant conditioning theory does not account for the variability in the results found in the literature. The BCI field is following the example of researcher on feedback who's vision evolved from the "Law of Effect" theory toward more complex ones such as the "Feedback Intervention Theory". Once acknowledged that the feedback can have differential impact on the learning, including negative impacts, then the characteristics of the feedback that favour the learning can be studied. This is what we offer to do in the following chapter.

Chapter 2

Which feedback have been used?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - Can a physical learning companion be useful for mental-imagery based BCI user training?
	5. **Contribution 2** - Do experimenters influence MI-BCI training?
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

While it is recognized that feedback can improve learning, its effects are variable [Carabalona, 2010]. These variations in the efficiency of the feedback have notably been associated with the different features of feedback. Many researchers have attempted to clarify which features enhance its positive effect [Bonnet et al., 2013, Jeunet et al., 2015b, Mladenović et al., 2017]. We focused on three questions which, once answered, should enable the main characteristics of the feedback that is currently used in BCI user training to be defined. First, in Section 2.1 we report which information the feedback does provide to the learner during MI-BCI user training. Current feedback convey information regarding the performances of the learner. The definition of these performances and their informative value to the learners are explored. We also assess the impact of the social presence and emotional feedback that can be conveyed throughout BCI training. Second, in Section 2.2, we wonder how these information are and should be presented to the users. Several modalities of feedback have been explored. We present their different advantages and disadvantages. Finally, in Section 2.3, we inquire when feedback is presented. The aim of this chapter is to provide an overview of the different types of feedback that have been used in BCI, but also in neurofeedback and other fields, discuss their impact on BCI user training and present the theoretical background behind the experimental studies that were led during this thesis.

2.1 Content of feedback - Which information does feedback provide?

A feedback can be characterized depending on the information that it conveys. In this section we distinguish two types of information that the feedback already conveys during mental-imagery based training. First, we focus on the information provided to the learner regarding their BCI performances. Then, we explored the emotional and social dimensions of the feedback. We present the current knowledge we have on their impact on the user training.

2.1.1 Feedback of results

The feedback provided to the users during MI-BCI training is currently oriented toward the “Knowledge of results”, also called evaluative feedback, i.e., an output measure regarding the achieved value or the deviation from the desired value. Mostly, the feedback used in MI-BCI represents the classification accuracy (CA), i.e., the percentage of mental commands that are correctly recognized by the system [Jeunet et al., 2016b, Lotte and Jeunet, 2018]. Classifiers provide a binary output depending on if the task performed by the user has been correctly or incorrectly recognized. It does not provide information regarding why the task has or has not been recognized and how to improve the performances. Research on skill learning in other fields inform us that a knowledge of results is particularly useful to skilled learners who already have sufficient cognitive model of the task to interpret the feedback into the necessary corrections to make to their behaviour [Magill, 1994].

A feedback of results can be composed of either or both positive feedback, i.e., when there is a match between the instruction and the task recognized by the system, and negative feedback, i.e., when there is no match and the system failed at recognizing the task performed by the learner. Participants trained with both negative and positive tactile feedback reported that a negative feedback disrupted their performance of the task [Cincotti et al., 2007]. Though, it was never found to have a negative impact on classification [Cincotti et al., 2007, Leeb et al., 2013]. Using only positive feedback can bias the perception of the learners. Indeed, without any negative feedback learners that do not know how BCIs work might not understand that the machine has not recognized their task. This might lead them to believe that they did better than they actually did. The performances seem to be enhanced if a positive feedback is provided [Kübler et al., 2001, Faller et al., 2012]. Positively biasing the feedback, i.e., artificially increasing the performances of the user, seems beneficial for new or inexperienced BCI users, but harmful for advanced BCI users [Barbero and Grosse-Wentrup, 2010]. The beneficial impact of a positive bias could be related to an increase of immersion and motivation [Barbero and Grosse-Wentrup, 2010, Mladenović et al., 2017].

Some studies have been led in order to enrich the traditional evaluative feedback. [Kaufmann et al., 2011] proposed a richer "multimodal" feedback providing information about the task recognized by the classifier, the strength/confidence in this recognition as well as the dynamics of the classifier output throughout the whole trial. Sollfrank et al. chose to add information concerning the stability of the EEG signals to the standard feedback based on CA [Sollfrank et al., 2016], while Schumacher et al. added an explanatory feedback based on the level of muscular relaxation to this CA-based feedback [Schumacher et al., 2015]. This additional feedback was used to explain poor CA as a positive correlation had been previously suggested between muscular relaxation and CA. Finally, [Zich et al., 2015] provided learners with a 2-dimensional feedback based on a basketball metaphor: ball movements along the horizontal axis were determined by classification of contra- versus ipsilateral activity (i.e., between the two brain's hemispheres), whereas vertical movements resulted from classifying contralateral activity of baseline versus MI interval. By adding some dimensions to the standard CA-based feedback, these feedback provided more information to the learner about the way to improve their performance.

Nonetheless, all of them are still mainly based on the CA, which may not be appropriate to assess users' learning [Lotte and Jeunet, 2017]. The CA has been used to characterise both the machine and user learning [Lotte and Jeunet, 2018]. Though, it may not reflect properly successful EEG pattern self-regulation. First, because the CA is dependent on the classifier and on the data that were used to train the classifier [Lotte and Jeunet, 2018]. Using a different type of classifier or using different data to train the classifier will lead to a different estimation of the user's performances and skills. Therefore, variations of this metric might not reflect users' performances or learning. Second, classifiers are trained to recognized patterns of activation produced at a specific period of training. The training of users should lead to a change in these patterns of activation. Therefore, with the progress of the training, the classifier might not be adapted to recognize the new patterns of activation. To solve this issue the classifier is retrained or adapted, often every session, to take into account the difference in the user's state and in the position of the EEG cap. Though, changes of classifier lead to difference in the feedback. Users would have to learn to interpret this new feedback, which might impede the learning. This challenge of training independently the human and the machine that are interdependent is called the "man-machine learning dilemma" [Pfurtscheller and Neuper, 2001] (see Section 1.2.2 The Graz-BCI standard protocol).

Lotte and Jeunet tried to conceptualise BCI users' skills through this sentence: "MI-BCI skills correspond to the ability of the user to voluntarily produce brain activity patterns that are distinct between mental tasks, and stable within mental tasks, so that they can be translated reliably and consistently into control commands. The more stable and distinct the brain activity patterns, the higher the MI-BCI skill." [Lotte and Jeunet, 2018]. Based on this definition, they propose several new metrics aiming at better evaluating the BCI users' skills [Lotte and Jeunet, 2018]. These metrics offer new insight on the distinction of the EEG patterns produced for each task, how distinct they are from the resting state and how stable they are. A first evaluation of these metrics based on the analysis of previous experimental results, indicate that these new metrics could supplement the classification accuracy to have a better understanding of the user training. These results need to be replicated. Once these new metrics are validated, new experiments using them as informative feedback to the users should be performed.

Regardless of the metric used to provide feedback, users might not be able to translate the latter into relevant strategies to improve their performances. Feedback providing such specific information on how to improve the results are described as oriented toward a "Knowledge of performances". Such feedback is not provided in current MI-BCI trainings. In Section 9.3.1 Toward a supportive feedback oriented toward a knowledge of performances, we argue for the use of such feedback, present the different challenges that need to be overcome in order to do so, as well as potential solutions to overcome these challenges.

2.1.2 Social presence and emotional feedback

2.1.2.1 Current knowledge regarding social presence and emotional feedback for learning

Emotions were shown to have a significant impact on learning from a theoretical, practical and neurophysiological point of view [Meyer and Turner, 2002, Bower, 1981]. Emotions are encoded in memory with the feedback that is provided and influence its recall. For instance, Bower has shown that emotions were encoded as part of the recalled event in memory. This association leads to a difference in recall depending on the emotional context during encoding and recall of memories. Memories associated to a particular emotion are better recalled when feeling the same emotion [Bower, 1981]. Conversely, memories encoded with a particular emotion are less recalled when feeling a different emotion [Bower, 1981]. Emotional events are better remembered than non emotional events [Levine and Pizarro, 2004]. Unexpected and high emotional intensity events are encoded in memory with much more details and lead to long term memories with photographic accuracy [Levine and Pizarro, 2004]. Memories associated to high emotional states might keep a greater consistency over time [Levine and Pizarro, 2004]. From a neurophysiological point of view, the amygdala was shown to mediate the memorisation of event depending on their emotional value [Levine and Pizarro, 2004].

Specific emotions are associated with different contexts of elicitation, which are also associated with differential motivations, information-processing strategies and problem-solving strategies. Positive emotions are usually felt when goals are reached and no urgent problem needs to be solved. Therefore, the general goal of happy people would be to maintain this situation. Happy people are likely to give more importance to a wide range of information from their environment, to rely more on general knowledge and effortless heuristics to process information [Levine and Pizarro, 2004]. Positive emotions, induced by emotional support, can also result in increased creativity and flexibility during a problem solving task [Isen et al., 1987]. Negative emotions, however, arise from situations where there is an immediate threat or when we fail. It was shown that people feeling negative emotions pay attention to less information from there surroundings, focusing on elements that would improve the situation and prevent the situation from occurring again [Levine and Pizarro, 2004]. They are prone to effortful processing, careful and systematic analysis of information [Levine and Pizarro, 2004]. Therefore, as emotions influence our motivations, information-processing strategies and problem-solving strategies, they should be leveraged to improve the effectiveness of a feedback. Not to forget that emotions focus the attention toward the relevant elements of the environment that are necessary to respond to the emotional situation [Levine and Pizarro, 2004]. People in different emotional states probably pay attention to different aspects of feedback. For example, Levine and Pizarro conjecture that people who are afraid pay more attention to threats and means to avoid them. Though, anger caused by an obstacle to reach a goal, could lead people to be more aware of goal related information and to the agent causing the impediment [Levine and Pizarro, 2004].

To our knowledge, the supportive dimension, that includes social presence and emotional support, has been very little formally investigated in the context of MI-BCI user-training. Nijboer et al. showed that mood, assessed prior to each BCI session (using a quality of life questionnaire), correlates with BCI performances [Nijboer et al., 2008]. Some BCI experiments provided emotional feedback using smiling faces to indicate the user if the task performed had been recognized by the system [Kübler et al., 2001, Leeb et al., 2007]. While associated with good performance and user experience, neither of these studies offered a formal comparison with a standard feedback. Recently, Zapala et al. did formally compare the use of a smiley over a plain ball but did not find any difference of performances or control over SMR between the two groups [Zapała et al., 2018]. A similar study, led in neurofeedback by Mathiak et al. [Mathiak et al., 2015], showed that providing participants with an emotional and social feedback as a reward enabled better control than a typical moving bar over the activation of the dorsal anterior cingulate cortex (ACC) monitored using fMRI. The feedback consisted of an avatar's smile, whose width varied depending on the user's performance. The better the performance, the wider the smile. This type of feedback can be considered as both emotional and social because of the use of an avatar.

The use of social feedback in BCI has been encouraged in several papers [Sexton, 2015, Lotte et al., 2013, Mattout, 2012, Kleih and Kübler, 2015]. The work of Izuma et al. showed that a social feedback can be considered as a reward just as much as a monetary one [Izuma et al., 2008]. Yet, the influence of a reward has already been demonstrated in BCI. Indeed, it has been shown that a monetary reward can modulate the amplitude of neurophysiological activities, including those involved during MI-BCI [Sepulveda et al., 2016, Kleih et al., 2011]. However, researches about the use of a social feedback in BCI remain scarce and often lack of control groups. One of the main original purposes of BCI was to enable their users to communicate. Some researchers have created tools to provide such type of communication in social environments, e.g., Twitter [Edlinger and Guger, 2011]. Though, no comparison was made within equivalent non-social environments. Studies from Bonnet et al., Obbink et al. and Goebel et al. presented games where users played in pairs collaborating and/or competing against each other [Bonnet et al., 2013, Obbink et al., 2011, Goebel et al., 2004]. Bonnet et al. showed that when playing a MI-BCI video game, a 2 players condition improved the user experience, in particular fun and motivation, compared to a single-user condition [Bonnet et al., 2013]. It could even improve the performance of the best-performing participants [Bonnet et al., 2013]. This reinforces the idea that a social presence is useful in MI-BCI. Providing emotional support and social presence seems to be a very promising approach for improving MI-BCI training both in terms of performance and user experience. Indeed, in most training protocols, MI-BCI users go through their training alone, in front of a computer for often an hour or so. They lack support, which is essential for maintaining motivation and acquiring skills [Meyer and Turner, 2002]. This analysis of the literature led to the contribution presented in Chapter 4 where we present the result of the design, implementation and test of the first learning companion dedicated to providing social presence and emotional feedback during MI-BCI user training.

2.1.2.2 Role of experimenters

Experimenters are currently the main source of social presence and emotional feedback during MI-BCI training. In one of the first papers on neurofeedback, reporting results on participants controlling alpha rhythms, Nowlis and Kamiya hypothesised that a bias arising from the experimenter could have influenced their performances [Nowlis and Kamiya, 1970]. However, experimenters' implication in the training is rarely reported in MI-BCI papers. Previous results showed that experimenters can influence the user-experience of their participants by manipulating their expectations. Pressner and Savitsky reported that modification to the mood, supposedly originating from the control over alpha production through neurofeedback training, were not associated with the presence of a contingent feedback but with the expectancy of their participants that the training would result in a positive or negative experience [Pressner and Savitsky, 1977]. Also, in a recent neurofeedback study, Wood and Kober found that women participants trained by women experimenters did not learn to up-regulate their sensorimotor rhythm power and theta/beta power. However, the other groups of participants formed using the gender of participants and experimenters did learn [Wood and Kober, 2018]. They found a strong positive correlation between the locus of control in dealing with new technologies and the learning outcome for women participants trained with women experimenters. Their results suggest that stereotypes/psychosocial factors could have an impact on neurofeedback and maybe on BCI user training.

Experimenter related biases are an important concern in numerous other fields of research such as ethics and business [Miyazaki and Taylor, 2008], social research [Rosnow and Rosenthal, 1997], biology [Warren II et al., 2017] or economic research [Zizzo, 2010]. Rosenthal, who was part of the first to stress the importance of studying the influence of experimenters, describes experimenters as “imperfect tools” [Rosenthal, 1963]. Indeed, the literature from different fields states that experimenters may consciously or unconsciously affect their results. Experimenters can influence participants’ responses, behaviour and performances via direct and/or indirect interactions [Rosnow and Rosenthal, 1997].

Unexpected effects can arise from psychosocial factors. Stereotypes seem to have a very important impact on test performances, mostly when the test is difficult [Spencer et al., 1999]. Stereotyped person tend to behave in a stereotype-consistent way [Wheeler and Petty, 2001]. For example, elderly people tend to walk more slowly or to have impaired memory performances if they feel stereotyped [Wheeler and Petty, 2001]. It is hypothesised that the stress of possibly being judged or of self-fulfilling a stereotype adds an extra pressure to the participant that may interfere with the results obtained [Spencer et al., 1999]. The “stereotype threat theory” was developed by Steele [Steele, 1997]. It states that negatively stereotyped people under-perform on tests and that this decrease is modulated by a threat-like feeling felt by the stereotyped person. Such undermining effect of stereotype was found for cognitive test administered by a white person to someone of colour [Steele and Aronson, 1995]. In this case, coloured people were conscious about this stereotype threat. The difference in performance vanishes when a coloured experimenter administers the test [Marx and Goff, 2005]. Experimenters can modulate the impact of the stereotype by acknowledging the fear of the person and explicitly stating that the object of the stereotype does or does not influence the results of the experiment [Spencer et al., 1999]. Much cultural stereotypes are gender-based. One of which is that women have weaker math abilities. In a first experiment, Spencer et al. have asked a highly selected sample of men and women to perform difficult maths tests and found that women did underperform compared to men. In a second experiment they either told participants that gender was shown to have an impact on the performances or that it was not. When being told that the test was shown to have gender-dependent results, women greatly underperformed in comparison to men. Though, when women were told that the results were gender-independent, men and women had similar performances [Spencer et al., 1999]. Several other cases of results modulated by psychosocial factors exist. A pain-related study, showed that men participants tend to report higher cold pressure pain to a man experimenter than to a woman one [Levine and De Simone, 1991]. A more recent study, which replicated the results, found no interactions in the physiological data depending on experimenters’ and participants’ gender [Aslaksen et al., 2007]. These results suggest that men participants reporting lower pain to women experimenters is probably due to psychosocial factors. Another similar study found that the professional status of the experimenter also has an influence on the report and tolerance of pain [Kállai et al., 2004]. Participants that were tested by a professional experimenter tolerated pain for a longer time than the participants tested by a student experimenter. Furthermore, stereotypes are not always negative. For example, elderly people can be considered as wise [Wheeler and Petty, 2001]. Interestingly, stereotypes can also be activated by people that do not fit the stereotype characteristic. For instance, college students can start walking more slowly if an elderly stereotype is activated for them [Wheeler and Petty, 2001]. The "ideomotor theory" is based on a behavioural priming effect and better explains these other influences of stereotypes. Activated stereotypes do not always lead to a behavioural assimilation of the stereotype [Dijksterhuis, 2001]. Concretely, when activated, the stereotype primes the behaviour of the person, which is then more likely to be performed. However, this theory does not explain why in few cases, the activation provokes the opposite behaviour as the one from the stereotype [Wheeler and Petty, 2001]. This seems mostly true for activation of stereotypes in people not belonging to the targeted stereotyped group [Wheeler and Petty, 2001].

Therefore, stereotypes can influence experimental results. Experimenters through their own characteristics, such as their gender, age, race or professional status, can modulate this stereotype-related influence [Rosenthal, 1963]. Stereotypes regarding scientists might also influence the results of participants [Quick, 1971]. This influence could be modulated by participants' gender and attitude toward the subject of research [Quick, 1971].

"Experimenter outcome-orientation bias" occurs when the expectancy and motivation of experimenters to obtain specific results becomes determinant in the findings of those results [Rosenthal, 1963]. Rosenthal et al. asked thirty experimenters to have participants rate the success or failure potential of people using their pictures only [Rosenthal, 1963]. While all experimenters gave the same instructions to their participants, their expectations regarding the overall rating they should obtain were artificially biased. Experimenters were either told that they would have high or low ratings. The results from the two groups of experimenters were significantly different and tended to confirm the bias that experimenters had. This bias of expectations regarding the participants might also arise from the expertise developed by experimenter throughout their previous experiments [Rosenthal, 1963].

The "experimenter demand effect" bias, which can occur when participants unconsciously try to fit the appropriate image reflected by the experimenter's behaviour and therefore want to please and assist the experimenters in obtaining their expected results, is related to the "experimenter outcome-orientation bias" [Rosnow and Rosenthal, 1997]. The way experimenters convey their expectancy remains unclear. It might arise from verbal or non-verbal conditioning of the experimenter, that would subtly reinforce target behaviour(s) of the participants [Rosenthal, 1963]. Participants react to the behaviour, e.g., gaze and touch, and emotions of the experimenter [Kleinke, 1977, Exner Jr and Erdberg, 2005]. For instance, based on the interpretation of inkblots, it seems that when experimenters are anxious, participants tend to be more responsive to their expectations [Exner Jr and Erdberg, 2005]. Also, overtly hostile experimenters seem to elicit stereotyped, passive and less hostile responses [Exner Jr and Erdberg, 2005].

Figure 2.1 represents different mechanisms of bias that could originate from experimenters.

In conclusion, social presence and emotional feedback are also called supportive feedback, as they are meant to increase the effort, motivation and engagement of the participants throughout the learning. As any feedback, they must be carefully studied as they can be double-edged. They can benefit the learning outcome [Nijboer et al., 2008, Mathiak et al., 2015]. These benefits might depend on the profile of

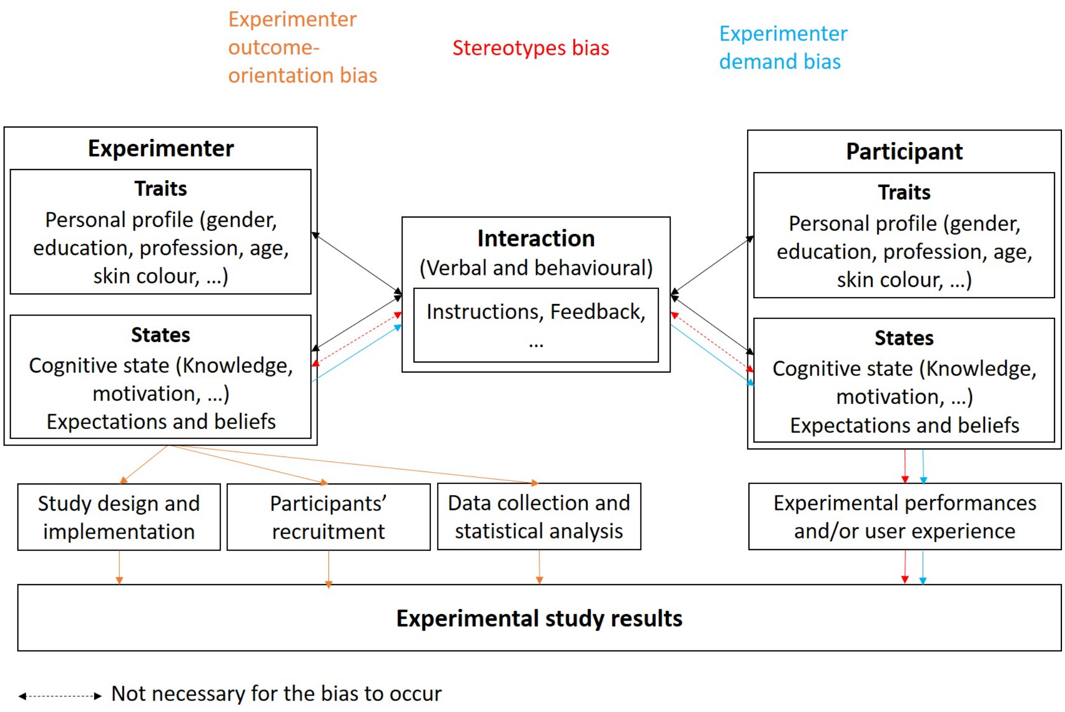

Figure 2.1: Sources of bias that might arise from the experimenters, participants and their interaction during an experimental study.

participants [Bonnet et al., 2013]. Such feedback, as any feedback, can have a detrimental impact on the user training and the reliability of experimental results when it is incorrectly designed and assessed [Wood and Kober, 2018]. This motivated the study that we report in Chapter 5 regarding the influence of the interaction between participant's and experimenter's gender on BCI performances and user experience.

2.2 Feedback modality - How is the feedback presented?

The impact of feedback does not only depend on its content, but also on how this content is presented to the learner. Augmented feedback is provided through external sources or displays, e.g., visual, auditory or haptic displays. Currently, visual stimuli are the most common type of feedback, most probably because vision is the sense on which daily life perception relies the most. The optimisation of the feedback through the adaptation of its modality has been a subject of investigation in several fields such as motor training or rehabilitation [Sigrist et al., 2013, Huang et al., 2006]. Motor skill related studies provide very relevant insights on the type of feedback to use depending on the type of training [Sigrist et al., 2013]. The complexity of the motor task to learn, as well as the skills of the learner, have a main influence on the type of modalities to favour [Sigrist et al., 2013]. The more complex a motor task is and the more effective should be the use of a multimodal feedback [Sigrist et al., 2013]. Feedback modality has an impact on the dependency that learner might develop over a feedback [Ronsse et al., 2010]. Ronsse et al. asked their participants to learn how to perform a complex hand coordination task while being provided with either a visual or an auditory feedback. They found that participants provided with visual feedback were dependent on the latter but not the participants provided with an equivalent auditory one. They hypothesised that a dependency was developed toward the visual feedback because its relevance eclipsed the intrinsic feedback. Thus, only the augmented feedback, and not the intrinsic feedback, was taken into account during the training. When the augmented feedback was removed, the participants trained with visual feedback had less knowledge than the ones trained with auditory feedback to interpret their intrinsic feedback. Their study also provides insights on the neurological correlates of this dependency. fMRI results post-training revealed that when participants performed the task without feedback, only participants presented with visual feedback had an activation of sensory areas associated with visual feedback presentation despite the removal of the visual feedback [Ronsse et al., 2010]. The characteristics of the modality of presentation, e.g., the salience, also have an impact on feedback effectiveness. For example, the presentation of a visual feedback with a weak salience, i.e., contrast, enabled a better learning outcome than a visual feedback with a good contrast and no visual feedback at all. It is hypothesised that lowering the contrast diminishes the relevance of the feedback. Consequently, the intrinsic feedback was still processed during training as it remained relevant enough and no dependency toward the visual feedback was developed [Robin et al., 2005].

Current MI-BCI and neurofeedback training mostly rely on visual feedback [Cincotti et al., 2007, Neuper and Pfurtscheller, 2009]. Though, in an ecological setting, visual resources dedicated to vision, visual attention or gaze focus, would be engaged by the interaction with the environment. For example, when controlling a wheelchair, a great amount of visual resources are dedicated to the monitoring of the surroundings. Visual resources might also be solicited by the mental imagery task, specially if the person performs visual, and not kinaesthetic, motor imagery. Using a visual feedback could result in an over solicitation of visual resources that could lead to a high cognitive load and to a decrease of MI-BCI performances [Carabalona, 2010]. Also, visual abilities of people that could benefit from MI-BCI could be impaired. Therefore, along with visual feedback, the use of auditory and tactile feedback or a combination of them have been tested. Modalities of presentation do vary depending on the application of the training. For example, motor rehabilitation mostly focused on visual and somatosensory feedback while locked-in patients, who are no longer able to focus their gaze, can be provided with auditory feedback [Cervera et al., 2018, Hinterberger et al., 2004]. Regardless of the modality of feedback used to convey the feedback, the “Control-display mapping”, i.e., a spatial and non spatial congruence between the task that users are asked to perform and the feedback that they receive, is important. It enables a faster response times, fewer errors and more efficient task completion [Thurlings et al., 2012]. It was also associated with lower cognitive load and higher user satisfaction [Thurlings et al., 2012]. For example, when asked to imagine a right hand movement, providing a feedback on the right hand is considered as congruent whereas providing a feedback on the left hand would be considered as incongruent. In the following paragraphs, we will describe the results obtained with training using either unimodal or multimodal feedback presented on the visual, tactile and/or auditory modalities.

2.2.1 Abstract to realistic and embodied visual feedback

Usually feedback are visual ones (see Section 1.2 Models of BCI training for more information regarding standard training protocols). Traditionally, the feedback is provided in the form of either an extending bar, a cursor movement or a moving object whose trajectory must be controlled [Neuper and Pfurtscheller, 2009]. While this representation is easy to implement and intuitive, it is often boring and may result in a decrease of motivation [Lotte et al., 2013, Jeunet et al., 2015b]. The improvement of visual feedback has been the subject of numerous studies.

When performing mental imagery, several strategies can be adopted. For example, imagining playing piano or imagining waving at someone would be two strategies for performing motor imagery. Imagining an apple rotating about a vertical axis or a cube rotating about an horizontal axis are two examples of object rotation strategies. Most often, participants are instructed to explore different mental imagery of their choice. Though, classical training feedback, such as extending bars, are not congruent with the mental image of the participants, i.e., image of an object or a body part. This disparity between the feedback and the strategy adopted by the participants could limit the efficiency of the feedback [Alimardani et al., 2018]. Increasing the congruency between the mental task performed by the participant and the feedback seems to be a way of improving feedback. When considering motor imagery, the reference for a motor imagery strategy is the corresponding motor execution. Motor action and mental imagery of the same movement lead to similar cortical activation [Jeannerod, 1994]. Neuroimaging studies found that combining motor imagery and action observation can induce stronger neurophysiological response than either one of those tasks alone [Sale and Franceschini, 2012]. Mirror neurons, associated with high-level of information such as goals and intentions, have been associated with this increase in neurophysiological activity [Alimardani et al., 2018].

Congruent realistic visual stimuli were explored as a way to improve the relevance of a feedback for a motor-imagery task. A congruent realistic visual stimulus of a body part could increase the sense of agency, imagined kinaesthetic sensations and sense of embodiment [Alimardani et al., 2018]. Sense of embodiment arise from the feeling of ownership and control felt by a person toward an external device. This embodiment is supposed to promote higher sense of agency, i.e, feeling of control over the result of our actions, and intrinsic motivation. EEG correlates of this sensation of embodiment were found in the mu-band over the fronto-parietal cortex by Evans and Blanke [Evans and Blanke, 2013]. Ono et al. compared the learning outcome of four groups training over five sessions with either no feedback, a classical bar varying length or a realistic hand performing hand grasping movement either congruently placed over the arms or incongruently placed at eye level. They found that the group with congruent feedback had the best performances and the smallest variability between participants [Ono et al., 2013]. Feeling of embodiment seems correlated with MI-BCI performances [Alimardani et al., 2016]. Embodiment and short term motor-imagery skills learning is increased when positive bias is added to the feedback [Alimardani et al., 2016]. In the short term, the more realistic the feedback is, the greater the embodiment and motor-imagery performances seem to get [Alimardani et al., 2016]. This influence of the congruence of the feedback might explain why Neuper and al. did not find differences of performances between one group training with a realistic visual feedback of a grasping hand and the other group with an abstract moving bar. Indeed, the realistic visual feedback was non congruently placed at eye level. Both groups had significantly lower ERD during feedback presentation compared to a pre-session without feedback, which indicates that both groups did learn to produce the target brain activity [Neuper et al., 2009].

The complexity of the feedback might also have an impact [Leeb et al., 2007, Zapała et al., 2018, Scherer et al., 2008, Sollfrank et al., 2016]. Participants seem more inclined to continue the training if the environment is visually more complex [Leeb et al., 2007]. A more complex visual feedback was also shown to increase the performances [Zapała et al., 2018, Sollfrank et al., 2016]. Using game-like, 3D or Virtual Reality do also represent opportunities to increase users' engagement and motivation [Ron-Angevin and Díaz-Estrella, 2009, Lécuyer, 2016, Marshall et al., 2013]. It was hypothesised that gameplay mechanisms, i.e., methods of interaction used in video games, should be applied to MI-BCI training [Marshall et al., 2013]. For instance, the complexity of the interaction with the BCI could be progressively increased to enhance the user experience by avoiding frustration and increasing motivation [Marshall et al., 2013]. These researches promote creating feedback more immersive and attractive.

Other studies investigated new ways of providing some task specific and more tangible feedback. Frey et al. and Mercier et al. created tools using augmented reality to display the user's EEG activity respectively on the head of a tangible humanoid called Teegi (see Figure 2.2) and superimposed on the reflection of the user [Frey et al., 2014, Mercier-Ganady et al., 2014].

Figure 2.2: User visualizing his brain activity using Teegi [Frey et al., 2014].

Regardless of the realism of a visual feedback, it can be improved by increasing its salience, i.e., the importance of the feedback compared to surrounding stimuli. The salience of an element can be manipulated to focus the attention of the participant on the relevant elements of a visual display of the feedback [McLeod et al., 1991]. Zapala et al. compared the use of a blinking ball (at a 4Hz frequency) to a non-blinking ball to provide feedback to their participants [Zapała et al., 2018]. They found no differences in performances between the two groups. Though, participants trained with the blinking ball had a significant decrease in SMR rythm (β band) during right hand MI after training compared to before the training and to participants trained with a non-blinking ball. They hypothesised that the flashing might have, as expected, focused the attention of the participants on the ball though it might also have caused fatigue [Zapała et al., 2018].

2.2.2 Tactile to somatosensory feedback

Tactile and somatosensory feedback, through the use of vibrotactile stimulation, functional electrical stimulation (FES), orthosis/exoskeleton or vibrations on the muscles and tendons were used for BCI user training. Tactile and somatosensory feedback are provided through the somatosensory system. The somatosensory system is part of both the central and peripherical nervous system (i.e., muscles, joints, skin and fascia). It transmits and processes the somatosensory extrinsic and instrinsic information regarding touch, pressure, pain, temperature, position, movement and vibration.

Initial research on somatosensory feedback focused on tactile feedback through the use of vibrotactile motors. Visual and auditory cues are easily perceived by surrounding persons. In comparison, a tactile feedback enables a higher level of privacy [Jeunet et al., 2015b]. In interactive situations the tactile modality is also less overtaxed than visual and auditory ones. Thus, providing feedback through the tactile modality could be more ecological and limit the cognitive overload of MI-BCI users [Jeunet et al., 2015b]. Vibration variations of intensity, spatial location or patterns of stimulation, e.g., wave or square forms, can be used to convey information to the learner.

Different sensitivity over vibrotactile stimulation were found depending on the location of the stimulation on the body, the age of the person and the frequency of stimulation [Cincotti et al., 2007]. See the articles from Cincotti et al. and Jeunet et al. for an analysis of the type of vibrotactile characteristics [Cincotti et al., 2007, Jeunet et al., 2015b]. Cincotti et al. notably recommend to use vibrating frequencies between 50 to 300Hz, on body location where there is no bones directly below the skin [Cincotti et al., 2007]. Errors in detecting positions and intensities of stimuli seem related to respectively close positions and intensities of stimulation [Cincotti et al., 2007]. Jeunet et al. found that a vibration of 40Hz to 60Hz was most appropriate for stimulations on the palm of the hand [Jeunet et al., 2015b]. They also found that when vibration actuators were activated one by one, instead of simultaneously to create the illusion of continuity in the sensation, people found the feedback more pleasant and distinguishable.

Compared to a simple visual feedback, a continuous vibrotactile haptic feedback, provided on the neck, the neck and forearms or on the palm of the hands, does seem to be just as efficient in terms of increase of neurophysiological response and performance improvement [Cincotti et al., 2007, Gwak et al., 2014, Lukoyanov et al., 2018]. Stimulations on the wrist or fingers, do not seem to have an impact on the performances, despite the higher density of mechanoreceptors on the fingers than on the wrist [Missiroli et al., 2019]. Wider and more stable ERDs were however observed when the stimuli were finger-located [Missiroli et al., 2019]. Comments from participants indicate that a tactile feedback felt more natural [Cincotti et al., 2007]. Even though the performances post training with visual and vibrotactile feedback seem similar, haptic feedback could interfere with the motor imagery task, especially when providing negative feedback during misclassification [Cincotti et al., 2007]. The real benefit from tactile feedback compared to visual feedback seems to arise when the visual attention or cognitive load is high [Cincotti et al., 2007, Jeunet et al., 2015b, Gwak et al., 2014]. When the visual modality is highly solicited, providing tactile feedback can remove the overload present when a visual feedback is provided and decrease the amount of false positive rate [Gwak et al., 2014]. Jeunet et al., compared a simple continuous (4Hz) visual feedback, i.e., extending bar, to an equivalent tactile feedback, i.e., vibrotactile sensations on hands' palm, in a multitask context with visual distractors. They found that visual and tactile feedback led to comparable user experiences and that both enabled control of the MI-BCI. Though, the performances were significantly better with the tactile feedback [Jeunet et al., 2015b]. The risk of using actuators is that they could interfere with the EEG signals. Cincotti et al., report detecting vibrotactile responses on averaged signals with actuators located on the shoulders [Cincotti et al., 2007]. Though, they do not report any interference with their classification accuracy [Cincotti et al., 2007]. The differences between visual and tactile feedback were only studied over one session [Cincotti et al., 2007, Gwak et al., 2014, Lukoyanov et al., 2018, Jeunet et al., 2015b]. Even though no studies reveal any desensitisation over one session, a long term use of a tactile feedback could lead to a decrease in the perceived intensity of the feedback. The evolution of the influence of a tactile feedback over more sessions would be necessary to validate the adaptability of a tactile feedback. This led us to the proposition of the experimental contribution reported in Chapter 7, were we evaluated the long term influence of a vibrotactile feedback and realistic visual feedback in comparison with a realistic visual feedback only.

Another type of vibrating stimulation enables a proprioceptive stimulation. Non-invasive proprioceptive stimulations based on patterns of vibration applied over muscle tendons enable creation of the illusion of movement without people moving [Roll and Gilhodes, 1995]. Such a method was already proven to be relevant for providing feedback during MI-BCI user training [Leonardis et al., 2012, Barsotti et al., 2017]. In addition to the difference of price and size, a main advantage of a kinaesthetic vibratory feedback is that it would probably be safer to use for a wider range of patients. Indeed, kinaesthetic vibratory feedback would not require any real movement from the patient to create afferent somatosensory stimulation [Schröder et al., 2018].

As proprioceptive sensations are essential to motor planning, control and adaptation, somatosensory feedback has mostly been used for motor rehabilitation purposes. Two methods, i.e., functional electrical stimulation (FES) and orthosis/exoskeleton, have mostly been tested to artificially move a limb of the patient while the latter imagines or tries to perform a movement [Ang et al., 2015, Frolov et al., 2017, Biasiucci et al., 2018, Li et al., 2014]. Proprioceptive feedback seems more efficient that a realistic visual feedback for post-stroke motor rehabilitation [Ono et al., 2014]. Ono et al. compared two groups of six patients with severe motor hemiplegia. One group trained with a realistic visual feedback and the other group trained with a somatosensory feedback conveyed by an orthosis extending the fingers of the patients. Only patients on the group training with somatosensory feedback presented functional motor improvements post-training [Ono et al., 2014]. Because this experiment included only a few participants, further studies are needed to confirm this result. However, studies on neurotypical participants tend to confirm that result by demonstrating that proprioceptive feedback has a better influence on MI-BCI user training than a visual feedback. For instance, a functional electrical stimulation increased the learning curve of two healthy participants out of three compared to a classical abstract feedback [Bhattacharyya et al., 2016]. It was also found to be more motivating than the visual feedback [Bhattacharyya et al., 2016]. Also, a proprioceptive feedback, conveyed using an orthosis, was found more effective than a visual feedback to control beta-ERD during kinaesthetic motor imagery neurofeedback training of neurotypical participants [Vukelić and Gharabaghi, 2015]. This increase was associated with greater connectivity between the beta-band activity of the bilateral fronto-central regions and theta-band activity of the left parieto-occipital regions [Vukelić and Gharabaghi, 2015].

2.2.3 Auditory feedback

Early neurofeedback research usually used auditory feedback to train participants to modulate their alpha rhythms [Hart, 1968, Tyson, 1982]. Hinterberger et al. compared the use of an auditory, a visual and a multimodal feedback composed of both visual and auditory feedback over a training to regulate SCP amplitude during three sessions [Hinterberger et al., 2004]. The performances with an auditory feedback were significantly worse than with a visual feedback.

The first study to evaluate the feasibility of an auditory feedback for MI-BCI user training was led by Nijboer et al. in 2007 [Nijboer et al., 2008]. It was one of the first studies to assess the impact of the modality of feedback on MI-BCI user training. They focused on auditory feedback because complete locked-in patients often have compromised vision and may not benefit from a visual feedback. However, their auditory abilities are usually uncompromised. They compared the performances of two groups training either with visual or auditory feedback during three sessions. The results are in accordance with the ones of Hinterberger [Hinterberger et al., 2004]. The performances with the auditory feedback were significantly worst than the ones of the visual feedback during approximately the first half of the training. The learning curve was overall positive for the group trained with auditory feedback and neutral or slightly negative for the group trained with visual feedback. Some participants training with visual feedback seemed to have decreasing motivation over the training. It is possible that the auditory feedback requires more attentional resources than a visual feedback [Nijboer et al., 2008]. McCreadie et al. also found consistent results [McCreadie et al., 2014]. When people train with auditory feedback, they tend to begin with lower performances and steadily increase their performances over time. When they train with visual feedback, they initially tend to have decreasing performance but then tend to improve. No statistical difference were found between performances associated with visual and auditory feedback. The type of auditory feedback, i.e., mono, stereo or 3D, does not seem to have an impact on the performances [McCreadie et al., 2014].

Overall, these results indicate that an auditory feedback can be an alternative to a visual one. However, it might take a few sessions to reach performances equivalent to a visual feedback.

2.2.4 Multimodal feedback

In everyday life, the brain relies on information arising from multiple senses which often complement and confirm each other. This redundancy increases the degree of confidence associated with the perception [Stein and Meredith, 1993]. Just as a congruency between the task and the feedback modulates the learning outcome [Thurlings et al., 2012], in a multimodal feedback a between-feedback congruency is necessary [Jeunet et al., 2015b]. The integration of the multiple and incongruent sources of information can increase the amount of cognitive load and errors [Thurlings et al., 2012]. Sense of ownership over a body part of our self depends on the integration of multiple exteroceptive and interoceptive sources of information. One can expect that a feedback provided on different modalities would increase this sense of embodiment and the agency over the feedback.

Using a virtual visual feedback in addition to a proprioceptive stimulation did not elicit significantly higher illusion of movement [Leonardis et al., 2012]. However, a higher classification accuracy was obtained when both visual and proprioceptive feedback were used conjointly in comparison with a visual feedback alone [Leonardis et al., 2012].

Other studies concur with the result that using both visual and somatosensory feedback has a beneficial impact on the BCI user training [Gomez-Rodriguez et al., 2011, Darvishi et al., 2015]. For instance, using a proprioceptive feedback, through the use of an orthosis, in addition to a simple visual feedback was found to significantly increase the BCI performances [Gomez-Rodriguez et al., 2011, Darvishi et al., 2015] and the information transfer rate, i.e., the number of correct detections of the user's mental state per second or minute [Darvishi et al., 2015] compared to a simple visual feedback alone. Also, the use of a proprioceptive stimulation method based on vibration patterns in addition to a realistic visual feedback led to higher classification accuracy and more stable ERDs than a realistic visual feedback alone [Barsotti et al., 2017].

BCIs providing multimodal feedback composed of both visual and somatosensory stimulations can also improve the functional motor abilities of post-stroke patients [Ang et al., 2014, Wada et al., 2019]. Though, research outside of the BCI field indicate that the characteristics of the sensory stimulation can modulate the impact on motor rehabilitation [Cameirao et al., 2012]. For example, Cameirao et al. found that the rehabilitation outcome is greater when using an haptic stimulation (force-feedback) than when using a somatosensory (exoskeleton) stimulation in addition to a virtual visual stimulation. They hypothesised that the limit in the kinematics of the movements imposed by the exoskeleton was limiting the development of compensatory strategies and thereby the rehabilitation.

Results regarding the influence of a multimodal feedback composed of both auditory and visual stimuli are less conclusive than the ones regarding visual and somatosensory stimuli. When comparing an auditory and visual feedback jointly or separately, Hinterberger found that a multimodal feedback composed of both visual and auditory feedback showed the smallest learning effect [Hinterberger et al., 2004]. This result indicates that combining modalities might impede the learning. The competition between the different modalities for attentional resources might limit the benefits of the feedback. Contradictory results were found by Sollfrank et al. who performed an experiment comprising five sessions of training and found no real influence of a multimodal visual and auditory feedback on performances compared to a the visual feedback alone. However, participants reported that the multimodal feedback seemed more helpful, more motivating and less frustrating compared to unimodal feedback [Sollfrank et al., 2016]. Gargiulo et al. found that the level of expertise might have an impact on the influence of the modalities of feedback. They compared the performances of experienced and naive participants over one session when they trained first with a simple visual feedback, i.e., moving ball, and then with the same feedback with an auditory feedback in relation with the position of visual feedback on the screen [Gargiulo et al., 2012]. They found that the modality of feedback did not have any impact on the performances of already experienced participants. Two-third of naive participants had slightly better performances with the multimodal feedback than with the visual feedback. Auditory feedback could limit the frustration associated with the lack of control of a visual feedback [Gargiulo et al., 2012].

2.3 Feedback timing - When and how often is the feedback be provided?

In addition to the content and the modality of presentation of the feedback, the timing of its presentation leads to a differential impact on the learning outcome. The field of motor skill learning provides relevant information regarding the timing of feedback. For instance, the amount of feedback received does correlate with learning but without a strong association between the two variables [Magill, 1994]. The complexity of the task influences the frequency of the data that should be provided. The more complex a task is, the more frequent the feedback should be [Baca, 2008]. Though, a frequent feedback can have a negative impact on the retention of the learning [Baca, 2008, Winstein and Schmidt, 1990]. Indeed, the amount of dedicated cognitive process to analyse the feedback increases with the amount of feedback provided [Baca, 2008]. A feedback can be considered too frequent when it causes a significant increase of workload forcing the learners to ignore the intrinsic feedback and causing a dependency toward the feedback [Magill, 1994].

The question of when the feedback should be provided is related to the frequency but also has an independent answer. Experiments in motor skill learning indicate that, compared to a continuous feedback provided after each trial, a discrete feedback summarizing the performances of several trials, might be more efficient to retain learning and minimise the risk of dependency toward the feedback [Baca, 2008]. Indeed, delaying feedback is leaving time to the learner to self-estimate their performances. It enables the development of self estimation of error detection abilities and corrective behaviour, which diminishes the risk of a dependency toward the feedback [Sigrist et al., 2013]. Though, a discrete feedback does not prevent a dependency effect [Sigrist et al., 2013]. Also, beginner learners might not have the ability to evaluate the target behaviour and thus might not be able to self estimate their error [Sigrist et al., 2013]. When learners do not yet have the ability to assess their performance in regard to the goal, then a continuous feedback is more effective [Sigrist et al., 2013]. A continuous feedback provided during a performance should be the most effective as it enables a comparison between the intrinsic feedback originating from the performance of the task and the feedback [Magill, 1994]. The shorter the delay, the better learners may be able to relate the feedback to their own actions and intrinsic feedback [Baca, 2008]. Therefore, the shorter the time is between the feedback and the task, the better should be the learning. Furthermore, a continuous feedback attracts an external focus of attention, which was found to benefit the learning by promoting an automatisation of the task, particularly for motor learning [Sigrist et al., 2013]. It can also prevent a cognitive overload due to the presence of too many information arising from the task by stressing out the relevant information for the task and simplifying a complex task [Sigrist et al., 2013]. The frequency of the feedback should decrease with the increasing skills of the learners [Sigrist et al., 2013].

Self paced feedback could be a compromise between continuous and discrete feedback. It enables learners to ask for a feedback whenever they feel is necessary. The involvement of the learner in the learning process leads to an increase of intrinsic motivation [Wulf, 2007]. Self paced feedback was shown to be more effective than imposed feedback in motor learning [Sigrist et al., 2013]. It is even more effective when learners decide prior to performing a trial when to receive the feedback rather than after [Sigrist et al., 2013]. Learner tend to request feedback after good trials, when feedback provides a positive reinforcement and enhances motivation [Sigrist et al., 2013].

The analysis of the literature from other fields provides quite relevant informations. For instance, it indicates that the frequency of the feedback could be related to the attentional state of the users. A frequent feedback could lead to an increase in the attentional resources needed to process it. If the frequency is too high for the limited cognitive abilities to process it, then a decrease in performances is to be expected [Magill, 1994]. These findings led us to make a first experimental contribution toward assessing attentional states during BCI training. We report this contribution in Chapter 8.

The feedback is a consequence of the performance of the learner. It is provided to the learner at a certain frequency. This frequency depends on the amount of acquired data related to the performance of the learner. For BCI, the amount of data depends on the sampling rate of the neurophysiological method used to record the brain activity from the participant. Most often, it ranges from hundreds to thousand of data per second in EEG to under ten data per second in fMRI. The feedback is based on a sample, or window, of these EEG data. The feedback is considered discrete, or terminal, if it is provided at the end of one or several trials. The feedback is considered continuous, or concurrent, if participants receive information during the trial, while they perform mental imagery task. Based on the review of the literature on motor skills learning, it can be hypothesised that an excessive guidance could be detrimental to the learning outcome during BCI user training [McFarland et al., 1998]. It was also hypothesised that feedback should follow as fast as possible the detection of a mental state [McFarland et al., 1998]. A continuous feedback seems more efficient for BCI user learning than a discrete feedback [Neuper et al., 1999]. However, continuous visual feedback might have a differential impact on the learners [McFarland et al., 1998]. To our knowledge, the first paper reporting the assessment of the influence of the feedback for neurofeedback was written by Joseph T. Hart and published in 1968 [Hart, 1968]. Joseph T. Hart trained his participants to up regulate their alpha rhythm during ten sessions, sessions one and ten did not comprise any feedback regardless of the group that the participants belonged to. The participants were divided into three groups depending on if they received feedback for each trials and sessions, each trial only or each session only. Their results indicate that feedback provided for each trial is more effective and even more if it is combined with a feedback at the end of the session. However, some participants that only received feedback at the end of the sessions did learn to increase their alpha.

To infer the task that the learner is performing, a window of neurophysiological recording is considered. The accuracy of the feedback depends on the length of this window. The bigger the window is and the lower the signal-to-noise ratio gets enabling a better accuracy of the feedback [Grosse-Wentrup et al., 2009]. Though, the bigger the window is and the more delayed the feedback gets. The decision-speed represents the time needed for the user to send a command through the BCI. A trade-off must be made to maximise the accuracy of the feedback without delaying the feedback too much [Grosse-Wentrup, 2011]. This trade-off might vary depending on the application. Indeed, if the aim is to reliably control a wheelchair or prosthesis, minimizing the errors is more important than the speed of the system [Krausz et al., 2003]. However, if the aim is to spell as fast as possible, then the decision-speed is important and the errors do not have a critical impact [Krausz et al., 2003]. The information transfer rate measures this trade-off. It corresponds to the number of correct detection of the user's mental state per second or minute. An equation to compute the information transfer rate was proposed by Wolpaw et al [Wolpaw et al., 2000a]. They reported a maximal transfer rate between 5 to 25 correct detection per minute at best. Krausz et al. investigated which could be the maximal transfer rate of four paraplegic participants [Krausz et al., 2003]. In this protocol, the decision-speed corresponds to the length of the trial. A ball is progressively falling throughout the trial. The aim of the participant was to imagine two movements between right hand, left hand and feet movements to control the horizontal direction of the ball so that it reached a target located on the bottom right or left of the screen. The speed of the falling ball could be modified by the experimenters. They found that best performers could reach the target in 2 seconds with only one second of feedback with 15 to 28% of offline errors. The maximal transfer rate was between 8 to 17 correct detection per minute. A physiological limit associated with the production of alpha rhythm seemed to limit the transfer rate [Krausz et al., 2003]. We argue that such measure should be used more often to assess the difference between feedback.

A short delay between the task and the feedback might be even more important for motor skill learning, particularly in the context of post-stroke motor rehabilitation. Indeed, post stroke rehabilitation is based on the co-activation of the efferent motor system and the afferent somatosensory system. Such paired associative stimulation causes long-term potentiation neuroplasticity [Stefan et al., 2000] and improved functional recovery [Biasiucci et al., 2018]. It was shown on healthy participants that the shorter the delay was between an afferent somatosensory stimulation (i.e., low-frequency median nerve stimulation) and a transcranial magnetic stimulation, the more plasticity was observed in the motor cortex [Stefan et al., 2000]. Darvishi et al., explored the impact of a lower feedback frequency (<100ms) than previous studies (200-300ms) on a single-case study of a chronic post-stroke patient with upper-limb motor impairments trained during 10 sessions. They provided the patient with somatosensory stimulation using an orthosis [Darvishi et al., 2017]. The experiment led to a clinically significant motor improvement of the patient (increase of the ARAT score by 13 points) which seems to indicate that a low feedback frequency is applicable.

Bandwidth feedback, i.e., feedback provided only when the error in performance exceeds a certain threshold are encouraged for motor learning as they foster effective behaviour [Sigrist et al., 2013]. Such feedback could be interesting to use for BCIs. Neurofeedback already use thresholds to detect mental state and provide feedback [Kober et al., 2013]. Though, setting the threshold is difficult. A threshold placed too low might reward the learner for non effective corrections and is more subject to noise in the intrinsic feedback. However, a high placed threshold might be detrimental to the motivation of the learner.

2.4 Conclusion

In this chapter, a review of the different feedback that are currently used for BCIs, neurofeedback and other fields, such as motor skill learning, is made. Three main characteristics of feedback are successively considered.

First, we focused on the information that feedback conveys, i.e., the content of feedback. The general literature regarding feedback reveals that to be effective, the content of feedback should be directive (indicating what needs to be revised), facilitative (providing suggestions to guide learners) and should offer verification (specifying if the answer is correct or incorrect). These different features increase the motivation and the engagement of learners [Williams, 1996, Hattie and Timperley, 2007, Ryan and Deci, 2000]. As already underlined in [Lotte et al., 2013], classical BCI feedback satisfies few of such requirements. Generally, BCI feedback are not explanatory (they do not explain what was good or bad nor why it is so), nor goal directed and do not provide details about how to improve the answer. Moreover, they are often unclear and do not have any intrinsic meaning to the learner. For example, BCI feedback is often a bar representing the output of the classifier, which is a concept most BCI users are unfamiliar with. Also, despite recommendations from the literature [Sexton, 2015, Lotte et al., 2013, Mattout, 2012, Kleih and Kübler, 2015], emotional feedback and social presence have received little attention for MI-BCI user training. We argue that the influence of more complex forms of emotional feedback and social presence, such as the one provided by the experimenter, should be assessed. In Part II, we provide two contributions aiming at assessing the influence of two complex forms of social presence and emotional feedback. First, in Chapter 4, we report the results of the design, implementation and test of the first learning companion aiming at providing social presence and emotional feedback during MI-BCI training. Second, in Chapter 5, we report the results of an experiment to evaluate the influence of the experimenter's and participant's gender on MI-BCI performances.

Second, the modality of feedback presentation is investigated. Most feedback are currently provided through the visual modality using moving objects or extending bars for a majority of studies. Realistic visual feedback was used to improve the sense of embodiment and agency over the feedback [Ono et al., 2013, Alimardani et al., 2016]. More complex forms relying on video games, 3D or virtual reality also seem promising to improve the intrinsic motivation and attractiveness of the user training [Lécuyer, 2016, Marshall et al., 2013]. However, visual feedback might not be adapted to ecological conditions of use where visual cognitive resources will most likely already be solicited by other tasks [Carabalona, 2010, Jeunet et al., 2015b]. Several modalities have been explored depending on the aim of the training, e.g., post-stroke motor rehabilitation, and sensory abilities of potential end users, e.g., locked-in patients. A vibrotactile feedback seems as effective as a visual equivalent [Cincotti et al., 2007, Gwak et al., 2014, Lukoyanov et al., 2018]. The benefit of using a tactile feedback arise when the visual modality is overloaded [Jeunet et al., 2015b, Cincotti et al., 2007, Gwak et al., 2014]. However, the long term effects of a vibrotactile feedback remained unknown. Proprioceptive feedback seem more efficient that a visual feedback [Vukelić and Gharabaghi, 2015, Bhattacharyya et al., 2016], which is particularly relevant for post-stroke motor rehabilitation [Ono et al., 2014]. Auditory feedback was also considered for applications with locked-in patients who often have a compromised vision that would probably impede the benefit of a visual feedback [Nijboer et al., 2008]. Auditory feedback seem to be have a worst influence on the initial performances compared to a visual feedback [McCreadie et al., 2014, Nijboer et al., 2008]. Though, after a few sessions of training, the performances with visual and auditory feedback seem comparable [McCreadie et al., 2014, Nijboer et al., 2008]. Multimodal feedback composed of both visual and auditory stimuli do not seem more efficient than a unimodal visual feedback either [Sollfrank et al., 2016, Gargiulo et al., 2012]. However, a multimodal feedback seems preferable to an equivalent visual one when considering somatosensory feedback [Leonardis et al., 2012, Gomez-Rodriguez et al., 2011, Darvishi et al., 2015, Barsotti et al., 2017]. In Part III, we report one theoretical and one experimental contribution regarding the adaptation of the modality of feedback. In Chapter 6, we state that even though sensory abilities of the end-user population are often taken into account, the somatosensory abilities of post-stroke patient were almost not assessed in previous randomized controlled BCI studies for post-stroke motor rehabilitation. In Chapter 7, we compared the long term influence of a multimodal feedback composed of both a realistic visual and vibrotactile stimuli and an unimodal one with realistic visual stimuli only.

Third, we investigated when feedback should be presented. A continuous feedback is theoretically and practically more recommended [McFarland et al., 1998, Neuper et al., 1999]. Short delays between the performance of the task and the presentation of a feedback seem preferable for the user to associate their behaviour to the corresponding performance. A trade-off must be found between the reliability of the information provided to the learner and the frequency of presentation of such information [Grosse-Wentrup et al., 2009, Wolpaw et al., 2000a, Krausz et al., 2003]. The result of this trade-off depends on the application considered for the BCI. Results from other fields indicate that the attentional state is impacted differently depending on the frequency of the feedback. In Part IV, we made a first experimental contribution toward assessing the attentional state during MI-BCI training.

Currently, feedback is often compared to simple and traditional forms of visual feedback. This is a first step toward a comprehensive view of the impact of the different characteristics of feedback and their interaction. Future studies should provide more information on how combining the different characteristics of feedback influence the user training. Our analysis of the literature reveals that the impact of the characteristics of feedback often vary depending on the participants. The level of expertise of the participants could have an impact on the type of modality of feedback to favour [Gargiulo et al., 2012]. We believe that adapting the feedback to the profile of the user would enable improvement of the user training. Understanding, who benefits the least from the current training might provide us with some relevant information on how to improve the training.

Chapter 3

Who benefits from the feedback?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - Can a physical learning companion be useful for mental-imagery based BCI user training?
	5. **Contribution 2** - Do experimenters influence MI-BCI training?
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

The previous chapter informed us that learners have specific profiles and potential specific needs regarding the type of feedback that they should be provided with. Identifying which are the characteristics of the learners that already benefit from the feedback might enable us to (1) better understand the underlying mechanisms of BCI user training and the role of feedback, (2) better understand the variability in performances between-studies and between-participants found in the literature and (3) better adapt the training to the users. It has been the subject of several studies [Kleih and Kübler, 2015, Jeunet, 2016, Jeunet et al., 2016c, Kadosh and Staunton, 2019]. First, we present traits, defined by [Chaplin et al., 1988] as "stable, long-lasting, and internally caused" characteristics of a person, that were shown to impact BCI performances. Second, we present states, defined by [Chaplin et al., 1988] as "temporary, brief, and caused by external circumstances", that were shown to influence BCI performances and how they can be monitored using physiological sensors [Kleih and Kübler, 2015, Jeunet et al., 2015a, Kadosh and Staunton, 2019].

3.1 Influence of learners' traits

First, we focused on the learners' traits. Inspired by the models proposed in [Batail et al., 2019] and [Jeunet, 2016], we subdivided the factors influencing the neurofeedback/BCI user training into four categories: (1) task-specific factors, (2) cognitive and personality traits (3) demographic and experience related factors and (4) technology acceptance related factors.

3.1.1 Task-specific factors

Task-specific factors are related to the tasks that the users are asked to perform to control the BCI. In our case, the users are asked to perform mental imagery tasks, e.g., motor imagery or mental rotations. Identified task-specific factors are encompassed in spatial abilities, i.e., ability to produce, manipulate and transform mental images. Spatial abilities were often found to be predictors of mental-imagery based BCI user performances [Jeunet et al., 2017]. Higher spatial abilities are often associated with higher MI-BCI performances. Two main spatial abilities can be distinguished, mental imagery and visuomotor coordination abilities.

The first spatial ability is *mental imagery*, separated into mental rotation and motor imagery. Mental rotation scores, i.e., ability to imagine a three dimensional object rotating in space [Vandenberg and Kuse, 1978], were shown to strongly and positively correlate with the performances of a BCI based on three mental imagery tasks, i.e., mental rotation, mental subtraction and left hand movement imagery [Jeunet et al., 2015a, Lotte and Jeunet, 2018]. This result was replicated in an experiment with a BCI based on only motor imagery tasks [Jeunet et al., 2016a]. Motor imagery, the ability to imagine movements, encompasses two components. One is the visual component, when people visually picture themselves or someone else performing a movement. The other is the kinaesthetic component, when people associate somatosensory sensations to their representation of the movement [Liepert et al., 2016]. Previous results on neurotypical participants regarding the impact of visual and kinaesthetic abilities on motor imagery based BCI training are not conclusive. Two validated questionnaires exist to assess visual and kinaesthetic imagery abilities. The Kinaesthetic and Visual Imagery Questionnaire (KVIQ) [Malouin et al., 2007] and the Motor Imagery Questionnaire Revised-Second Edition (MIQ-RS) [Loison et al., 2013]. Vuckovic et al. found that offline performances when classifying right versus left hand motor imagery tasks were strongly correlated to the kinaesthetic imagery score of the KVIQ [Vuckovic and Osuagwu, 2013]. Also, the representation of subjective behaviours of the MIQ-RS was found to be a predictor of MI-BCI performances [Marchesotti et al., 2016]. Recently, higher kinaesthetic imagery abilities of participants were associated with a higher similarity between ERD occurring during executed movement and kinaesthetic imagination of the same movement [Toriyama et al., 2018]. However, Rimbert et al. did not find any correlation of the MIQ-RS scores with MI-BCI performances when classifying resting state versus right hand motor imagery, using visual feedback during the training [Rimbert et al., 2017]. The type of classification performed (i.e., right vs left hand [Vuckovic and Osuagwu, 2013, Marchesotti et al., 2016] and right or left hand vs rest [Rimbert et al., 2017]) or the number and placement of the electrodes (16 electrodes placed over the sensorimotor cortex [Vuckovic and Osuagwu, 2013, Marchesotti et al., 2016] and 32 electrodes placed over both the sensorimotor cortex and the parietal cortex [Rimbert et al., 2017]) may explain the differences observed.

The second spatial ability is *visuomotor coordination abilities*, i.e., the ability to synchronize visual information with movements to coordinate future action. Motor-skill learning is dependent of these abilities. Hammer et al. found that visuomotor coordination abilities, measured using the Two-Hand Coordination Test, could predict 11% of the variance of MI-BCI performances over 83 participants [Hammer et al., 2012]. This result was replicated in 2014 [Hammer et al., 2014]. These results are in accordance with the theory that neurofeedback training is similar to motor-skill learning [Hammer et al., 2012]. Though, these results could not be replicated by Botrel and Kübler [Botrel and Kübler, 2019]. They also did not find any impact of training participants' visuomotor coordination abilities on their subsequent BCI performances [Botrel and Kübler, 2019]. New experiments with a greater number of sessions could be more representative of the learning occurring during BCI user training [Benaroch et al., 2019].

3.1.2 Cognitive and personality traits

One of the main influences reported in the literature is the one of attentional traits and states on BCI performances [Kleih and Kübler, 2015, Kadosh and Staunton, 2019, Jeunet et al., 2016c]. Daum et al. found that patients with epilepsy that had longer digit or block-tapping spans had greater control over the slow cortical potential based BCI [Daum et al., 1993]. Patients with better verbal memory had a higher learning rate than the others [Daum et al., 1993]. The degree of concentration (assessed with the Attitudes Towards Work) was also found to predict 19% of the variance of MI-BCI performances [Hammer et al., 2012]. The attentional impulsivity measure, representing learners' ability to focus their attention, was also found to be correlated with MI-BCI performances [Hammer et al., 2014].

Several personality factors, assessed using the 16PF5 questionnaire [Cattell and P. Cattell, 1995], were found to be correlated with mental imagery based BCI performances [Jeunet et al., 2015a]. The more tensed, impatient and frustrated the participants were and the worst their performances were. The self-reliance, i.e., the ability of people be autonomous in their learning, was also positively correlated with BCI performances. Finally, the abstractedness ability, i.e., the creativity and imagination ability, was also positively correlated with mental imagery based BCI performances [Jeunet et al., 2015a]. Also, active learners, that prefer testing and discussing information to transform it into knowledge, seem to have better performances than reflective learners, that prefer examining introspectively the information [Jeunet et al., 2015a].

3.1.3 Demographic and experience

Most of the BCI studies were led with young participants, often under 30 years old. Though, patients that might benefit from therapeutic applications, such as post-stroke patients, are more frequently older adults [Zich et al., 2017]. The age seems to influence the lateralization of the brain activity during motor imagined but not during executed movements [Zich et al., 2017]. The activity patterns are less lateralized for older than younger adults, which can lead to a decrease of BCI performances [Zich et al., 2017]. An effect of age on younger population was also found by Adriane Randolph. She found that participants over 25 years old had better performances than participants under 25 years old [Randolph, 2012]. She also found that sex might influence BCI performances [Randolph, 2012]. Women might have better performances than men. There also seem to be a positive influence of the ability to play an instrument, the practice of several sports and playing video games [Randolph, 2012].

3.1.4 Technology acceptance

The locus of control represents the individuals' beliefs regarding their control over obtaining desired outcomes and avoiding undesired ones [Rotter, 1966]. The locus of control is considered internal or external if people believe that occurring events are respectively dependent or independent from their behaviour. The locus of control by dealing with technology was found to be both positively [Burde and Blankertz, 2006] and negatively (in neurofeedback) [Witte et al., 2013] correlated with MI-BCI performances. Witte et al. hypothesised that people with strong control belief may try harder to control the feedback. Thereby, they might be in a more agitated state of mind, which could impede their performances [Witte et al., 2013]. A positive correlation between the locus of control and the BCI performances is consistent with the vision of BCI user training as contingent learning. The effect of a reinforcement or inhibitory feedback depends on whether learners perceive it as related to their own behaviour, and not chance for example [Rotter, 1966]. A recent study of Wood and Kober found that the locus of control could have a differential impact on neurofeedback performances depending on psychosocial factors [Wood and Kober, 2018]. The locus of control of women participants training with women experimenters was strongly and positively correlated to their neurofeedback performances, but not for the other groups formed by participants' and experimenters' gender. Related to this effect of the locus of control, a correlation between the fear of incompetence and the BCI performances was found [Nijboer et al., 2008]. The sense of this interaction varied depending on the modality of feedback with which participants were provided, i.e., visual or auditory.

3.2 Influence of learners' states

Taking into account the state of the learner might enable a more timely adaptation of the training. Increase in the number of available low-cost sensors [Swan, 2012] and development in machine learning, enable real time assessment of some cognitive, affective and motivational processes influencing learning, such as attention for instance. Numerous types of applications are already taking advantage of these pieces of information, such as health [Jovanov et al., 2005], sport [Baca and Kornfeind, 2006] or intelligent tutoring systems [Woolf et al., 2010]. Assessing the attention, working memory, emotions and motivation of the users could thus be relevant to improve BCI learning as well.

3.2.1 Attentional states

Among the cognitive states influencing learning, attention deserves a particular care since it is necessary for memorization to occur [Fisk and Schneider, 1984]. Attention enables us to focus our cognitive resources on relevant stimuli and ignore the irrelevant ones. It is a key factor in several models of instructional design. For instance in the ARCS model, the letters stand for Attention, Relevance, Confidence and Satisfaction [Keller, 2010]. This model presents strategies to motivate and sustain the motivation throughout learning. Attention levels can be estimated in several ways. Based on the resource theory of Wickens, task performance is linked to the amount of attentional resources needed [Wickens, 2002]. Therefore, performances can provide a first estimation of the level of attentional resources the user dedicates to the task. However, this metric also reflects several other mental processes, and should thus be considered with care. Moreover, attention is a broad term that encompasses several types of concepts [Posner and Boies, 1971, Cohen et al., 1993]. For example, focused attention refers to the amount of information that can be processed at a given time whereas vigilance refers to the ability to pay attention to the apparition of an infrequent stimulus over a long period of time. Each type of attention has particular ways to be monitored, for example vigilance can be detected using blood flow velocity measured by transcranial Doppler sonography (TCD) [Shaw et al., 2009]. Focused visual attention, which refers to the selection of visual information to process, can be assessed by measuring eye movements [Glaholt, 2014]. While physiological sensors provide information about the physiological reactions associated with processes taking place in the central nervous system, neuroimaging has the advantage of recording information directly from the source [Frey et al., 2014]. EEG recordings enable to discriminate some types of attention with various levels of reliability given the method used. For instance, alpha band (7.5 to 12.5 Hz) can be used for the discrimination of several attentional states [Klimesch et al., 1998]. Also, the amplitude of event related potentials (ERP) are modulated by visual selective attention [Saavedra and Bougrain, 2012]. While specific experiments need to be carried out to specify the exact nature of the type(s) of attention involved in BCI training, there seem to be an influence of attentional states on BCI performances. Relationship between γ power (30 to 70 Hz) in attentional network and μ rhythm-based BCI performance have already been shown by Grosse-Wentrup et al. [Grosse-Wentrup et al., 2011b, Grosse-

Wentrup and Schölkopf, 2012]. Such linear correlation suggests the implication of focused attention and working memory [Grosse-Wentrup and Schölkopf, 2012] in BCI learning. The dorsolateral prefrontal cortex, associated with attention allocation, was also found to be significantly more activated for good MI-BCI performers than by bad MI-BCI performers [Halder et al., 2011]. Mindfulness, i.e., the ability to focus on the present moment and on the current task without being distracted by unrelated thoughts, was also found to positively correlate with the ability to control sensorimotor rhythm [Botrel and Kübler, 2019, Wood and Kober, 2018]. Mindfulness is associated with focused attention and self awareness. Training mindfulness can significantly increase the ability to control a MI-BCI [Tan et al., 2014].

3.2.2 Working memory

The working memory (WM) load or workload is another cognitive factor of influence for learning [Baddeley and Hitch, 1974, Mayer, 2009]. It is related to the difficulty of the task, depends on the user's available resources and the quantity of information given to the user. An optimal amount of load is reached when the user is challenged enough not to get bored and not too much compared with his abilities [Gerjets et al., 2014]. Behavioural measures of workload include accuracy and response time, when physiological measures comprise eye-movements [Harris et al., 1986], eye blinks [Ahlstrom and Friedman-Berg, 2006], pupil dilatation [de Greef et al., 2009] or galvanic skin response [Verwey and Veltman, 1996]. However, as most behavioural measures, these measures change due to WM load, but not only, making them unreliable to measure uniquely WM load. EEG is a more reliable measure of workload [Wobrock et al., 2015]. Gevins et al. [Gevins et al., 1998] showed that WM load could be monitored using theta (4 to 7 Hz), alpha (8 to 12Hz) and beta (13 to 30 Hz) bands from EEG data. Low amount of workload could be discriminated from high amount of workload in 27s long epochs of EEG with a 98% accuracy using Joseph-Viglione's neural network algorithm [Joseph, 1961, Viglione, 1970]. Interestingly they also obtained significant classification accuracies when training their network using data from another day (ie. 95%), another person (ie. 83%) and another task (ie. 94%). Several experiments have since reported online (ie. real time) classification rate ranging from 70 to 99% to distinguish two amounts of workload [Blankertz et al., 2010, Grimes et al., 2008]. Results depend greatly on the length of the signal epoch used: the longer the epoch, the better the performance [Grimes et al., 2008, Mühl et al., 2014]. The importance of monitoring working memory in BCI applications is all the more important because BCI illiteracy is associated with high theta waves [Ahn et al., 2013], which is an indicator of cognitive overload [Yamamoto and Matsuoka, 1990].

3.2.3 Emotions

Learners' state assessment has mostly focused on cognitive components, such as those presented above, because learning has often been considered as information processing. However, emotions also play a central role in learning [Philippot and Schaefer, 2001]. For example, Isen [Isen, 2000] has shown that positive affective states facilitate problem solving. Emotions are often inferred using contextual data, performances and models describing the succession of affective states the learner goes through while learning. Kort et al. [Kort et al., 2001] proposed such a model. Though, physiological signals, such as electromyogram, electrocardiogram, skin conductive resistance and blood volume pressure, can also be used [Picard and Healey, 1997, Picard, 2000]. Arroyo et al. [Arroyo et al., 2009] developed a system composed of four different types of physiological sensors. Their results show that the facial recognition system was the most efficient and could predict more than 60% of the variance of the four emotional states. Several classification methods have been tried to classify EEG data and deduce the emotional state of participants. Methods such as multilayer perceptron [Lin et al., 2007], K Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), Fuzzy K-Means (FKM) or Fuzzy C Means (FCM) were explored [Murugappan et al., 2008, Murugappan et al., 2010], using as input alpha, beta and gamma frequency bands power. Results are promising and vary around 75% accuracy for two to five types of emotions. Note, however, that the use of gamma band power features probably means that the classifiers were also using EMG activity due to different facial expressions. Recognizing emotion represents a challenge because most of the studies rely on the assumption that people are accurate in recognizing their emotional state and that the emotional cues used have the intended and similar effect on every participant. Moreover, many brain structures involved into emotion are deep in the brain, e.g., the amygdala. Activity from these areas is often very weak or even invisible in EEG. Mood was found to correlate with BCI performances [Nijboer et al., 2008, McCreadie et al., 2014].

3.2.4 Motivation

Motivation is interrelated with emotions [Harter, 1981, Stipek, 1993]. It drives us to pursue and achieve our goals. Motivation is often approximated using the performances [Blankertz et al., 2010]. There are two types of motivation. Intrinsic motivation reflects our motivation to perform an action for the act of performing this action. The extrinsic motivation represents our motivation to perform a task for the external benefice that could arise from this action, e.g., money or respect. Several EEG characteristics are modulated by the level of motivation. For example, this is the case for the delta rhythm (0.5 to 4 Hz) which could originate from the brain reward system [Knyazev, 2012]. Motivation is also known to modulate the amplitude of the P300 event related potential (ERP) and therefore increases performance with ERP-based BCI [Kleih et al., 2011, Leeb et al., 2007]. Both motivation and emotions influence positively biofeedback learning [Miller, 1982, Yates, 2012, Kübler et al., 2001, Hernandez et al., 2016] and MI-BCI performances [Hammer et al., 2012, Neumann and Birbaumer, 2003, Nijboer et al., 2008].

3.3 Conclusion

In the previous sections, we have presented different traits and states of the users that can impact their ability to control a BCI. Until now the traits and states are often correlated to users' average BCI performances and not to their learning curve.

It would be interesting in the future to know if the characteristics that were found to be related to BCI performances are related to initial abilities or to the evolution of the performances and the acquisition of BCI-related skills. Model prediction of BCI performances based on traits and states of the participants sometimes fail to reliably predict the performances across experiments [Benaroch et al., 2019]. Differences in experimental protocols of the studies included in the models might partly explain this lack of generalisability of the models. For instance, a biased feedback does have a differential impact depending on the BCI-related skills of the learners [Barbero and Grosse-Wentrup, 2010].

Interestingly, this differential impact of the feedback depending on the learners' traits and states could be leveraged. To optimize the learning process, the training, and in particular the feedback, should be adapted to the traits and states of the user. This idea was already hypothesised by Neuper and Pfurtscheller in 2009 [Neuper and Pfurtscheller, 2009]. We argue that the feedback should initially be adapted to the traits of the user. Such adaptation is already made by research to adapt to the population they are working with. For example, locked-in patients, who lost gaze control and thus cannot use visual feedback anymore, are often presented with auditory feedback. Some studies also use two modalities of feedback to take into account potential sensory deficits. Young et al., reported adapting the modality of feedback to the sensory abilities of the participants, i.e., visually impaired participants were provided with auditory feedback [Young et al., 2014]. Though, in Chapter 6, we argue that the somatosensory deficit that can be caused by a stroke are not taken into account during MI-BCI based post-stroke motor rehabilitation.

Also, an analysis of the profiles of learners that currently do not benefit from the training, and thereby the feedback, might be informative of the improvements that should be made to the training and feedback. For instance, non-autonomous and tensed participants seem to have greater difficulty in controlling a BCI [Jeunet et al., 2015a]. We hypothesis that this might, at least in part, result from a lack of social presence and emotional support, which have yet been tested very little in MI-BCI, despite recommendations from the educational literature (see Section 2.1.2 Social presence and emotional feedback). This assumption was tested in Chapters 4 and 5 where we report the influence of two complex forms of social presence and emotional feedback on MI-BCI user training. The variability in the results might be related to differences in traits or states of the learners. We can also hypothesis that depending on the mental imagery abilities of the users, different modalities of feedback could have a differential impact on their performances. Indeed, if participants' strategies mainly rely on visual imagery, maybe visual feedback increases the workload of the learner by soliciting cognitive resources of the same modality [Wickens, 2008]. In Chapter 7, we provide a contribution regarding the impact of the kinaesthetic and visual imagery on BCI user training.

Once the feedback adjusted to the state of the user, it could be adaptive and continuously take into account the state of the user. Cognitive, affective and motivational states impact the learning outcome and machine learning plays a key role in monitoring them. For instance, the attentional state, that was shown to have a strong impact on the BCI user training [Grosse-Wentrup et al., 2011b, Grosse-Wentrup and Schölkopf, 2012, Halder et al., 2011], could be taken into account to adapt the feedback. Little is known regarding the feedback frequency that should be used. We can hypothesis that the attentional state of the user could be leveraged to adapt the frequency of the feedback. In Part IV we report a first experimental contribution toward using EEG data to assess the different attentional states of the participants during MI-BCI training. In the following parts of this thesis, we will develop the different hypothesis that we evoked throughout this conclusion.

Part II

What information should feedback convey?

Research question

In the section 2.1 Content of feedback - Which information does feedback provide?, we stated that the content of the feedback is composed of two main components. First, feedback can convey knowledge to the participants *(see Section 2.1.1 Feedback of results)*. During MI-BCI training, information conveyed by the feedback are most often in the form of a knowledge of results, i.e., output measure regarding the achieved value or the deviation from the desired value. Though, feedback should be oriented toward a knowledge of performance, i.e., specific information regarding the differences between what participants have done and what they should have done to improve their performances. To provide knowledge of performance, a cognitive model of the BCI training would be necessary. Such a model would provide information about how the learner's profile (i.e., traits and states) and actions influence BCI performance and which feedback to favour accordingly [Jeunet, 2016, Jeunet et al., 2017]. It would be necessary to understand, predict and adapt the feedback accordingly.

Second, a feedback can have a supportive dimension when it enhances the learning through affective processes, such as increased effort, motivation or engagement. The section 2.1.2 Social presence and emotional feedback describes in length the literature on social presence and emotional feedback for learning in general and for MI-BCI training in particular. The following paragraphs summarize the main points, which are necessary for the understanding of this section. Educational and neurophysiological literature show the importance of a social feedback [Levine and Pizarro, 2004, Izuma et al., 2008]. However, this aspect of feedback as well as emotional support have been neglected during MI-BCI training. Nevertheless, literature shows that social presence and emotional support are very important to the learning process in general [Johnson and Johnson, 2009]. During MI-BCI training, the mood and motivation of participants were shown to impact their learning [Nijboer et al., 2008]. It was hypothesised that MI-BCI training would benefit from social presence [Sexton, 2015]. Very few studies were led to assess the impact of social presence and emotional feedback. Mixed results arise from the few studies using simple forms of such feedback, i.e., smiley faces, during MI-BCI training [Kübler et al., 2001, Leeb et al., 2007, Mathiak et al., 2015, Zapała et al., 2018]. Social presence show promising results through protocols having several participants interacting together while learning BCI [Bonnet et al., 2013, Obbink et al., 2011, Goebel et al., 2004].

Previous results of the literature indicate that "tensed" and "non-autonomous" people (based on the dimensions of the 16PF5 psychometric questionnaire [Cattell and P. Cattell, 1995]) are disadvantaged when controlling MI-BCIs [Jeunet et al., 2015a]. Interestingly, "non-autonomous" people are persons who rather learn in a social context [Cattell and P. Cattell, 1995]. "Tensed" people might also benefit from a reassuring social presence and emotional feedback. Therefore, it seems particularly promising to assess the impact of more complex forms of social presence and emotional feedback on MI-BCI training outcome, i.e., performances and user-experience, for people with such cognitive profiles.

Experimenters do already provide a complex form of social presence and emotional feedback during BCI training. Their influence might be mediated by their profile, their interaction with the participants and the participants' profile *(see Section 2.1.2 Social presence and emotional feedback)*.

Therefore, our aim was to study the influence of complex forms of emotional and social feedback on MI-BCI training. In the section 4 Contribution 1 - Can a physical learning companion be useful for mental-imagery based BCI user training?, we designed, implemented and tested the first learning companion dedicated to the improvement of user experience and/or user performances during MI-BCI training. Learning companions that are a type of educational agents, i.e., computational supports which enrich the social context during learning [Chou et al., 2003]. They can provide a complex form of social presence and emotional feedback in a controlled environment. First, we present the result of our process of design and implementation in the section 4.2. Then, in the section 4.3, we present the experiment we led to evaluate the influence of this learning companion on MI-BCI performances and user-experience.

In the section 5, we investigated the potential influence of experimenters. In neurofeedback and in other fields of research, a strong influence of the interaction between experimenters' and participants' gender has been shown. We present the experiment we led to test if such an influence could be found on MI-BCI performances and user-experience.

Finally, we conclude on the influence of supportive feedback on the MI-BCI training in the section 5.5.

Chapter 4

Contribution 1 - Can a physical learning companion be useful for mental-imagery based BCI user training?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - Can a physical learning companion be useful for mental-imagery based BCI user training?
	5. **Contribution 2** - Do experimenters influence MI-BCI training?
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

Collaborators: Camille Jeunet (PhD student at the time).

Related full papers: Pillette, L., Jeunet, C., Mansencal, B., N'Kambou, R., N'Kaoua, B., & Lotte, F. (2017, September). « PEANUT: Personalised Emotional Agent for Neurotechnology User-Training. » *7th International BCI Conference*, Graz, Austria.

Pillette, L., Jeunet, C., Mansencal, B., N'Kambou, R., N'Kaoua, B., & Lotte, F. (2018, June). « Towards Artificial Learning Companions for Mental Imagery-based Brain-Computer Interfaces. » *Workshop on Artificial Companion Affect Interaction Conference (WACAI 2018)*, Porquerolles, France.

Pillette, L., Jeunet, C., Mansencal, B., N'Kambou, R., N'Kaoua, B., & Lotte, F. (2019). A physical learning companion for Mental-Imagery BCI User Training. *International Journal of Human-Computer Studies*, 102380.

4.1 Introduction

Learning companions have been defined by [Chou et al., 2003] as follows:

> In an extensive definition, a learning companion is a computer-simulated character, which has **human-like characteristics** and plays a **non-authoritative role** in a **social learning environment**.

The benefit of learning companions over the other types of educational agents is that their role can greatly vary from student to tutor depending on the learning model used and the knowledge that the companion holds. At the moment, using an educational agent with an authoritative role of teacher for MI-BCI training is not realistic because of the lack of a cognitive model of the task. Such a model would provide information about how the learner's profile (i.e., traits and states) and strategies influences BCI performance and which feedback to provide accordingly [Jeunet, 2016, Jeunet et al., 2017]. It would be necessary to understand, predict and therefore improve the acquisition of BCI skills (see Section 2.1.1 Feedback of results). Since, it is not still well understood how users should perform mental imagery tasks to control effectively a BCI, the knowledge of the agent can not be significantly higher than that of the user. Thus, the user and the agent have to be on an equal footing and the choice of a learning companion imposed itself. Despite learning companions having already proven their efficiency in providing social presence and emotional support in different learning situations [Nkambou et al., 2010], they have never been used for MI-BCIs.

Some distance learning systems propose the use of learning companions to address the lack of social presence and emotional support [Robison et al., 2009]. For instance, *DragonBot* is a learning companion which has been used to teach children about nutrition [Short et al., 2014]. Given Nass's paradigm, learning companions can be seen as social actors which are just as capable of influencing users as any other social actor [Reeves and Nass, 1996, Wang et al., 2008]. Learning companions can have a positive impact on motivation [Lester et al., 1997], interest toward the task and efficiency while performing the task [Kim et al., 2006]. They can also induce emotions that favour learning, such as self-confidence [Arroyo et al., 2009].

The work presented in the following sections 4.2 and 4.3 aimed at designing, implementing and testing the first learning companion dedicated to the improvement of user experience and/or user performances during MI-BCI training. We called this learning companion PEANUT for *Personalized Emotional Agent for Neurotechnology User Training* (see Figure 4.1).

Figure 4.1: A participant training to use a BCI. He is learning how to perform different MI tasks (imagining a left-hand movement, performing mental calculation tasks and imagining an object rotating) to control the system. Along the training, PEANUT (on the left) provides users with social presence and emotional support, using interventions composed of facial expressions and pronounced sentences adapted to their performance and progression.

In the section 4.2 How should a learning companion be designed for BCI user training? we describe the different steps which guided our design of the companion, starting with our main contributions regarding: (1) the design of the behaviour of PEANUT, (2) the design of the physical appearance of PEANUT and (3) the implementation of PEANUT. Our design approach was carefully motivated and justified based on a review of the literature, the analysis of data from previous experiments and several user-studies. In the section 4.3 Can a physical learning companions improve MI based BCI user training? we then present the experiment which enabled us to test the adequacy of PEANUT and its characteristics for improving MI-BCI training to finally discuss these results.

4.2 How should a learning companion be designed for BCI user training?

While being potentially beneficial when well conceived, inappropriately designed companions can also have a detrimental impact on performance [Wang et al., 2008, Kennedy et al., 2015]. For instance, discrepancies between users' expectations towards the companion and its real capacities would lead to a bad perception of the companion [Norman, 1994]. For example, such a situation is likely to occur when the design of the companion suggests a high level of functionalities (e.g., highly realistic companion) whereas the implemented functionalities are basic ones (e.g., no possible interaction with the learner). As a consequence, the design process of such a companion must be undertaken cautiously [Wang et al., 2008]. In the following section we will present the results of the review of the literature as well as the different user-studies we led in order to create a learning companion which would be consistent in terms of physical appearance and behaviour.

4.2.1 Designing the behaviour of PEANUT

As it was already stated, theoretical knowledge is still lacking to provide informative feedback to users with an explanatory feedback. Moreover, during the training, the users are asked not to move in order to limit motor related artefacts that could create noise in the recorded brain activity. Therefore, a complex interaction between the user and the learning companion was hardly feasible. The behaviour of the companion as well as its physical appearance had to be consistent. They had to reflect the limited amount of information that the learning companion would be able to provide and focus on the emotional and social feedback that we aimed at providing. As a result, PEANUT provided the user with interventions composed of both a pronounced sentence and a facial expression expressing one or two consecutive of the following emotions: Serenity, Joy, Ecstasy, Acceptance, Trust, Admiration, Distraction, Surprise, Amazement, Sadness. All of them belong to the wheel of emotions of Plutchik [Plutchik, 2001]. We mostly chose positive emotions but also selected a few negative ones. The use of negative emotions, enabled us to display two consecutive emotions with a negative one followed by a positive one to create a contrast and increase the perceived intensity of the second emotion displayed. Their use also aimed at improving the empathy towards users and improve the social feedback by reflecting the emotional state users were likely to feel in the given learning phase [McQuiggan and Lester, 2007]. For example, when the performance (or progress) was decreasing, users might have felt sad to be failing. In such situation, the companion could exhibit sadness and then trust in order to maintain their motivation. The interventions were solely selected with respect to the MI-BCI performance and progression, which are objective measures reflecting the MI-BCI skills of users. The performance corresponds to the classification accuracy. The progress corresponds to the evolution of the performance over time. In the following paragraph we consider the context as both the current performance and progress. In order to design a relevant behaviour for PEANUT for a given context, different aspects had to be considered:

- Support content - Which intervention (sentence & facial expression) should the participant be provided with according to the context (performance & progression)?

- Intervention style - How should the intervention be expressed with respect to the context? When expressing an opinion, the interpretation remains subjective to the contexts and the participants [Karamibekr and Ghorbani, 2013]. For example, when hearing the sentence “You're doing good”, someone could perceive it as a supportive sentence in case of improvement, but in the context of a failure, it could be perceived as ironic and this interpretation is personal. Karamibekr and Ghorbani [Karamibekr and Ghorbani, 2013] have hypothesized that it could depend on the type of the sentence (e.g., exclamatory or declarative). In line with their results, we also hypothesized that the subject pronoun (e.g., second or third) used in the sentence could influence its perception. The second person would be more explicit, e.g., “You're doing good”, whereas the third would be more implicit, e.g., “Results are improving”. Therefore, we asked ourselves if a sentence should be exclamatory or declarative; personal (second person) or non-personal (third person) to be perceived as motivational.

- Performance and progression thresholds - To deal with the continuum of performances and progress specific to each user we chose to separate them into three levels i.e., poor/average/good for the performances and negative/neutral/positive for the progression. Therefore we needed to define thresholds to determine to which category a performance or progress would belong to relatively to each participant. The relevance of the interventions depends on these thresholds.

4.2.1.1 Support Content

The support content was elaborated after a review of both the educational and the intelligent tutoring system literature. The intervention style was selected based on a user-study. Hereafter is a list of the possible intervention categories of PEANUT, the context for which they were created, their goal and the literature justifying their use. An intervention corresponds to the association of a sentence and a facial expression (see also Figure 4.3 for an exhaustive description of the intervention selection rules).

- Temporal interventions are related to the temporal dimension of the experiment. They are divided into 2 categories, *Temporal-Start* and *Temporal-End*, the goal of which is to greet and say goodbye to the users, e.g., “I am happy to meet you”. Both these intervention types were associated with a facial expression of *Joy* for PEANUT. They aim at providing the companion with a polite behaviour, which is primordial for social interactions [Wang et al., 2008].

- Effort-related intervention categories i.e., *General-Effort* and *Support-Effort*, contain sentences like “Your efforts will be rewarded”. They value the efforts that are made by the participant throughout training [Dweck, 2002]. These sentences focus on the fact that learning is the goal, and are intended to minimize the importance of current performance while promoting long-term learning [Woolf et al., 2010]. More specifically, *General-Effort* and *Support-Effort* interventions are respectively adapted to negative or neutral progression and positive progression. Therefore, *General-Effort* and *Support-Effort* interventions were respectively associated with *Trust* and *Joy*.

- The category expressing empathy, i.e. *General-Empathy*, aims at letting users know that the companion understands that they are facing a difficult training process by using sentences such as "Don't let difficulties discourage you". Learning has been suggested to correlate with the amount of empathy and support received [Graham and Weiner, 1996]. This type of intervention was preferably provided for negative or neutral progression, especially when combined with bad performance. These interventions were associated with an animation ranging from *Sadness* to *Trust*.

- Categories associated with performance/results and progression, i.e. *Results-Good*, *Results-VeryGood* and *Progress-Good*, only target positive performance and progression, e.g., "You are doing a good job!". Positive intervention regarding the performances or progress, should respectively induce positive intrinsic motivation (i.e., performing an action for its own sake) or positive extrinsic motivation (i.e., performing an action for its outcomes, e.g., grades or praise) [Pekrun, 1992]. The sentences in this category were designed to motivate users by focusing on the positive performances and progress and therefore on the abilities users had already acquired [Jaques et al., 2004]. *Results-Good* and *Results-VeryGood* were respectively associated to *Joy* and *Admiration*. *Progress-Good* was associated to an animation going from *Surprise* to *Trust*.

- The last category consisted in strategy-related interventions, i.e., *Strategy-Change* and *Strategy-Keep*, with sentences such as "You seem to have found an efficient strategy". These interventions aimed at encouraging people to keep the same strategy when progression was positive or to change strategy when it was negative/neutral. *Strategy-Keep* and *Strategy-Change* were respectively associated with *Joy* and an animation going from *Pensiveness* to *Joy*.

4.2.1.2 Style of the Interventions

Each intervention could have been provided in different styles, e.g., exclamatory and personal "You're doing good!" or declarative and non-personal "This is good.". We hypothesized that depending on the context, the users' perception of these different styles could vary. Therefore, we led a user-study to determine the style in which the intervention should be provided, depending on the context. This user-study consisted in an online questionnaire simulating a MI-BCI user-training process.

4.2.1.2.1 Materials & Methods

We created 3 online questionnaires, each of them simulating an MI-BCI training process in a different context of progress. The results of the participants predefined for each of the questionnaires and their evolution was either negative, neutral or positive depending on the questionnaire. Each questionnaire included 8 situations, with two possible interventions for each situation (which resulted in 16 intervention sentences per questionnaire). Each situation corresponded to an MI-BCI task that the participant was asked to perform (left-hand motor imagery, mental subtraction or mental rotation - as explained in Figure 4.1), followed by a feedback indicating an alleged success of the task (see Figure 4.2). This feedback was fixed in each of the questionnaires. It did not correspond to anything that the participant was doing and the participants were informed of that. After the situation was introduced, two different sentences were displayed on screen. Participants were asked to rate each sentence (on a Likert scale ranging from 1 to 5) based on five criteria: appropriate, clear, evaluative, funny, motivating.

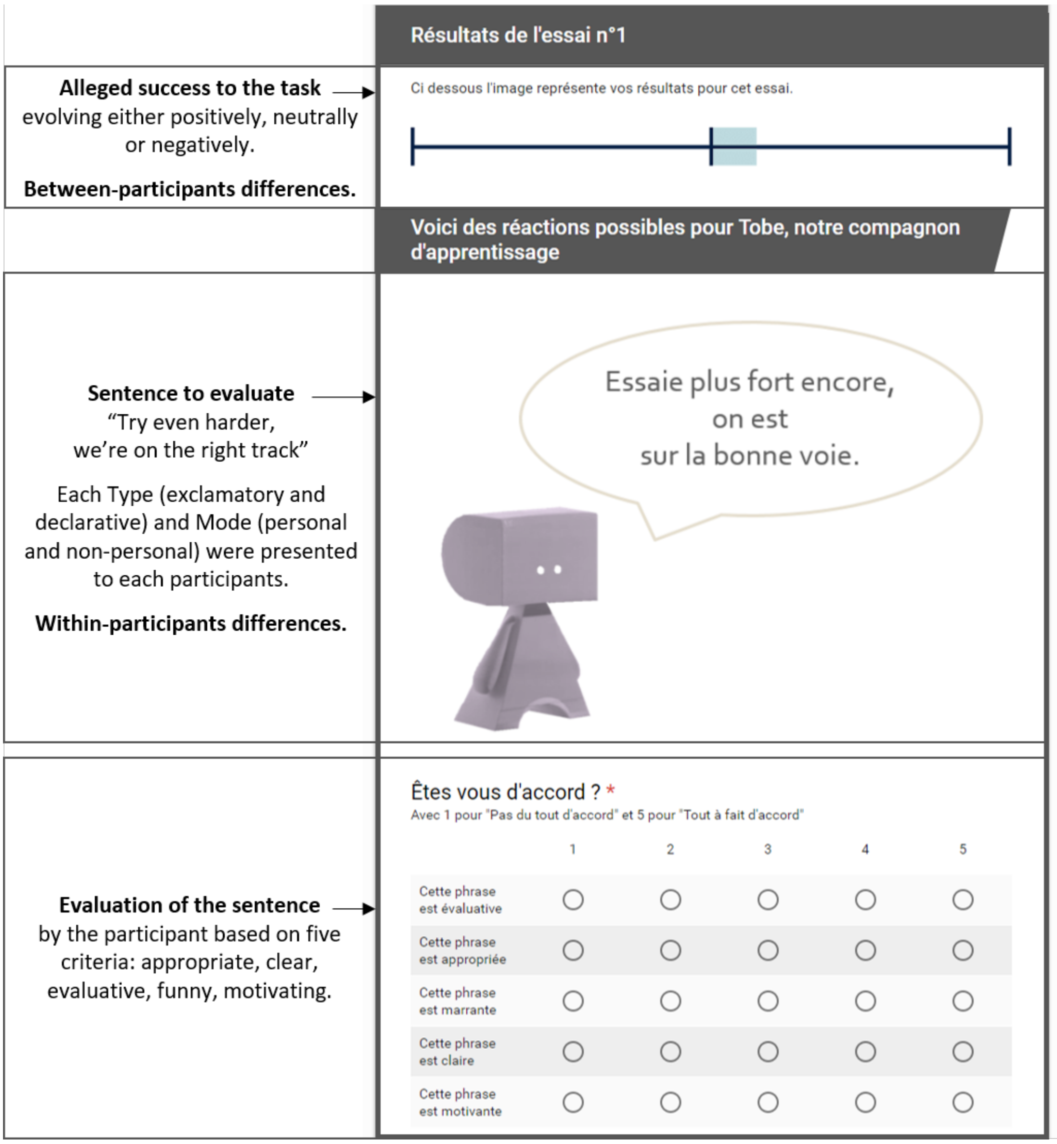

Figure 4.2: Commented example of a part of questionnaire written in french as it was provided to participants. The feedback bar indicates an alleged slightly good success to the participant. Then the participants are presented with a potential sentence that the companion could say in this particular context "Try even harder, we're on the right track" and have to evaluate the sentence based on five criteria: appropriate, clear, evaluative, funny and motivating.

The object of this questionnaire was to determine the impact of the *Context* (negative, neutral or positive progression), of the *Type* (exclamatory or declarative) and of the *Mode* (personal or non-personal) on the five dimensions introduced above. Thus, four kinds of sentences were presented in each context: exclamatory/personal, e.g., "You're doing good!", exclamatory/non-personal, e.g., "This is good!", declarative/personal, e.g., "You're doing good.", declarative/non-personal, e.g., "This is good.". 104 people answered the online questionnaires. Each of them was randomly allocated to one questionnaire, which makes around 34 participants per *Context*. We led five 3-way ANOVAs for repeated measures, one per dimension, to assess the impact of the *Context* (C_3 - independent measures), *Type* (T_2 - repeated measures) and *Mode* (M_2 - repeated measures) on each dimension.

4.2.1.2.2 Results

		Positive Progress		**Negative Progress**		**Neutral Progress**	
		Exclamatory	*Declarative*	*Exclamatory*	*Declarative*	*Exclamatory*	*Declarative*
		Avg ± Std	Avg ± Std	Avg ± Std	Avg ± Std	Avg ± Std	Avg ± Std
Appropriate	*Personal*	3,68 ± 0,13	3,73 ± 0,12	3,73 ± 0,12	4,02 ± 0,12	3,54 ± 0,13	3,64 ± 0,12
	Not personal	3,68 ± 0,13	3,92 ± 0,14	3,8 ± 0,12	3,59 ± 0,13	3,68 ± 0,13	3,09 ± 0,14
Clear	*Personal*	4,33 ± 0,13	4,06 ± 0,13	4,12 ± 0,12	4,51 ± 0,12	4,08 ± 0,12	4,07 ± 0,12
	Not personal	4,09 ± 0,14	4,4 ± 0,16	4,28 ± 0,13	4,11 ± 0,15	4,14 ± 0,13	3,61 ± 0,16
Evaluative	*Personal*	3,12 ± 0,14	3,2 ± 0,14	3,23 ± 0,14	2,86 ± 0,13	2,75 ± 0,14	2,78 ± 0,13
	Not personal	2,88 ± 0,15	2,84 ± 0,16	2,61 ± 0,14	3,1 ± 0,15	2,53 ± 0,15	2,64 ± 0,16
Funny	*Personal*	2,57 ± 0,15	2,13 ± 0,15	2,07 ± 0,14	2,14 ± 0,14	2,46 ± 0,15	2,29 ± 0,15
	Not personal	2,33 ± 016	2,14 ± 0,15	2,05 ± 0,15	1,9 ± 0,14	2,31 ± 0,15	1,82 ± 0,14
Motivating	*Personal*	3,87 ± 0,13	3,76 ± 0,12	3,61 ± 0,12	3,66 ± 0,12	3,51 ± 0,13	3,62 ± 0,12
	Not personal	3,53 ± 0,13	3,59 ± 0,14	3,36 ± 0,13	3,21 ± 0,13	3,42 ± 0,13	2,74 ± 0,14

Table 4.1: Mean rate given to the sentences depending on their Mode (Personal, Not personal), Type (Exclamatory, Declarative) and on the Progress (Positive, Negative, Neutral). For each of the Progress and dimensions, between the four possibilities of sentences depending on their Mode and Type, we highlighted in yellow all the corresponding values that were below the highest value minus its standard deviation for the Appropriate, Clear, Funny and Motivating dimensions or above the lowest value plus its standard deviation for the Evaluative dimension.

For the 5 dimensions, the ANOVAs showed *Context*Type*Mode* interactions: appropriate [F(2,101)=5.861 ; p≤0.005, η^2=0.104], clear [F(2,101)=21.596 ; p≤0.001, η^2=0.300], evaluative [F(2,101)=11.461 ; p≤0.001, η^2=0.185], funny [F(2,101)=4.114 ; p≤0.05, η^2=0.075], motivating [D(2,101)= 7.854; p≤0.001, η^2=0.135].

These results *(see Table 4.1)* seem to confirm that the *Type* and *Mode* of each intervention should be adapted to the *Context*:

Negative progression - In this context, people definitely prefer declarative and personal sentences that they find more appropriate, clear, funny, motivating and less evaluative.

Neutral progression - Here, people prefer personal sentences, but appreciate as much the declarative and exclamatory sentences for all the dimensions.

Positive progression - In this context, declarative and non-personal sentences are perceived as more clear, appropriate and less evaluative. Exclamatory and personal sentences are perceived as more funny and motivating.

4.2.1.2.3 Discussion

Our aim was to design a learning companion whose interventions were adapted to the performance and progress of the user. Based on our results, we chose to provide users facing a negative progression only with declarative personal interventions and those facing a neutral progression with randomly chosen declarative or exclamatory personal interventions. Finally, depending on the intervention goal, we chose to provide participants showing a positive progression with declarative non-personal sentences (when the goal was to give clear information about the task) or exclamatory personal sentences (when the goal was to increase motivation) (see Figure 4.3). One should note that when an exclamatory sentence was used for the intervention, the emotion displayed through the facial expressions of PEANUT was made more intense than for an equivalent declarative sentence (see more details about the facial expressions in Section 4.2.2 Physical Appearance of PEANUT).

These results are rather general and thus may prove useful for other training applications involving a learning companion, or more generally involving support during a training process. For instance, exclamatory sentences can be perceived as more aggressive than declarative sentences, and should therefore be avoided in situations of failure. Also, in case of failure, emotional support is very important. Thus, personal sentences should be favoured to make the user feel that the companion is really caring for them. On the contrary, good performers seem to consider that they do not really require this support and thus prefer general, non-personal interventions.

4.2.1.3 Performance and Progression Thresholds

For PEANUT to provide interventions based on the user's performances and progression, we had to determine thresholds of performance/progression delimiting intervals within which specific interventions should be provided. We decided to define 2 performance thresholds delimiting 3 intervals: bad, average and good performance. These thresholds were labeled the "low performance threshold" and the "high performance threshold". Similarly, we determined a "negative progression threshold" and a "positive progression threshold", separating negative from neutral, and neutral from positive progression, respectively. We estimated those thresholds and ensured that these estimations could reliably predict performance and progression thresholds in subsequent uses of the BCI by the user. To do so, we re-analyzed the data of 18 participants from a previous study reported in [Jeunet et al., 2015a]. In this experiment, the participants had to learn to perform the same three mental tasks as in the present study, over the course of 6 sessions, using the same training protocol (without the companion) as in the present paper. A session comprised 5 sequences called runs. A run was divided into 40 trials. Participants were asked to perform a specific mental task during each of these trials. Run 1 of session 1 was used to calibrate the system, i.e., for it to be able to deduce which task the user is performing by analyzing the differences in brain activity patterns when the user performs each of the tasks. We used the classification accuracy, i.e., the percentage of EEG time windows that were correctly classified as the mental task the user was asked to do for this trial, as the metric of performance for each trial (see Section 4.3.1.3 EEG Recordings & Signal Processing for details). In order to estimate the different thresholds, the data was analysed offline with Matlab.

4.2.1.3.1 Estimating the performance thresholds

We constructed the distribution of performance values over trials and defined the bad and good performance thresholds as the 25^{th} and the 75^{th} percentiles of that distribution, respectively. Thus, the bottom 25% of each participant's performances were considered bad performances, the top 25% good performances, and the remaining performances in-between were considered neutral. The question was to assess the feasibility of predicting future performance (and thus thresholds) based on the data collected at the beginning of the training (first run of the first session). Indeed, the sooner we are able to determine the performance thresholds, the sooner we can provide users with interventions adapted to their performance, thus maximizing the relevance of these interventions.

First, we checked whether we could estimate those thresholds on the first run with BCI use, i.e., on run 2 of session 1 (run 1 being the calibration run). We thus estimated the performance thresholds independently on run 2, and on runs 3, 4 and 5 of session 1 together. We then computed their correlations over participants, to find whether thresholds estimated on run 2 could be used to predict thresholds estimated on run 3, 4, 5. We obtained significant correlations of $r = 0.6422$ ($p < 0.01$) for bad performance thresholds, and of $r = 0.5482$ ($p < 0.05$) for good performance thresholds. Thus, in order to select the appropriate behaviour for PEANUT, we used the thresholds estimated on run 2 to compute the thresholds for runs 3, 4 and 5 of session 1 using the same ratio as the ones found in these control data. However, thresholds estimated on the data from a single run are bound to be less reliable than thresholds based on several runs. We thus studied whether thresholds estimated on runs 2 to 5 of the first session, could be used to predict the thresholds of the runs of subsequent sessions. They appear to be correlated with $r = 0.6628$ ($p < 0.01$) and 0.4438 ($p = 0.07$ - not significant but a trend) for bad and good performance thresholds respectively. Thus, to determine the behaviour of PEANUT for subsequent sessions, we computed the thresholds using the runs 2 to 5 of session 1 still using the same ratio as the ones found in these control data.

4.2.1.3.2 Estimating the progression thresholds

To estimate progression thresholds, we used the performances from N successive trials, and computed the slope of a linear regression relating time (here trial indexes) with performance. A positive/negative slope indicated a positive/negative progression, respectively. We then constructed the distribution of these regression slopes over trials, and determined the negative progression threshold as the 25^{th} percentile of this distribution, and the positive progression threshold as the 75^{th} percentile of this distribution. Similarly as for the performance thresholds, we studied whether we could predict the future progression thresholds from their estimation on the first runs. Nonetheless, progression estimation requires more trials than performance estimation (N versus 1). As such there are fewer progression measures in a single run, which in practice made it impossible to reliably predict the progression thresholds of runs 3, 4 and 5 by using run 2 alone for threshold-estimation. However, it appeared to be possible to predict progression thresholds for all the runs of sessions 2 to 6, from the threshold-estimated based on runs 2 to 5 of session 1. In particular, the positive progression threshold of the runs of the session 1 appeared to be significantly correlated with both the positive ($r = 0.4843$, $p < 0.05$) and negative ($r = -0.5476$, $p < 0.05$) progression thresholds from the runs of the subsequent sessions. Note that these correlations were obtained for $N = 6$. Indeed, we studied N between 2 and 10, and selected the best N as the one maximizing the correlations, to obtain the most reliable thresholds. Therefore, the progression thresholds from sessions 2 to 6 were estimated by computing the positive progression threshold from runs 2 to 5 of session 1 using the same ratio as the ones found in these control data. The companion thus provided progression related interventions only from session 2 onward.

These analyses also guided the choice of the frequency of the interventions of PEANUT. Since progression was measured over N=6 trials, we informally tested different intervention frequencies of about one every 6 trials. These informal tests with pilot testers revealed that interventions every 6 ± 2 trials seemed appropriate, as they were neither annoying nor too rare. PEANUT thus intervened at that frequency, the exact trial of intervention being randomly selected in the 6 ± 2 trials following the previous intervention.

4.2.1.4 Rule tree

Once all the parameters governing the behaviour of PEANUT had been determined, we were able to build the rule tree that enables the system to select one specific intervention (i.e., sentence & sentence style & facial expression) with respect to the context. Figure 4.3 is a schematic representation of this rule tree: based on a specific performance and progression, it executes a set of rules to select the appropriate intervention. For example, if the user had a good performance and a neutral progress then the rule tree would select an appropriate sentence which would either advice him to try a new strategy in a declarative sentence if it had been some time that the progress did not change, e.g., “Maybe you could try a new strategy.”, or an exclamatory or declarative sentence of encouragement, e.g., “You’re doing good!”.

4.2.2 Physical Appearance of PEANUT

Designing the appearance of PEANUT consisted in two steps: designing its body, and designing its face and facial expressions. The decisions concerning the face have been made based on a user-study. Those concerning the body were based on a review of the literature.

4.2.2.1 Body of PEANUT

To increase social presence we decided to make a physical companion instead of a virtual one [Hornecker, 2011, Schmitz, 2010] and used anthropomorphic features to

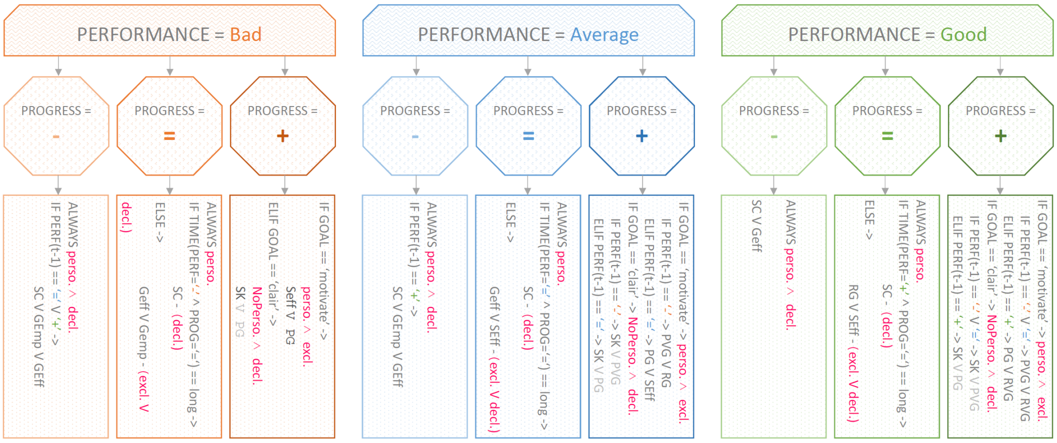

Figure 4.3: The rule tree corresponds to a set of rules that selects the interventions of PEANUT (i.e., type and mode of sentence) depending on users' performance and progression ("-"=negative, "="=neutral, "+"=positive). Type of sentences: "perso." for personal, "NoPerso." for non-personal ; Mode of the sentence: "decl." for declarative, "excl." for exclamatory. Interventions: "GEff" for general effort, "SEff" for support effort, "GEmp" for general empathy, "SK" for strategy keep, "SC" for strategy change, "RG" for results good, "RVG" for results very good, "PG" for progress good, "PVG" for progress very good. Moreover, the "$\wedge$" sign represents the logical operator "and" and the "$\vee$" sign represents the logical operator "or".

facilitate social interactions [Duffy, 2003].The combination of physical characteristics, personality/abilities, functionalities and learning function had to be consistent [Norman, 1994]. We were inspired by TEEGI [Frey et al., 2014] and TOBE [Gervais et al., 2016], two avatars providing users with tools to explore their inner state (EEG and physiological data, among others). Since their functions are simple and they are unable to interact with the user, their designers chose to propose cartoon-like characters with anthropomorphic child-like body shapes, which can induce positive emotions through design [Um et al., 2012]. The functionalities of our companion being basic as well, we also decided to design a cartoon and child-like companion rather than a realistic one. We used the voice of a child to record the interventions of PEANUT, which also enabled us not to associate PEANUT with a gender. We also took into account our own constraints deriving from the size of the smartphone we used to display the face of PEANUT and the learning environment. Finally, concerning the size of the companion, since PEANUT was on the desk right next to the computer screen on which the feedback was displayed, its proportions had to be suitable: not too small so that the body was proportional to its face, and not too large so that it could always be within a user's field of view without concealing the screen. This process resulted in a 30 cm high companion, see Figure 4.1.

4.2.2.2 Facial Expressions of PEANUT

Based on the results of PEANUT behaviour design, we wanted the companion to be able to express eight emotions: Trust, Joy, Surprise, Admiration, Boredom, Sadness, Anger and a Neutral expressions. We asked a designer to create three styles of faces (see Figure 4.4) [1]. We wanted the faces to be cartoon-like, so that they fitted the body and complied with the recommendations from the literature [Norman, 1994, Duffy, 2003, Um et al., 2012]. The object of the user-study introduced hereafter was to find the best style (among three) for PEANUT with respect to 5 dimensions: expressiveness, sympathy, appeal, childlike, consistent (with the expression it was supposed to convey).

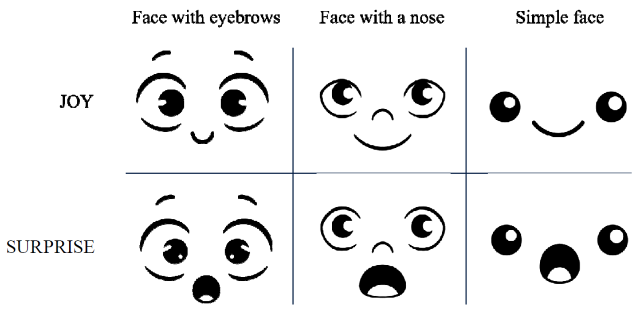

Figure 4.4: Three face styles, with the example of 2 emotions: Joy and Surprise. Participants of the dedicated user-study selected the face with eyebrows for PEANUT.

4.2.2.2.1 Materials & Methods

We created an online questionnaire which was divided into different items, with each item corresponding to one emotion. These items were presented in a random order. For each item, the three face styles were presented (in a counterbalanced order), side by side. Participants were asked to chose which of the three styles corresponded the most to each of the following dimensions: expressive, sympathetic, appealing, childlike and consistent. They were also asked to rate each style on a 5-point Likert scale, 1 corresponding to “I don’t like it at all” and 5 to “I like it a lot”. Ninety-seven participants answered the online questionnaire. We first led a 1-way ANOVA to determine if the rates associated with each style were different. Then, we led a 3-way ANOVA for repeated measures, to assess the impact of the face style (F_3 - repeated measures), the type of emotion (E_8 - repeated measures) and the dimension (D_5 - repeated measures) on the allocated score.

4.2.2.2.2 Results

On a 5-point Likert scale, the face with eyebrows was rated 3.58 ± 1.26, the face with a nose 2.96 ± 1.37 and the simple face 3.86 ± 1.10. The 1-way ANOVA for repeated measures revealed a main effect of the style [$F(1,93)=8.442$; $p \leq 0.005$, $\eta^2=0.083$]. The simple face and the face with eyebrows were significantly better rated than the face with a nose. However, there was no difference of rating between the simple face and that with eyebrows. Thus, we then performed a 3-way ANOVA for repeated

[1] To learn more about Marie Ecarlat’s work - http://marieecarlat.tumblr.com/

measures to evaluate the effect of the face, of the emotion and of the dimension on the rating. Results suggested a main effect of the style of face [F(1,93)=17.543 ; p≤0.001, η^2=0.159], of the emotion [F(1,93)=11.307 ; p≤0.001, η^2=0.108] and of the dimension [F(1,93)=12.184 ; p≤0.001, η^2=0.116]. Moreover, face*dimension [F(1,93)=58.531 ; p≤0.001, η^2=0.386], face*emotion [F(1,93) =11.307 ; p≤0.001, η^2=0.108] and dimension*emotion [F(1,93)=17.543 ; p≤0.001, η^2=0.159] interaction effects were revealed. The face with the eyebrows was significantly preferred to the others, which was strengthened by participants' comments indicating that eyebrows increased expressiveness. However, this face was not preferred for the Ecstatic (i.e., high intensity of Joy) and Admiration items. An analysis of the comments helped us improve those expressions. Several people felt like the shape of the eyes gave the impression the companion was about to cry and that it was squinting.

4.2.2.2.3 Discussion

Based on our results, we selected the face with eyebrows (see Figure 4.4) for PEANUT. We asked the designer to improve the expressions of Ecstatic (i.e., high intensity of Joy) and Admiration with respect to participants' comments. In a second instance, the designer animated each of the expressions. The animations enabled a transfer from a neutral expression to a high intensity of each of the selected emotions. For example, the *Joy* emotion had three possible levels of intensity, i.e., serenity, joy and ecstatic. Once, the behaviour and appearance of PEANUT developed, they had to be implemented in one whole system related to the BCI protocol which will be presented in the following section.

4.2.3 System Architecture

Implementing the whole BCI system as well as PEANUT required to design, assemble and connect multiple pieces of hardware and software. Users' EEG signals were first measured using EEG hardware (g.tec gUSBAmp, g.tec, Austria) and then collected and processed online using the software OpenViBE [Renard et al., 2010]. OpenViBE provided users with a visual feedback about the estimated mental task, and computed users' performances which were then transmitted to a home-made software, the "Rule Engine" using the Lab Streaming Layer (LSL) protocol [Kothe, 2014]. The rule engine processed performance measures received from OpenViBE to compute progression measures and browsed the Rule Tree described in Figure 4.3 in order to select an appropriate intervention (sentence and facial expression) for PEANUT with respect to the context. The selected intervention was then transmitted to an Android smartphone application, using WebSocket, which enunciated the sentence and animated the facial expression of PEANUT. This whole architecture is summarized in Figure 4.5 and described in more details in the following sections.

4.2.3.1 OpenViBE

OpenViBE is a software allowing to acquire and process EEG signals in real-time [Renard et al., 2010]. We used it here to estimate the mental task performed by the

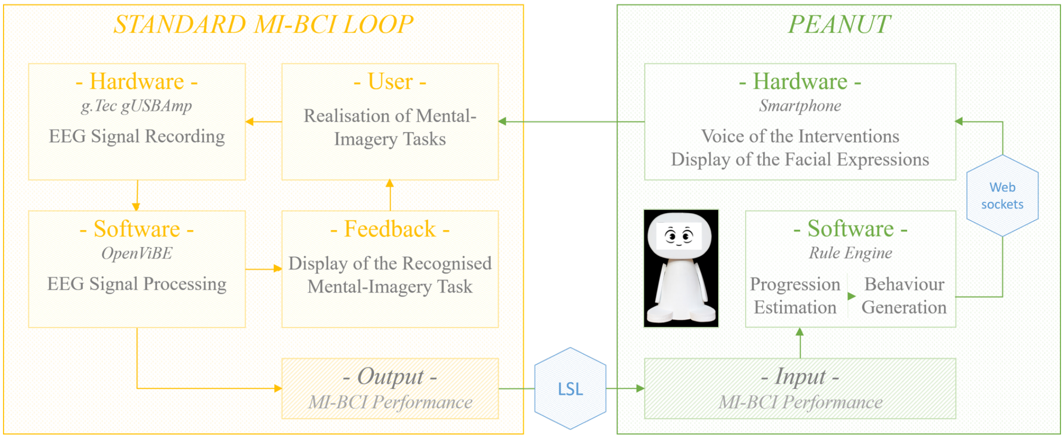

Figure 4.5: Software and hardware architecture of PEANUT.

user (see Section 4.3.1.3 EEG Recordings & Signal Processing), and display instructions and visual feedback (see Section 4.3.1.2 Experimental Protocol). OpenViBE was also used to compute users' performances online at each trial, and to transmit them to the Rule Engine.

4.2.3.2 Rule Engine

The Rule Engine software receives from OpenViBE the markers indicating the start and end of trials, as well as performance measures at the end of each trial. It first computes a progression measure (see Section 4.2.1.3.2 Estimating the progression thresholds) and then browses the rule tree in order to select the intervention type to be triggered. Each intervention type contained between 1 and 17 sentences. One of them was selected randomly, taking care not to take a sentence that had already been chosen in the same run (thanks to a small cache of already triggered sentences kept for each intervention type) in order to avoid repetition. Finally, the Rule Engine sent intervention identifiers to the smartphone application.

4.2.3.3 Smartphone - Sentence Enunciation, Facial Expression Animation

To display the facial animations and enunciate the sentences, we used a smartphone. Indeed, such a device integrates all the required hardware (CPU, screen and speaker) in a small form factor that can be embedded in the head of the companion to display its face. Practically, we used an Alcatel OneTouch Idol 3 with 5.5" screen, running Android 5.0.2. We designed an Android application that displays the face of the companion, plays animations and sounds when required. By default a neutral facial expression is shown, with eye-blinks occurring from time to time. When intervention identifiers were received from the Rule Engine, the application animated the facial expressions and enunciated the sentences. Each of the (126) sentences had been previously recorded (as explained in Section 4.2.2 Physical Appearance of

PEANUT). We used Praat software [Boersma et al., 2002] offline in order to realize phonetic alignment with the companion's mouth movements for each sentence. Thus, phonemes, that may be described as individual sounds that make up speech, were aligned on the speech signal. Furthermore, visemes correspond to the shape of the mouth when a phoneme is pronounced (several phonemes may correspond to a given viseme). The number of visemes depends on the language used and the desired fidelity. As our companion's style is cartoon-like, we did not aim for high fidelity: we used 35 phonemes and 8 visemes. Once the animations and sounds had been planned, the application combined visemes corresponding to phonemes in the chosen sound, and added them to the animation plan. Finally, the application scheduled animations and sounds for execution (for instance, to ensure that an animation did not start while the companion was blinking).

4.3 Can a physical learning companions improve MI based BCI user training?

Once the companion's behaviour and appearance had been designed and implemented, the next step consisted in testing its efficiency to improve MI-BCI user-training both in terms of MI-BCI performance and user experience. Below we present the study performed to test the efficiency of PEANUT.

4.3.1 Materials & Methods

4.3.1.1 Participants

Twenty-eight MI-BCI-naive participants (14 women ; aged 21.21±1.6 year-old) took part in this study, which was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. This study was also approved by the legal and ethical authorities of Inria Bordeaux Sud-Ouest (the COERLE, approval number: 2016-02) as it satisfied the ethical rules and principles of the institute. All the participants signed an informed consent form at the beginning of the experiment and received a compensation of 50 euros. The *experimental group* (N=10 ; 5 women ; aged 20.7±2.11 year-old), received emotional and social support adapted to their MI-BCI performance & progression throughout the MI-BCI training sessions. For the *control group* (N=18 ; 9 women ; aged 21.5±1.2), data from the 3 first sessions (out of 6) from a previous experiment [Jeunet et al., 2015a] were used. Participants from this study followed the same training protocol without the learning companion. The same data was used to define the equations to compute the thresholds (see Section 4.2.1.3 Performance and Progression Thresholds).

4.3.1.2 Experimental Protocol

Before the first session, participants were asked to complete a validated psychometric questionnaire, the 16PF5 [Cattell and P. Cattell, 1995], that enabled us to compute their "autonomy" and "tension" scores. Each participant took part in 3 sessions, on 3 different days. Each session lasted around 2 hours and was organized as follows: completion of questionnaires, installation of the EEG cap, five runs during which participants had to learn to perform three MI-tasks (around 60 min, including breaks between the runs), uninstallation of the EEG cap, completion of questionnaires, and debriefing. The MI-tasks, i.e., left-hand motor imagery, mental rotation and mental subtraction, were chosen according to Friedrich et al. [Friedrich et al., 2013]. "Left-hand motor imagery" (*L-HAND*) refers to the kinaesthetic continuous imagination of a left-hand movement, chosen by the participant, without any actual movement [Friedrich et al., 2013]. "Mental rotation" (*ROTATION*) and "mental subtraction" (*SUBTRACTION*) correspond respectively to the mental visualization of a 3 Dimensional shape rotating in a 3 Dimensional space [Friedrich et al., 2013] and to successive subtractions of a 2-digit number (ranging between 11 and 19) from a 3-digit number, both being randomly generated and displayed on a screen [Friedrich et al., 2013].

During each run, participants had to perform 45 trials (15 trials per task, presented in a random order), each trial lasting 8s (see Figure 4.6). At t=0s, an arrow was displayed with a left hand pictogram on the left (*L-HAND* task), the subtraction to be performed at the top (*SUBTRACTION* task) and a 3D shape on the right (*ROTATION* task). At t=2s, a "beep" announced the coming instruction and one second later, at t=3s, a red arrow was displayed for 1.250s. The direction of the arrow informed the participant which task to perform, e.g., an arrow pointing to the left meant the user had to perform a *L-HAND* task. In order to stress this information, the pictogram representing the task to be performed was also framed with a white square until the end of the trial. Finally, at t=4.250s, a visual feedback was provided in the shape of a blue bar, the length of which varied according to the classifier output. Only positive feedback was displayed, i.e., the feedback was provided only when there was a match between the instruction and the recognized task. Participants were instructed to find strategies that would maximize the length of the blue bar. The feedback lasted 4s and was updated at 16Hz, using a 1s sliding window. During the first run of the first session (i.e., the calibration run, see next Section), as the classifier was not yet trained to recognize the mental tasks being performed by the user, it could not provide a consistent feedback. In order to limit biases with the other runs, e.g., EEG changes due to different visual processing between runs, the user was provided with an equivalent sham feedback, i.e., a blue bar randomly appearing and varying in length, and not updated according to the classifier output, as in [Friedrich et al., 2013]. A gap lasting between 3.500s and 4.500s separated each trial.

The participants from the *experimental group* were accompanied by PEANUT during their training, from the second run of session 1 (after the calibration run). The interventions of PEANUT were adapted to each participants' performance during the first session, and to each of their performance and progression during the second and third sessions. Finally, after the last session we asked participants from both groups to assess the usability of the MI-BCI system using a questionnaire focusing on the 4 following dimensions: Learnability/Memorability (LM), efficiency/effectiveness (EE), safety (Saf.) and satisfaction (Sat.). Each dimension was associated with different sentences which the participants had to give their opinion about on a Likert

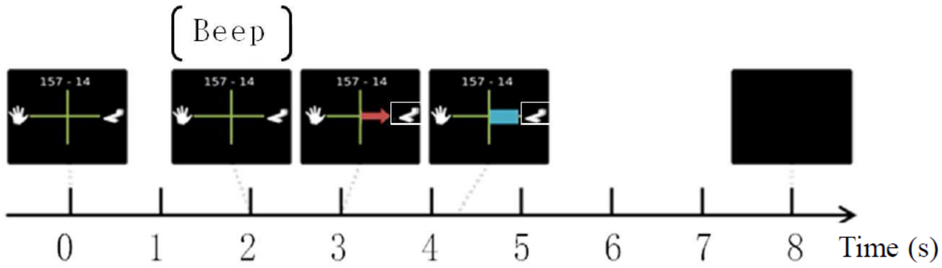

Figure 4.6: Timing of a trial.

scale ranging from 1 (i.e., do not agree at all) to 5 (i.e., totally agree). For example, the satisfaction was in part evaluated though the sentence “Overall, I am satisfied with the system”. Participants trained with PEANUT also had a questionnaire assessing the adequacy of the latter regarding its appearance, the content and the frequency of its interventions and its general appreciation. Once again, each dimension evaluated was associated with different sentences which the participants had to give their opinion about on a Likert scale ranging from 1 (i.e., do not agree at all) to 7 (i.e., totally agree). For example, the content of the intervention was in part evaluated though the sentence “I think that the interventions of the companion were relevant”.

4.3.1.3 EEG Recordings & Signal Processing

The EEG signals were recorded from a g.USBamp amplifier, using 30 scalp electrodes (F3, Fz, F4, FT7,FC5, FC3, FCz, FC4, FC6, FT8, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P3, P1, Pz, P2, P4, P6, PO7, PO8, 10-20 system) [Friedrich et al., 2013], referenced to the left ear and grounded to AFz. EEG data were sampled at 256 Hz. In order to classify the 3 mental imagery tasks on which our BCI is based, the following EEG signal processing pipeline was used. First, EEG signals were band-pass filtered in 8-30Hz, using a Butterworth filter of order 4. Then EEG signals were spatially filtered using 3 sets of Common Spatial Pattern (CSP) filters [Ramoser et al., 2000]. The CSP algorithm aims at finding spatial filters whose resulting EEG band power is maximally different between two classes. Each set of CSP filters was optimised on each user’s calibration run (i.e., the first run of the first session) to discriminate EEG signals for a given class from those for the other two classes. We optimized 2 pairs of spatial filters for each class, corresponding to the 2 largest and lowest eigen values of the CSP optimization problem for that class, thus leading to 12 CSP filters. The band power of the spatially filtered EEG signals was then computed by squaring the signals, averaging them over the last 1 second time window (with 15/16s overlap between consecutive time windows) and log-transformed. These resulted in 12 band-power features that were fed to a multi-class shrinkage Linear Discriminant Analysis (sLDA) [Lotte and Guan, 2010], built by combining three sLDA in a one-versus-the-rest scheme. As for the CSP filters, the sLDA were optimised on the EEG signals collected during the calibration run, i.e., during the first run of the first session. The resulting classifier was then used online to distinguish between the 3 MI-tasks during the 3 sessions. The sLDA classifier output (i.e., the distance of the feature vector from the LDA separating hyperplane) for the mental imagery task to be performed was used as feedback provided to the user. In particular, if the required mental task was performed correctly (i.e., correctly classified), a blue bar with a length proportional to the LDA output and extending towards the required task picture was displayed on screen and updated at 16Hz. This processing pipeline led to a total of 64 classification outputs per trial (16 per second for 4 seconds). OpenViBE thus computed the user's performance for this trial as the rate of correct classification outputs among these 64 outputs, and sent it to the rule engine, which in turn computed progression measures.

4.3.1.4 Variables & Factors

We used both the mean and the peak classification accuracy as a measure of performance. These measures are traditionally used by the community. The mean accuracy represents the percentage of time windows from the feedback periods that were correctly classified. The peak classification was computed by averaging the performances obtained during the time window of the feedback period for which the classification accuracy over all trials is maximal (see Section 4.3.1.3 EEG Recordings & Signal Processing for more details on the classifier). We studied the impact of the group (no companion, PEANUT) on participants' MI-BCI performances, with respect to the session and participant's profile ("autonomy" and "tension" scores according to the 16PF5 questionnaire [Cattell and P. Cattell, 1995]). We also evaluated the impact of the group on MI-BCI usability and on the perception of the companion, with respect to MI-BCI performance.

4.3.2 Results

We checked the normality of the variables that we obtained using Lilliefors corrected Kolmogorov-Smirnov tests. If the variables were Gaussian, we performed t-tests to compare the two groups. In the opposite case we performed Mann-Whitney U tests. Mean and peak performances from each session had a normal distribution ($p \geq 0.1$). We also verified that there was no confounding factor between our two groups. Participants from the two groups were statistically similar before the training. There were no significant differences of age [Mann-Whitney U test, U=50, p=0.06], initial performances computed using a 5-fold LDA classification on CSP characteristics from the first run of the first session where PEANUT was not present for either group [t-test, $t(26)=0.85$; $p=0.4$], tension [Mann-Whitney U test, U=75.5, p=0.49] or autonomy [Mann-Whitney U test, U=60.5, p=0.16].

4.3.2.1 Influence of PEANUT on MI-BCI Performances

Then, we compared the group's MI-BCI performance in terms of mean and peak classification accuracy. We performed a 2-way repeated measures mixed ANOVA with *"Group*Session"* as independent variables and the repeated measures of mean or peak performance over the session as dependent variable. When using the mean performances as dependent variable, results revealed no significant effect of the *"Group"*

[F(1,26)=0.63; p=0.43, η^2=0.02], *"Session"* [F(2,52)=0.03; p=0.97, η^2=0], nor *"Session*Group"* [F(2,52)=0.79; p=0.46, η^2=0.03], i.e., the evolution of the performances over the sessions. Similar results were obtained with the peak performances. They revealed no significant effect of the *"Group"* [F(1,26)=0.87; p=0.36, η^2=0.03], *"Session"* [F(2,52)=0; p=1, η^2=0], nor *"Session*Group"* [F(2,52)=0.46; p=0.64, η^2=0.02], i.e., the evolution of the performances over the sessions. Averaged over all runs and sessions, the group with no companion (N=18) and the group with PEANUT (N=10) respectively obtained peak performances scores of 65.73% ± 6.21 and 63.14% ± 8.4 and mean performances scores of 52.76% ± 5.62 and 50.74% ± 7.77 (see Figure 4.7).

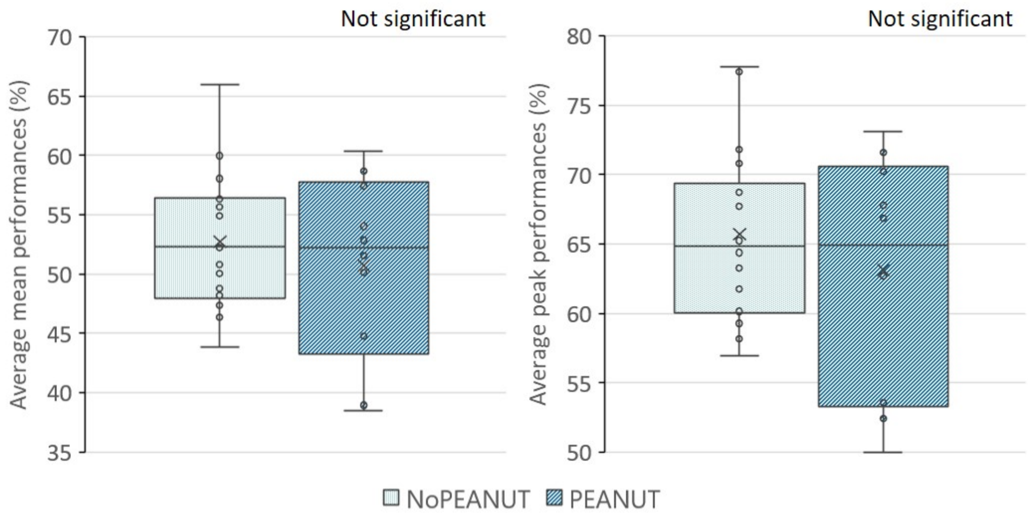

Figure 4.7: Average mean and peak performances for both the experimental and the control group.

Nevertheless, we performed analyses to assess the impact of users' profile on performance, depending on the group. The influence of the "autonomy" of participants training without PEANUT on their MI-BCI performances previously found in [Jeunet et al., 2015a] when taking into account the 6 sessions of the participants' training could still be found when taking into account only the first 3 sessions to compare the results of both groups. We observed a positive correlation of the mean and peak performances with the autonomy of the participants who had a classical training without PEANUT [Spearman correlation ; mean: r=0.54, p=0.02 ; peak: r=0.5, p=0.03] which means that participants who like to work in group tend to be disadvantaged. Interestingly, an opposite significant negative correlation between the measure of autonomy and the mean and peak performances over the sessions for the participants trained with PEANUT [Spearman correlation, mean: r=-0.78, p=0.01, peak: r=-0.75, p=0.01] which means that participants who are prone to work in a group tend to perform better than those who rather work alone when PEANUT is part of the training. To further investigate the influence of PEANUT and the autonomy of the participants on their BCI performances, we separated the participants into two groups depending on their autonomy. The threshold between high and low autonomy was defined using the median autonomy score (i.e., score of 5, 10 being the maximum). We then led 2-way ANOVAs to determine the influence of *Group* (PEANUT or no PEANUT) and the *Autonomy* (Autonomous or non Autonomous) on MI-BCI performances. Results indicate a *Group*Autonomy* interaction for both mean performances [F(1,24)=6.35 ; p=0.02, η^2=0.21] and peak performances [F(1,24)=7.23 ; p=0.01, η^2=0.23] (see Figure 4.8). Overall these results confirm the importance of this personality trait for BCI training as was suggested in [Jeunet et al., 2015a]. They also indicate a possible differential influence of a learning companion on MI-BCI performances depending on the personality trait.

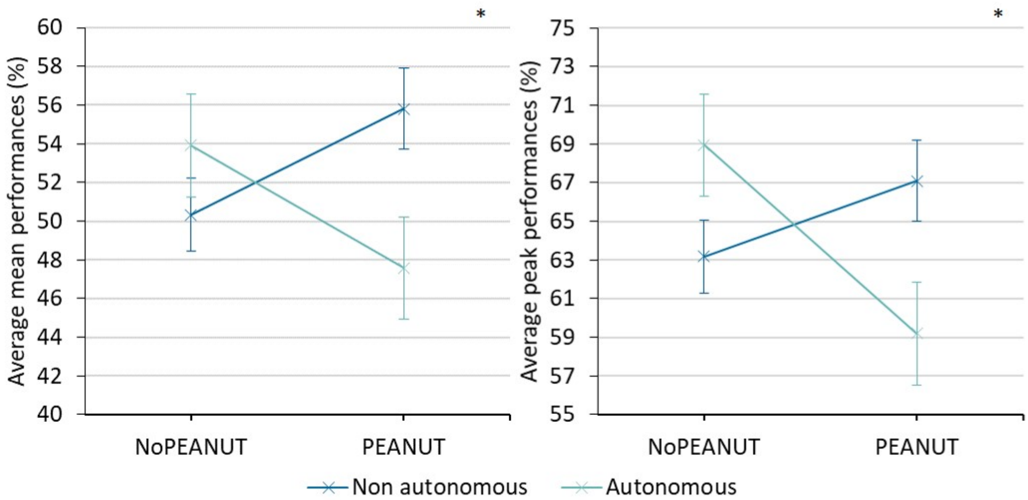

Figure 4.8: Average mean and peak performances of the participants depending on there *Autonomy* and the *Group* they belonged to.

However, the previous influence of tension on MI-BCI performances found on the participants trained without PEANUT in [Jeunet et al., 2015a] when taking into account the 6 sessions of the participants' training could not be found when taking into account only the first 3 sessions [Spearman correlation ; mean: r=-0.25, p=0.33 ; peak: r=-0.21, p=0.4]. It could neither be found on the results of the participants trained with PEANUT [Spearman correlation ; mean: r=-0.14, p=0.7 ; peak: r=-0.13, p=0.72]. This aspect of psychological profile influence on MI-BCI performances might require further investigations with longer term experiments.

We also observed a strong negative correlation between the performances and the measure of sensibility (based on the dimension of the 16PF5 psychometric questionnaire) of the participants trained with PEANUT [Spearman correlation ; mean: r=-0.89, p=10^{-3} ; peak: r=-0.91, p$\leq 10^{-3}$]. The more sensitive people were, the less likely to have good MI-BCI performances they were. This correlation is not found for the participants trained without PEANUT [Spearman correlation ; mean: r=-0.04, p=0.88 ; peak: r=-0.06, p=0.82].

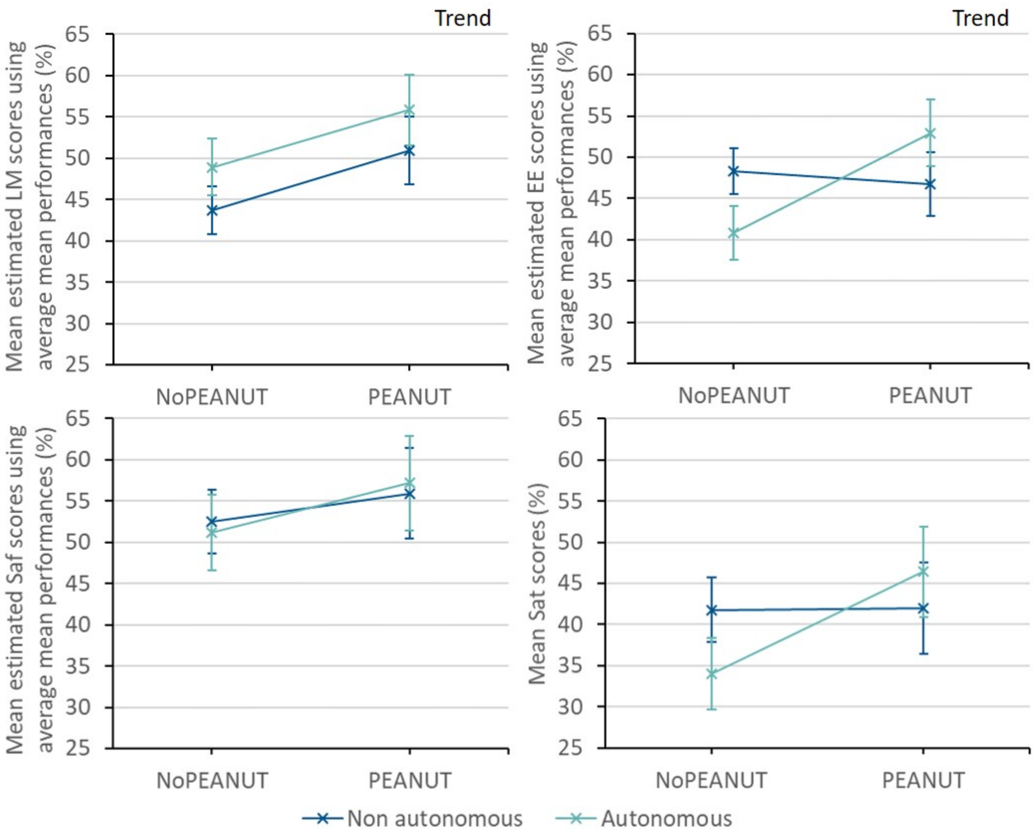

Figure 4.9: Usability scores, with respect to users' group and autonomy, corrected using the average mean performance if needed.

4.3.2.2 Influence of PEANUT on the user experience

Then, we analysed the influence of *Autonomy* and *Group* on usability scores, which were divided into 4 dimensions: learnability/memorability (LM), efficiency/effectiveness (EE), safety (Saf), satisfaction (Sat) [Heutte et al., 2016]. We performed four 2-way ANCOVAs (one per dimension) with the *Autonomy* and *Group* as factor, the usability score for the target dimension as dependent variable and the mean or peak classification accuracy as co-variable for the LM, EE and Saf dimensions to remove the influence of performances on their evaluation (Spearman correlation; mean: LM [r=0.58, p=10^{-3}], EE [r=0.54, p$\leq 10^{-2}$], Saf [r=0.59, p=10^{-3}], Sat [r=0.07, p=0.73] ; peak: LM [r=0.56, p$\leq 10^{-2}$], EE [r=0.56, p$\leq 10^{-2}$], Saf [r=0.548, p$\leq 10^{-2}$], Sat [r=0.03, p=0.89]) (see Figures 4.9 and 4.10).

Results reveal a close to significant effect of the group on the LM dimension [mean: D(1,28)=3.68, p=0.07, η^2=0.14 ; peak: D(1,28)=3.99, p=0.06, η^2=0.15]. On average, participants who were provided with PEANUT consider the system's learnability/memorability to be higher by 7.4% than those without PEANUT. A *Group*Autonomy* interaction [mean: D(1,28)=3.2, p=0.09, η^2=0.12 ; peak: D(1,28) =4.05, p=0.06, η^2=0.15] on the EE dimension also tends to be significant when using the peak performance as covariate. Autonomous participants reported feeling that they were more Efficient/Effective by 13.4% when PEANUT was present. To the contrary, non autonomous participants reported feeling that they were less Efficient/Effective by 1.8%.

4.3.2.3 Characteristics of PEANUT

Finally, we analysed the results of the open questionnaire that participants in the experimental group answered about the characteristics of PEANUT, i.e., appearance, content and frequency of intervention, general appreciation. We summed the responses to the Likert scales for each characteristic and divided them in relation to the maximum score that could have been given to these questions to obtain the following percentages. The higher the percentage is and the better the participants rated the characteristic of PEANUT. On average, the users rated the different characteristics as follows: appearance [M=82,14%, SD=13.07%], content [M=56.9%, SD=16.92%] and frequency of intervention [M=80.36%, SD=13.1%], general appreciation [M=67.14%, SD=19.22%] (see Figure 4.11).

The appearance of PEANUT and the frequency of its intervention seem to have been appreciated. Though, improvements should probably be made regarding the content of its interventions and the general appreciation of PEANUT. The comments from the participants provide further information. Two participants reported not understanding its role and expected a more informative feedback. This is in line with recommendations from the literature but providing an informative feedback still remains a challenge (see *Related work*). Two also reported that the sentences did not always seem in agreement with the visual feedback they received. This could be because the rule tree took into account the last performance of the user when choosing a sentence regarding the progression of the user but could still lead to PEANUT congratulating participants when their last performance was not promising. For example, PEANUT could still tell participants that they were improving when their

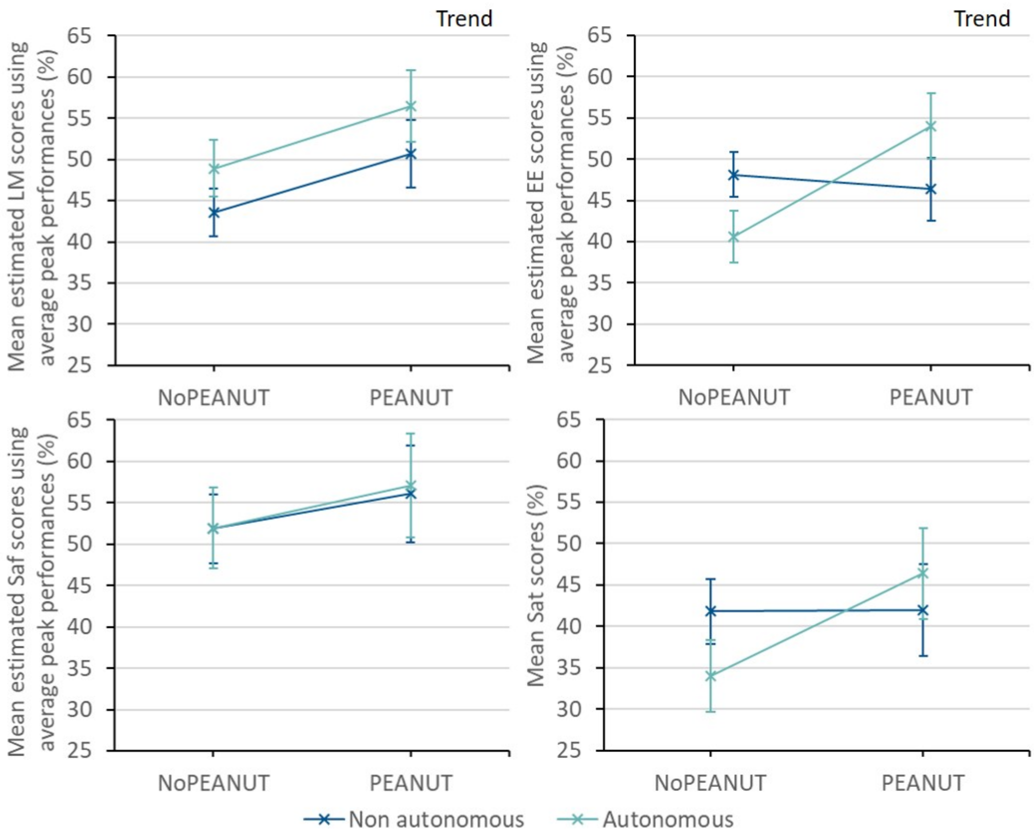

Figure 4.10: Usability scores, with respect to users' group and autonomy, corrected using the average peak performance if needed.

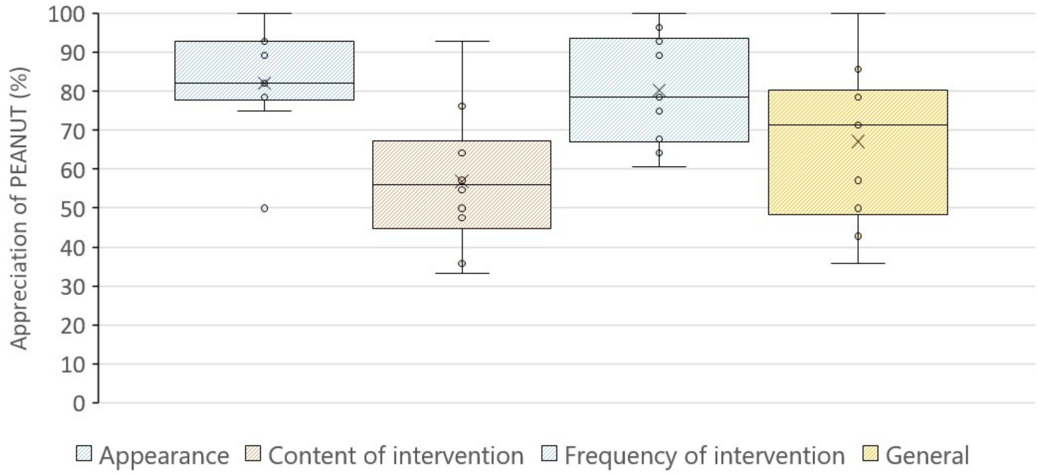

Figure 4.11: Percentage of appreciation of PEANUT regarding its appearance, content and frequency of intervention and general appreciation.

last performance was considered as poor. Lastly, a positive correlation was found between the "tension" of the participants and the content of intervention of PEANUT [r=0.671, p=0.034], as well as between their "anxiety" and the responses they gave regarding the content of intervention [r=0.671, p=0.034] and the general appreciation [r=0.703, p=0.023] of PEANUT. This indicates that the more tensed participants tended to be, the more they appreciated PEANUT in general and its content of intervention.

4.3.3 Discussion

First of all, we found that non-autonomous users, who had lower MI-BCI performances than the others when using a classical feedback, seem to have better performances by 3.9% than the others when using PEANUT. Second, using PEANUT seems to have improved the usability of the MI-BCI. Participants who trained with PEANUT gave on average 7.4% higher learning/memorability scores than the members of the control group. Furthermore, autonomous participants trained with PEANUT found that they were more efficient than the ones trained without PEANUT by 13.4% on average. However, PEANUT had a negative impact on the performances of sensitive and autonomous participants. This could be related to the margin of improvement reported by the participants regarding the content of the interventions of PEANUT who expected a more informative feedback. Even though PEANUT was providing feedback in-between trials, some participants may also have been distracted by it and not have benefited from the feedback as much as the others [Kennedy et al., 2015]. Finally, the influence of a learning companion depends on the task and the user's personality [Silverman et al., 2001]. Therefore, the impact of PEANUT could be limited by the fact that it does not adapt to the user's personality and because it does not reduce the complexity of the task.

Through the feedback provided by PEANUT, participants in the experimental group were informed of the evolution of their performances and advised to keep or change strategies. These meta-information regarding the performance, which were not present for the control group, might also explain the observed differences. However, as the improvement was only present for the non-autonomous participants we believe that the social presence and the emotional feedback were the main factors underlying the improvement of the performances. Despite the promising results, our study suffers from the limited number of participants included in it. This limitation needs to be overcome in future experiments to be able to generalize the results.

4.4 Conclusion and Prospect

In the previous sections 4.2 and 4.3, we introduced the design, implementation and evaluation of the first learning companion dedicated to MI-BCI user-training: PEANUT. The strength of this experimental protocol is the design of the companion: a combination of recommendations from the literature, the analysis of data from previous experiments and user-studies. PEANUT was evaluated in an MI-BCI study (10 participants trained with PEANUT, 18 control participants, 3 sessions per participant). This study revealed that using PEANUT had an impact on performances depending on the autonomy of the users. Indeed, there seems to be a beneficial influence of PEANUT on non-autonomous persons, who were shown to have lower performances than the others in previous studies [Jeunet et al., 2015a]. Furthermore, PEANUT tends to have a beneficial impact on the user experience. Both autonomous and non autonomous users found it easier to learn and memorize how to use the MI-BCI system. While the specific target application explored here was MI-BCI control, many of the results could benefit other applications. First, our user studies provided useful insights about the kind of interventions, and more particularly concerning the style (exclamatory/declarative, personal/non-personal) that users prefer depending on their performance and progression. Second, our user studies suggested that the use of eyebrows favours expressiveness in cartoon-like companions, independently of BCI use, which is in line with the work of Ekman who highlighted the major influence of eyebrows for expressing numerous emotions such as happiness, surprise or anger [Ekman, 1993].

PEANUT could potentially be used to help users train to control other applications. Since PEANUT provides interventions based only on performance and progression, it could possibly be used in other application training procedures in which these two metrics are relevant, e.g., biofeedback and physiological computing [Fairclough, 2009] or even computer-assisted motor and sports training [Jovanov et al., 2005], in which a social and emotional feedback should also be carefully considered [Mencarini et al., 2016]. To this end, we designed and implemented PEANUT for a low cost, using only open-source and free software. Ultimately, the emotional and social feedback could be improved by adapting it to the psychological profile of the users. For example, autonomous participants do not seem to benefit from the presence of PEANUT so it would be worth specifically studying their expectations. Emotional feedback and social presence could also be improved by using emotion estimation algorithms. For instance, by using passive BCIs [Zander and Jatzev, 2009], which enable the extrapolation of some mental states of the users from their brain activity, physiological computing, or emotion facial expressions from video [Picard, 2003, D'Mello et al., 2012].

Chapter 5

Contribution 2 - Do experimenters influence MI-BCI training?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - A physical learning companion can be useful for MI-BCI user training depending on learners' autonomy
	5. **Contribution 2** - Do experimenters influence MI-BCI training?
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

Collaborators: Aline Roc (Master student at the time).

Related full papers: Roc, A., Pillette, L., N'Kaoua, B. & Lotte, F., « Would Motor-Imagery based BCI user training benefit from more women experimenters? ». *8th International BCI Conference*, Graz, Austria.

Roc, A., Pillette, L., N'Kaoua, B. & Lotte, F., « Influence of Experimenters on Mental-Imagery based Brain-Computer Interface User Training ». In preparation.

5.1 Introduction

The results from the experiment with PEANUT indicated that social presence and emotional feedback could have an impact on MI-BCI performances. The prevalent and complex source of social presence and emotional feedback during experiments originates from the human supervision (e.g., experimenter or caregiver). While providing emotional feedback and social presence, people present BCIs to users and ensure smooth users' progress with BCI use. Though, very little is known about the influence experimenters might have on MI-BCI training outcome (see Section 2.1.2 Social presence and emotional feedback).

The section 2.1.2 Social presence and emotional feedback) describes in length the literature on experimenter biases. The following paragraphs summarize the main points, which are necessary for the understanding of this section. When reviewing the literature of different fields on the experimenter biases, we found that several of them were related to experimenters' gender, participants' genders and an interaction of the experimenters' and participants' gender [Spencer et al., 1999, Levine and De Simone, 1991, Rosenthal, 1963]. Many cultural stereotypes are gender-based. For example, women are often seen as having weaker math abilities or computer skills than men [Spencer et al., 1999]. Often, when people are aware of a stereotype, they tend to adopt a behaviour that confirms the stereotype [Rosenthal, 1963]. Wood and Kober found that experimenters could have a differential impact on neurofeedback training depending on their gender, the gender of their participants and the level of locus of control in dealing with new technologies [Wood and Kober, 2018]. They relate this difference of performances to psychosocial factors.

Results from other fields than neurofeedback and BCI, indicate that the interplay of participant's and experimenter's genders may also shape the experimenter demand effect. When participants are instructed by an opposite-sex experimenter, they seem more likely to act in ways that confirm the experimenter's hypothesis [Nichols and Maner, 2008]. Also, men participants seem to elaborate more on autobiographical memory report with women experimenters than with men experimenters and more than women participants in general [Grysman and Denney, 2017]. Proxemics studies, which study the amount of space that people feel necessary to set between themselves and others, provide another example of gender interaction. Men participants seem to keep a shorter distance from women than from men [Uzzell and Horne, 2006]. Interestingly, participants also prefer a larger comfort and reachability distance when facing a virtual man as compared to a virtual woman [Iachini et al., 2016]. Another gender-related example would be that defensiveness is associated with greater relative left frontal activation in the presence of experimenters from the opposite-sex compared to experimenters from the same-sex [Kline et al., 2002]. Thus, participants who work with an opposite-gender or same-gender experimenter can have different neurological responses, such as differences in their EEG recordings [Chapman et al., 2018].

To summarize, during MI-BCI experimental protocols, experimenters most probably play a key role [Sexton, 2015]. For instance, they introduce the technology to the participants, provide the participants with advice regarding how they should perform the MI tasks and keep the participants motivated throughout the training. The previous section 4.3 Can a physical learning companions improve MI based BCI user training? demonstrated the influence that social presence and emotional feedback could have on user experience and MI-BCI performances. Our analysis of the literature clearly indicates a potential impact of the experimenter. Despite the main role that experimenters have in the experimental process and the literature regarding the impact of social and emotional feedback, no studies had yet been led in MI-BCI to evaluate the influence experimenters might have on their own experimental results.

These observations led us to think that a gender-interaction could have an effect on MI-BCI experimental results. We led an experiment with 6 experimenters who each trained 10 participants (5 men and 5 women) to use a motor imagery based BCI over several runs in a single session. The aim of our study was to investigate if there was an influence of the experimenters' gender depending on the participants' gender on MI-BCI performances and progression (i.e., the evolution of performances across a session).

5.2 Materials & methods

5.2.1 Participants

Fifty-nine healthy MI-BCI naïve participants (29 women; age 19-59; $\bar{X}$=29; SD=9.32) completed the study. None of them reported a history of neurological or psychiatric disorder. Experimenters who conducted the study were six scientists (3 women; age 23-37; $\bar{X}$=29.2; SD=5.60) among whom two were experienced in BCI experimentation, having conducted more than 100 hours of EEG-based BCI experiments, (1 woman) and four beginners who were trained to perform a BCI experiment beforehand. Each experimenter was randomly assigned to 10 participants (5 women and 5 men) they had never met before the session.

Our study was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. Both participants and experimenters gave informed consent before participating in the study. In order to avoid biased behaviour, this study was conducted using a deception strategy, partially masking the purpose of the study. Participants were told that the study aimed at understanding which factors (unspecified) could influence BCI progress and/or performance. Experimenters were aware of the goal of the study. The study has been reviewed and approved by Inria's ethics committee, the COERLE.

5.2.2 Experimental protocol

Each participant participated in one MI-BCI session of 2 hours. The session was organized as follows: (1) consent form signature and completion of several questionnaires (around 20 min), (2) installation of the EEG cap (around 20 min), (3) six 7-minute runs during which participants had to learn to perform two MI-tasks, i.e., imagine right or left hand movements (around 60 min, including breaks between the runs), (4) completion of post-session questionnaires (around 5 min) and (5) uninstallation and debriefing (around 10 min).

During each run, participants had to perform 40 trials (20 per MI-task, presented in a random order), each trial lasting 8s. At t = 0s, an arrow was displayed on the screen. At t = 2s, an acoustic signal announced the appearance of a red arrow, which appeared one second later (at t = 3s) and remained displayed for 1.250s. The arrow pointed in the direction of the task to be performed, namely left or right to imagine a movement of the left hand or the right hand. Finally, at t = 4.250s, a visual feedback was provided in the shape of a blue bar, the length of which varied according to the classifier output. Only positive feedback was displayed, i.e., the feedback was provided only when the instruction matched the recognized task. The feedback lasted 3.75 s and was updated at 16Hz, using a 1s sliding window. After 8 seconds of testing, the screen turned black again. The participant could then rest for a few seconds, and a new cross was then displayed on the screen, marking the beginning of the next trial.

The training protocol used was the Graz protocol [Pfurtscheller and Neuper, 2001] which is divided into two steps: (1) training of the system and (2) training of the user. The first two runs were used as calibration in order to provide examples of EEG patterns associated with each of the MI tasks to the system. During the first two runs, as the classifier was not yet trained to recognize the mental tasks being performed by the user, it could not provide a consistent feedback. In order to limit biases with the other runs, e.g., EEG changes due to different visual processing between runs, the user was provided with an equivalent sham feedback, i.e., a blue bar randomly appearing and varying in length.

We respected the following recommendations: encourage the user to perform a kinesthetic imagination [Neuper et al., 2005] and leave users free to choose their mental imagery strategy [Kober et al., 2013], e.g., imagining waving at someone or playing the piano. Participants were instructed to find a strategy for each task so that the system would display the longest possible feedback bar. Instructions were written in advance so that all the participants started with the same standardized information.

5.2.3 Questionnaires

We assessed personality and cognitive profile for both experimenters and participants with the 5th edition of the 16 Personality Factors (16PF5) [Cattell and P. Cattell, 1995], a validated psychometric questionnaire to assess different aspects of personality and cognitive profile. This questionnaire identifies 16 primary factors of personality, including tension and autonomy. Participants also completed a mental rotation test measuring spatial abilities [Vandenberg and Kuse, 1978].

Our participants also filled pre and post experiment questionnaires especially developed for the assessment of BCI participants' states and user-experience by Aurore Hakoun, Samy Chikhi and François-Benoît Vialatte (in process of validation, see Annexe) [Jaumard-Hakoun et al., 2017]. Based on validated questionnaires, it determines five dimensions of user-state and/or user-experience. Three of them are assessed pre and post training and evaluate the mood, mindfulness and motivational states of the user. Two of them assess the user-experience post-training through the cognitive load, i.e., amount of cognitive process required to control the MI-BCI system, and the agentivity, i.e., feeling of control of the participant over the feedback provided by the MI-BCI. The evolution of the participant's states also provides an information regarding the user-experience.

5.2.4 EEG Recordings & Signal Processing

To record the EEG signals, 27 active scalp electrodes, referenced to the left earlobe, were used (Fz, FCz, Cz, CPz, Pz, C1, C3, C5, C2, C4, C6, F4, FC2, FC4, FC6, CP2, CP4, CP6, P4, F3, FC1, FC3, FC5, CP1, CP3, CP5, P3, 10-20 system). Electromyographic (EMG) activity of the hands was recorded using two active electrodes situated 2.5cm below the skinfold on each wrists. Electrooculographic (EOG) activity of one eye was recorded using three active electrodes. Two of them, situated below and above the eye and one on the side. They aimed at recording vertical and horizontal movements of the eye. Physiological signals were measured using a g.USBAmp (g.tec, Austria), sampled at 256 Hz, and processed online using OpenViBE 2.1.0 [Renard et al., 2010].

To classify the two MI tasks from EEG data, we used participant-specific spectral and spatial filters. First, from the EEG signals recorded during the calibration runs, we identified a participant-specific discriminant frequency band using the heuristic algorithm proposed by Blankertz et al. in [Blankertz et al., 2008] (Algorithm 1 in that paper). Roughly, this algorithm selects the frequency band whose power in the sensorimotor channels maximally correlates with the class labels. Here we used channels C3 & C4 after spatial filtering with a Laplacian filter as sensorimotor channels, as recommended in [Blankertz et al., 2008]. We selected a discriminant frequency band in the interval from 5 Hz to 35 Hz, with 0.5Hz large bins. Once this discriminant frequency band identified, we filtered EEG signals in that band using a Butterworth filter of order 5.

Then, we used the Common Spatial Pattern (CSP) algorithm [Ramoser et al., 2000] to optimize 3 pairs of spatial filters, still using the data from the two calibration runs. Such spatially filtered EEG signals should thus have a band power which is maximally different between the two MI conditions. We then computed the band power of these spatially filtered signals by squaring the EEG signals, averaging them over a 1 second sliding window (with 1/16th second between consecutive windows), and log-transforming the results. This led to 6 different features per time window, which were used as input to a Linear Discriminant Analysis (LDA) classifier [Lotte and Jeunet, 2018]. As mentioned above, this LDA was calibrated on the data from the two calibration runs. These filters and classifier were then applied on the subsequent runs to provide online feedback.

5.2.5 Variables & Factors

Our first aim was to evaluate the influence of the gender of the experimenters and participants on the MI-BCI performances of the participants over a series of 4 runs with online BCI use. Two measures were used to assess the performance of the participants.

The first performance metric we used is the online Trial-wise Accuracy (TAcc). This metric is computed by first summing the (signed) LDA classifier outputs (distance to the separating hyperplane) over all epochs (1s long epochs, with 15/16 s overlap between consecutive windows) during a trial feedback period. If this sum sign matched the required trial label, i.e., negative for left hand MI and positive for right hand MI, then the trial was considered as correctly classified, otherwise it was not. The TAcc for each run was estimated as the percentage of trials considered as correctly classified using this approach. TAcc is the default accuracy measure provided online in the MI-BCI scenarios of OpenViBE, and the only performance metric that the experimenters were seeing online. It should be noticed that this metric takes into account the classifier output and is thus also related to the feedback bar length as it is proportional to the classifier output. Our participants were instructed to train to obtain not only a correct classification, but also a feedback bar as long as possible, the TAcc metrics thus take into account both aspects. Offline, we also computed the more standard Epoch-wise Accuracy (EAcc) as the percentage of epochs (1s long time windows) from the feedback periods that were correctly classified. However, this metric only considers whether the classification was correct, but not the feedback bar length as it does not take into account the classifier output.

Because brain signals are really small in amplitude and EEG suffer from very low signal to noise ratio (SNR), i.e. high vulnerability to artefact sources, we controlled for the most common artefact sources, i.e., electrooculography (EOG) and electromyography (EMG). To do so, we computed two performances per source of artefacts. The training dependant EOG or EMG accuracies, are computed using a CSP and an LDA calibrated on the data, filtered in the participant-specific discriminant frequency band, from the two calibration runs and applied on the subsequent runs to obtain a measure of EOG or EMG accuracy per run. The training dependant accuracies reflects the frequency and similarity in the performance of eye or hand movements during the calibration and the training phases. The second metrics, called the run dependent EOG or EMG accuracies, are computed using a cross validation method. Data, filtered in the participant-specific discriminant frequency band, from each run are divided into five subsets of data. The CSP and an LDA are successively calibrated on each set and tested on the remaining four sets. The run dependent EOG or EMG metric of each run is the mean classification accuracy obtained for the five subsets. The run dependent accuracies reflects the frequency and similarity in the performance of eye or hand movements during each run.

Second, we wanted to assess the potential impact on the user experience. The user experience is defined by the two percentages provided by the questionnaire of Aurore Hakoun et al. [Jaumard-Hakoun et al., 2017] regarding the amount of cognitive load and agentivity felt during the training. It is also defined by the evolution of mood, mindfulness and motivation, assessed in percent, of the participants between the beginning and end of the training. This evolution is assessed by subtracting the measure post training to the measure pre training. The higher the percentage, the more the participants increased their reported levels of positive emotions and calm, mindfulness, motivation, cognitive load and sense of agency.

Finally, we wanted to know if other characteristics of the experimenters' and/or participants' profile than the gender could provide first elements of comprehension regarding the potential difference in MI-BCI performances or user-experience. We focused on characteristics of the profile that were shown to have an influence on MI-BCI performances in previous studies [Jeunet et al., 2015a]. Participants with low mental rotation scores, i.e., MRS, [Vandenberg and Kuse, 1978], tensed and/or non-autonomous (both measured using the 16PF5 questionnaire [Cattell and P. Cattell, 1995]) were shown to have lower MI-BCI performances than the others [Jeunet et al., 2015a]. Positive mood, motivation and mindfulness were also shown to have a positive impact on MI-BCI performances [Nijboer et al., 2008, Tan et al., 2014].

5.3 Results

5.3.1 Comparability of the groups

Among 59 participants, 3 outperformed the others (by more than two SDs) both in term of TAcc (respectively, outliers $\bar{X}1$=98.13, $\bar{X}2$=98.13, $\bar{X}3$=99.38; $\bar{X}$grp=62.78%; SDgrp=16.2) and EAcc (outliers $\bar{X}1$=88.94, $\bar{X}2$=90.36, $\bar{X}3$=94.51; $\bar{X}$grp=59.33%; SDgrp=12.3). Thus, the following analyses are based on the results of 56 participants (27 women).

Before it all, we verified if the distribution of the data collected was normal using Shapiro-Wilk tests. The variables describing the mental rotation scores (p=0.34), tension (p=0.06), autonomy (p=0.14), difference of mindfulness (p=0.08) and motivation (p=0.13) post and pre training and agentivity post training (p=0.16) of our participants could be considered as having a normal distribution. Though, the TAcc and EAcc metrics for the different runs did not have normal distributions ($p \leq 10^{-3}$). Neither did the measure of cognitive load post training (p=0.02), difference of mood post and pre training ($p \leq 10^{-2}$), and the measures of mood (p=0.03), mindfulness ($p \leq 10^{-2}$) and motivation ($p \leq 10^{-3}$) pre training had normal distributions.

We also checked that groups formed by participants' gender, i.e., *"ParGender"*, and experimenters' gender, i.e., *"ExpGender"*, had comparable profiles. To check that groups were comparable, we ran 2-way ANOVAs with *"ExpGender*ParGender"* as independent variables and either MRS, tension or autonomy as dependent variable.

Results indicate that groups are comparable in terms of tension. Though, participants' gender influence their MRS [F(1,52)=17.47; $p \leq 10^{-3}$, η^2=0.25]. Men ($\bar{X}$men= 0.07; SD=0.02) had higher MRS than women ($\bar{X}$women=0.05; SD=0.02), which is in accordance with the literature [Linn and Petersen, 1985]. Furthermore, participants training with men or women experimenters did not have the same level of autonomy [F(1,52)=4.01; p=0.05, η^2=0.07]. Participants training with men experimenters ($\bar{X}$menExp=6.35; SD=1.74) were more autonomous than participants training with women experimenters ($\bar{X}$womenExp=5.67; SD=1.66). Therefore, we controlled for the potential influence of these variables in our subsequent analyses by using them as covariates in ANCOVAs (see section 5.3.2.2 Checking for confounding factors).

5.3.2 Influence of participants' and experimenters' gender on MI-BCI performances

5.3.2.1 Main analyses

Then, we analysed the influence of the gender of the experimenters and participants on the MI-BCI performances of the participants over the runs, i.e., *"Run"*. To this extent, we performed a 3-way repeated measures mixed ANOVAs with *"ExpGender*ParGender*Run"* as independent variables and the repeated measures of performance over the runs, i.e., TAcc or EAcc, as dependent variable. Even though the normality of the data is a pre-requisite of an ANOVA, the ANOVA is considered as robust against the normality assumption and, to the best of our knowledge, no other non parametric test enabled such analysis to be performed.

First, we performed such ANOVA using the TAcc. After correction of sphericity using the Huynh-Feldt method (epsilon=0.92), the results revealed no simple effect of *"Run"* [$F(2.8,144)=1.81$; $p=0.15$, $\eta^2=0.03$], *"ExpGender"* [$F(1,52)=0.54$; $p=0.47$, $\eta^2=0.01$] nor *"ParGender"* [$F(1,52)=0.09$; $p=0.76$, $\eta^2=0.01$]. They also revealed no interaction of *"Run*ExpGender"* [$F(2.8,144)=0.08$; $p=0.96$, $\eta^2=10^{-2}$] nor *"ParGender*ExpGender"* [$F(1,52)=0.60$; $p=0.44$, $\eta^2=0.01$]. Though, the *"Run*ParGender"* interaction was significant [$F(2.8,144)=5.98$; $p=0.001$, $\eta^2=0.1$]. Figure 5.1 represents the evolution of the participants' TAcc depending on their gender.

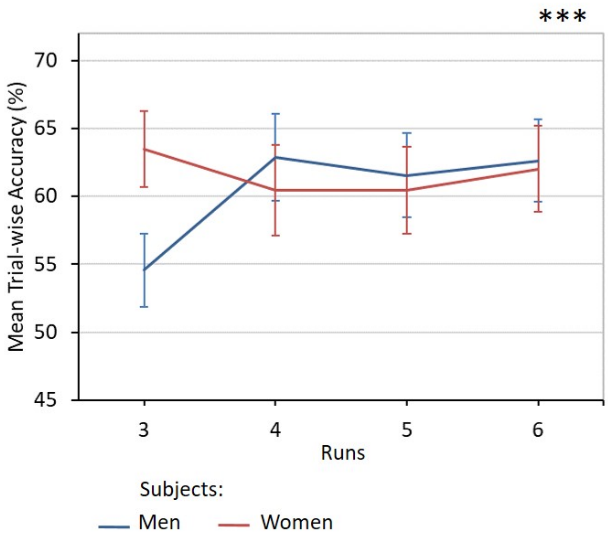

Figure 5.1: TAcc evolution depending on participants' gender.

A significant *"Run*ParGender*ExpGender"* interaction was also found [$F(2.8,144)=3.46$; $p=0.02$, $\eta^2=0.06$]. Figure 5.2 represents the participants' TAcc evolution depending on the participants' and experimenters' gender.

Next, we performed this same analysis using the EAcc. After correction of sphericity using the Huynh-Feldt method (epsilon=0.8), the results revealed no sim-

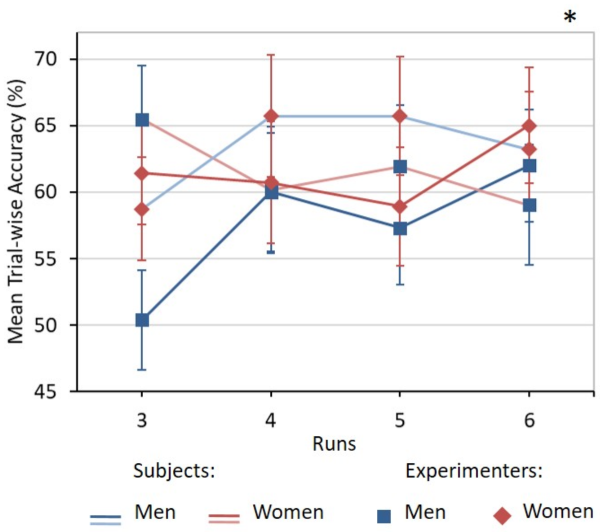

Figure 5.2: TAcc evolution depending on the participants' and experimenters' gender.

ple effect of *"Run"* [F(2.4,125)=1.53; p=0.22, η^2=0.03], *"ExpGender"* [F(1,52)=0.26; p=0.61, η^2 $\leq$0.01] and *"ParGender"* [F(1,52)=0.23; p=0.64, η^2 $\leq$0.01]. They revealed no interaction of *"Run*ParGender"* [F(2.4,125)=1.92; p=0.14, η^2=0.04], *"Run* ExpGender"* [F(2.4,125)=0.23; p=0.83, η^2=0.01] nor *"ParGender*ExpGender"* [F(1, 52)=0.92; p=0.34, η^2=0.02]. Finally, the interaction of *"Run*ParGender*ExpGender"* [F(2.4,125)=1.38; p=0.26, η^2=0.03] was not significant either.

5.3.2.2 Checking for confounding factors

As stated before, the groups of participants formed using the participants' and experimenters' gender had differences in terms of mental rotation scores and autonomy. Therefore, we studied the potential impact of these differences on our results. First, we checked if a correlation could be found between our metrics of performances and these variables. No significant correlation was found between the autonomy and the TAcc (r=-0.07, p=0.62) nor the EAcc (r=-0.11, p=0.40). The correlations between the mental rotation score and the TAcc (r=-0.24, p=0.08) or the EAcc (r=-0.13, p=0.36) was not significant either.

Second, we ran our same main analysis of section 5.3.2 using the autonomy, i.e., *"Autonomy"*, or the mental rotation score, i.e., *"MRS"*, of the participants as covariate. When performing the analysis on the TAcc we found no impact of the autonomy (*"Autonomy"* [F(1,51)=0.26; p=0.61, $\eta^2<10^{-2}$], *"Autonomy*Run"* [F(2.48,126.6)=0.81; p=0.47, η^2=0.02]) or the mental rotation score (*"MRS"* [F(1,51) =1.75; p=0.19, η^2=0.03], *"MRS*Run"* [F(2.47,125.79)=1.52; p=0.22, η^2=0.03]). When investigating the EAcc we did not find any single effect or interaction of the autonomy (*"Autonomy"* [F(1,51)=0.44; p=0.51, $\eta^2=10^{-2}$], *"Autonomy*Run"* [F(2.1,107.14)=1.46; p=0.24, η^2=0.03]) or the mental rotation score (*"MRS"* [F(1,51)=1.05; p=0.31, η^2=0.02], *"MRs*Run"* [F(2.18,111,18)=1.35; p=0.27, η^2=0.03]) as well.

5.3.2.3 Assessing the influence of participants' tension

In a previous study, tension was shown to negatively correlate with BCI performances [Jeunet et al., 2015a]. High tension scores computed from the 16PF5 questionnaire indicate highly tensed, impatient and frustrated personalities whereas low scores indicate relaxed, patient and composed personalities. We checked if an influence of participants' tension could be found in our results by performing an analysis of correlation between participants' tension and our measures of performance. It revealed a correlation between participants' tension and both the TAcc [Spearman correlation, $r(56)=-0.39$, $p<10^{-2}$] and EAcc [Spearman correlation, $r(56)=-0.29$, $p=0.03$] metrics.

Therefore, we investigated if tension could explain the differences of performances' evolution depending on the participants' and experimenters' gender. To have a better understanding of how the tension impacts the results, we separated the participants into two groups depending on their tension *"ParTension"*. The threshold between high and low tension was defined using the median tension score (i.e., score of 6, 10 being the maximum). Then, we performed a 3-way ANOVA with *"ParTension*ExpGender*ParGender"* as independent variables and one of the measures of performance averaged over all runs, i.e., TAcc or EAcc, as dependent variable.

When using the TAcc as a measure of performance, we did not find any simple effect of *"ExpGender"* [$F(1,48)=1.51$; $p=0.23$, $\eta^2=0.03$], nor *"ParGender"* [$F(1,48)=1.72$; $p=0.2$, $\eta^2=0.04$]. Though, a trend toward a weak impact of *"ParTension"* was found [$F(1,48)=3.8$; $p=0.06$, $\eta^2=0.07$]. No interactions were found for *"ExpGender*ParGender"* [$F(1,48)<10^{-3}$; $p=1$, $\eta^2<10^{-3}$], *"ParTension*ParGender"* [$F(1,48)= 0.18$; $p=0.67$, $\eta^2<10^{-2}$], *"ParTension*ExpGender* ParGender"* [$F(1,48)=0.47$; $p=0.5$, $\eta^2=0.01$]. Though a significant interaction was found between *"ParTension*ExpGender"* [$F(1,48)=18.94$; $p<10^{-3}$, $\eta^2=0.28$].

When using the EAcc as measure of performance we did not find any simple effect of *"ExpGender"* [$F(1,48)=1.12$; $p=0.3$, $\eta^2=0.02$], nor *"ParGender"* [$F(1,48)=2.59$; $p=0.11$, $\eta^2=0.05$]. Though, a weak but significant impact of *"ParTension"* was found [$F(1,48)=4.43$; $p=0.04$, $\eta^2=0.08$]. No interactions were found for *"ExpGender*ParGender"* [$F(1,48)= 0.02$; $p=0.89$, $\eta^2<10^{-3}$], *"ParTension*ParGender"* [$F(1,48)=0.1$; $p=0.75$, $\eta^2<10^{-2}$], *"Par- Tension*ExpGender*ParGender"* [$F(1,48)=0.72$; $p=0.1$, $\eta^2=0.02$]. Though, a significant interaction was found between *"ParTension*ExpGender"* [$F(1,48)=21.98$; $p<10^{-3}$, $\eta^2=0.31$].

Figures 5.3 and 5.4 represent the performances of tensed and non-tensed participants in average and depending on the gender of the experimenters.

5.3.2.4 Checking the influence of experimenters' tension

Previous results found that a similarity between participants' and experimenters' profile could lead to higher bias in experimental results. Therefore, we analysed the level of tension of our experimenters. The tension of the three men and three women experimenters were respectively of [5, 5 and 7] and [3, 4 and 5]. Indicating a higher level of tension among men experimenters than among women experimenters. Therefore, we investigated further to know if the influence of the experimenters' came

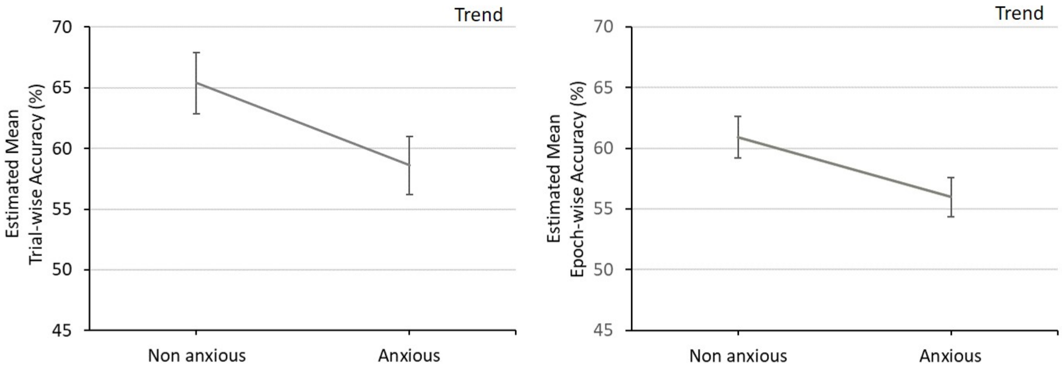

Figure 5.3: Estimated performances depending on participants' tension.

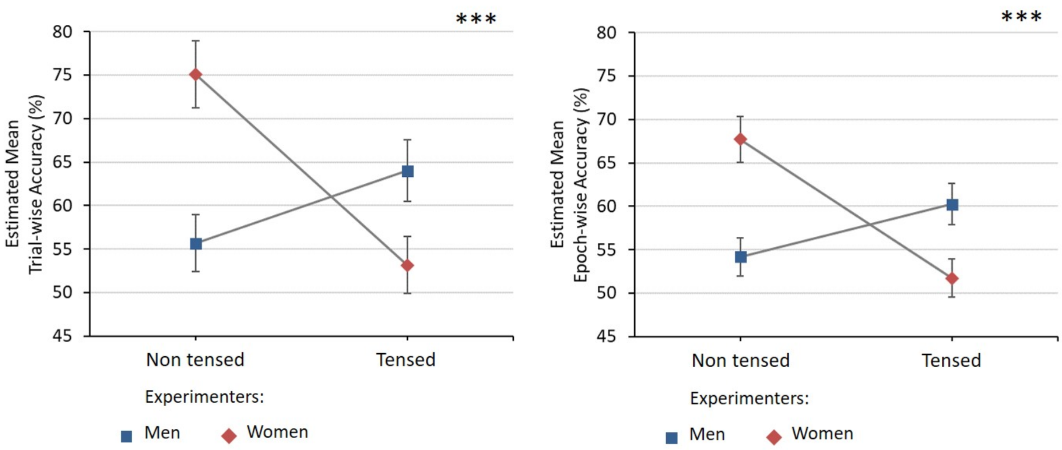

Figure 5.4: Estimated performances depending on participants' tension and experimenters' gender.

from a psychosocial factor related to their gender or from their level of tension which was higher among men experimenters than women participants.

We checked if there was of correlation between the tension of the experimenter and the performances of the participants. We did not find any correlation of the experimenters' tension and the TAcc [Spearman correlation, r(56)=0.03, p=0.83]. Nor did we find any correlation of the experimenters' tension with the EAcc [Spearman correlation, r(56)=0.11, p=0.44].

A similar analysis to the one performed on the participants' tension was not performed as separating experimenters into two groups depending on their level of tension would not be relevant. Indeed, it would be quite similar to the groups formed by the gender of the experimenters.

5.3.2.5 Checking the influence of EMG artefacts

Then, we verified if EMG artefacts, or real unsolicited hand movements from our participants, could explain the results that we obtained with EEG accuracies.

First, we inspected the potential relation between mean performances, i.e., TAcc and EAcc, and EMG accuracies, i.e., training dependant and run dependant, by performing analyses of correlation. We did not find any correlation between the mean training dependant EMG accuracy and the mean TAcc [Spearman correlation, r(54)=-0.2, p=0.15] nor with the mean EAcc [Spearman correlation, r(52)=-0.15, p=0.29]. No correlation could be found either between the mean run dependant EMG accuracy and the TAcc [Spearman correlation, r(53)=-0.1, p=0.49] or the EAcc [Spearman correlation, r(51)=-0.86, p=0.55].

We then looked for a potential effect of the run and the participants' and experimenters' gender on EMG. We ran two 3-way repeated measures mixed ANOVAs with *"ExpGender*ParGender*Run"* as independent variables and one of the EMG accuracy, i.e., training dependant or run dependant, as dependent variable. No simple effect or interaction was found for either of these analyses.

5.3.2.6 Checking the influence of EOG artefacts

Similarly to the previous section, we inspected if EOG artefacts or eye movements performed by our participants could explain the results that we obtained with EEG accuracies.

We inspected the potential relation between mean performances, i.e., TAcc and EAcc, and EOG accuracies, i.e., training dependant and run dependant, by performing analyses of correlation. We did not find any correlation between the mean training dependant EOG accuracy and the mean TAcc [Spearman correlation, r(54)=-0.23, p=0.11] nor with the mean EAcc [Spearman correlation, r(52)=-0.17, p=0.22]. A significant correlation could be found between both the mean run dependant EOG accuracy and the TAcc [Spearman correlation, r(56)=0.31, p=0.02] and the EAcc [Spearman correlation, r(54)=0.36, $p<10^{-2}$].

We hypothesized that these significant correlations resulted from EEG acquisitions from the electrodes positioned to measure EOG. Indeed, when the same analysis was performed using cross validation on data filtered on EOG frequency band, i.e., 0.5-4Hz, we did not find any correlation with the mean TAcc [Spearman correlation, r(54)=0.05, p=0.73] nor with the mean EAcc [Spearman correlation, r(52)=0.12, p=0.39].

Then, we looked for a potential effect of the run and the participants' and experimenters' gender on EOG. We ran three 3-way repeated measures mixed ANOVAs with *"ExpGender*ParGender*Run"* as independent variables and one of the EOG accuracy, i.e., training dependant, run dependant in participant-specific discriminant frequency band and run dependant in 0.5-4Hz, as dependent variable. No single effect or interaction was found for the analyses with the training dependant EOG accuracy. A significant effect of *"Run"* [F(3,153)=3.06; p=0.03, η^2=0.06] was found on the run dependant in 0.5-4Hz frequency band accuracy. Also, an effect of the interaction of *"Run*ParGender"* [F(3,147)=3.28; p=0.02, η^2=0.06] was significant for the run dependant on participant-specific discriminant frequency band accuracy.

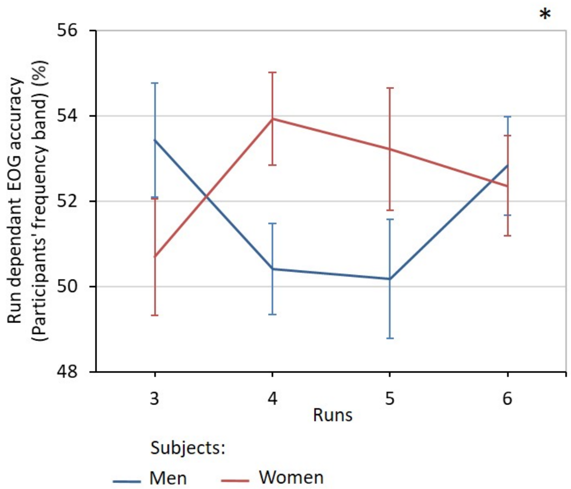

Figure 5.5: Mean percent of run dependant EOG accuracy, computed on data filtered in participant-specific discriminant frequency band, over the runs depending on the gender of the participants.

Finally, we investigated the impact that EOG might have had on our EEG classification accuracies. We ran four 3-way repeated measures mixed ANCOVAs with *"ExpGender*ParGender*Run"* as independent variables, one of the measures of performance, i.e., TAcc or EAcc, as dependent variable and one mean measure of offline EOG accuracy, either with the data filtered in 0.5-4Hz or in the participant-specific discriminant frequency band, as covariate.

For both ANCOVAs with the TAcc or EAcc as dependent variable and the offline EOG accuracy computed on data filtered in the participant-specific discriminant frequency band we found a signifiant single effect of the covariate [respectively, F(1,51)=4.52; p=0.04, η^2=0.08 and F(1,51)=5.76; p=0.02, η^2=0.1]. Previously significant results remained significant and no other single effect or interaction were revealed.

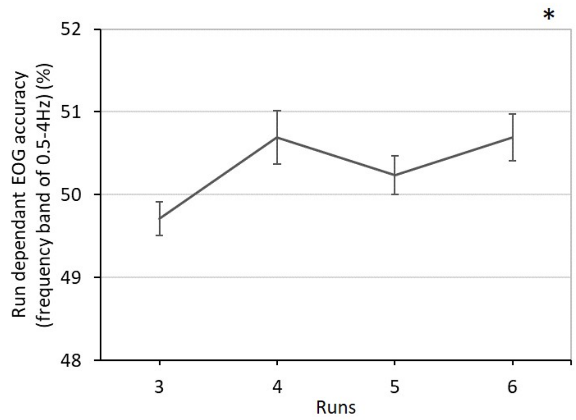

Figure 5.6: Mean percent of run dependant EOG accuracy, computed on data filtered in 0.5-4Hz, over the runs.

5.3.3 Influence of participants' and experimenters' gender on user-experience

Finally, we analysed the influence of participants' and experimenters' gender on the five dimensions of the user-experience, i.e., mood, mindfulness, motivation, cognitive load and agentivity.

First, we checked if the performances had an impact on the reported user-experience measures. We found that the TAcc was correlated to the agentivity post training [Spearman correlation, r(56)=0.38, $p<10^{-2}$]. The EAcc was correlated as well to the agentivity post training [Spearman correlation, r(56)=0.34, p=0.01].

We also checked if the tension had an influence on the user-experience but we did not find any for the mood [Spearman correlation, r(56)=-0.09, p=0.52], mindfulness [Spearman correlation, r(56)=0.11, p=0.43], motivation [Spearman correlation, r(56)=-0.15, p=0.27], cognitive load post training [Spearman correlation, r(56)=0.11, p=0.42] and agentivity post training [Spearman correlation, r(56)=-0.17, p=0.21].

Therefore, we performed five 2-way ANOVAs or ANCOVAs, one per dimension, with *"ExpGender*ParGender"* as independent variables, either the measure of cognitive load, the agentivity, mood, mindfulness or motivation as dependent variable and one of the performances averaged over all runs, i.e., TAcc or EAcc, as covariate depending on the influence it had on the dependent variable.

No influence was found on the cognitive load reported post training of the *"ExpGender"* [F(1,52)=1.65; p=0.2, η^2=0.03], *"ParGender"* [F(1,52)=2.89; p=0.1, η^2=0.05], *"ExpGender*ParGender"*[F(1,52)=0.05; p=0.95, $\eta^2<10^{-3}$].

No influence was found either on the agentivity of the *"ExpGender"* [F(1,52)=0.03; p=0.85, $\eta^2=10^{-3}$], *"ParGender"* [F(1,52)=0.01; p=0.92, $\eta^2<10^{-3}$], *"ExpGender* ParGender"* [F(1,56)=0.44; p=0.51, $\eta^2<10^{-2}$] using the TAcc as covariable. Neither was there any influence found with the EAcc as covariable of *"ExpGender"* [F(1,56)=0.08; p=0.78, $\eta^2=10^{-2}$], *"ParGender"* [F(1,52)=10^{-3}; p=0.97, $\eta^2<10^{-3}$], *"ExpGender* ParGender"* [F(1,52)=0.52; p=0.47, η^2=0.01].

No influence was found on the difference of mood reported post and pre training of the *"ExpGender"* [F(1,52)=0.06; p=0.81, η^2=10^{-3}], *"ParGender"* [F(1,52)<10^{-2}; p=0.93, η^2<10^{-3}], *"ExpGender*ParGender"*[F(1,52)=0.13; p=0.72, η^2<10^{-2}].

No influence was found on the difference of mindfulness reported post and pre training of the *"ExpGender"* [F(1,52)=0.04; p=0.85, η^2=10^{-3}], *"ExpGender*ParGender"* [F(1,52)=0.92; p=0.34, η^2=0.02]. Though, a significant impact of *"ParGender"* [F(1,52)=6.23; p=0.02, η^2=0.11] was found. This effect can be visualized in Figure 5.7.

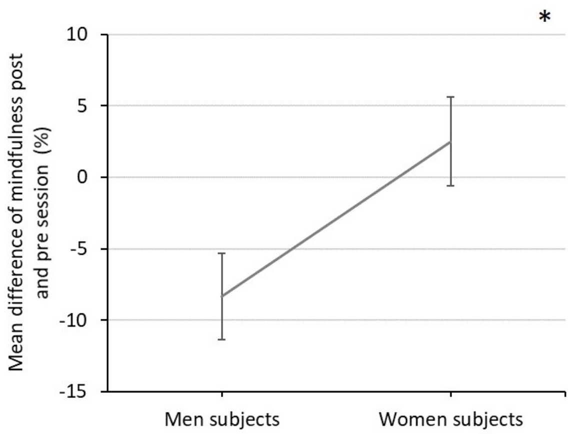

Figure 5.7: Mean percent of mindfulness pre and post training depending on the gender of the participants.

No influence was found on the difference of mood reported post and pre training of the *"ExpGender"* [F(1,52)=0.63; p=0.43, η^2=0.01], *"ParGender"* [F(1,52)=0.78; p=0.38, η^2=0.02], *"ExpGender*ParGender"*[F(1,52)=0.97; p=0.33, η^2=0.02].

5.4 Discussion

We analysed results using two metrics of performances. The TAcc, which represented what the participants were instructed to improve during training, and the EAcc, a traditional measure of BCI performances. Initial differences in mental rotation scores and autonomy between groups did not seem to bias results.

No single influence of the experimenters' and/or participants' gender on the mean accuracy performance was found. Though, we found a significantly different evolution across runs of the TAcc between men and women participants (see Figure 5.1). Women participants seemed to start the training with already good TAcc, which decreased during the second run and increased again during the last run. Men participants however, started with rather low TAcc and then drastically improved during the second run and then stagnated to reach slightly higher final TAcc than women.

In addition, experimenters' gender seemed to have an influence on this previous interaction. Indeed, the evolution of the TAcc appears to depend on participants' and experimenters' gender (see Figure 5.2). On the one hand, we found the same tendency for men participants to start with lower TAcc at the beginning of the session independently of the experimenter's gender. However, men seemed to start with drastically lower TAcc when they were training with men experimenters. They also seemed to have higher TAcc throughout the session when they were training with women experimenters. On the other hand, women participants seemed to start with higher TAcc when training with men experimenters, though their TAcc tended to drop throughout the session. However, when training with women experimenters, they seemed to have a great increase in TAcc during the last run. Current results do not seem to be biased by the mental rotation scores nor the autonomy of the participants. Indeed, the same analysis that led us to these conclusions were run with these variables as covariate. Results do not reveal any impact of these variables and do not change the significance of the results. Their did not seem to be any bias of our results by eye or hand movements.

Nichols and Maner found that participants who are instructed by an opposite-sex experimenter tend to confirm the experimenter's expectation regarding the experimental results [Nichols and Maner, 2008]. Overall, our participants seemed to perform better when they trained with an experimenter of the opposite gender which is coherent with their finding. Our results also seem to be consistent with the results of Stevenson and Allen who found that women participants performed better with men experimenters [Stevenson and Allen, 1964]. Though, the decrease of performance found for women participants training with men experimenters could be related to an activated stereotype of women ability in technology.

When investigating the influence of the tension of the participants on these results, we found results in accordance with the ones of Jeunet et al [Jeunet et al., 2015a]. Tensed participants seem to have lower performances than non tensed participants. An influence of participants anxiety was already found in early researches on regulation of alpha [Tyson, 1982]. Our results revealed that the influence of the participants' tension on MI-BCI performances seems to be modulated by the gender of the experimenter. Tensed and non tensed participants had greater performances when training with respectively men experimenters and women experimenters. The tension of the experimenters seemed to be higher for men experimenters compared to women experimenters. We did not find any significant influence of experimenters' tension on participants' performances. The number of participants did not enable an analysis of both the experimenters' and participants' gender and tension at once, as the number of participants per group would have been too low. Furthermore, experimenters' level of tension was highly dependent on their gender. However, such analysis would have enabled us to test if a similarity of experimenters' and participants' psychological profiles could lead to higher potential bias in the results. [Rosenthal, 1963] found that participants were more likely to respond to experimenters' expectancy when their level of anxiety was similar to their experimenter's level of anxiety. They hypothesised that a similarity of experimenters' and participants' psychological profiles could lead to higher potential bias in the results. We can make the same hypothesis as [Rosenthal, 1963] to explain our results. Larger scaled experiments with a greater number of experimenters would provide insight on this hypothesis.

Interestingly enough, our result regarding the impact of a participants' and experimenters' gender does not match those of a recently published neurofeedback study

[Wood and Kober, 2018]. We do concord on the fact that an interaction of participants' and experimenters' gender has an influence on performances. Though, Wood and Kober found that the combination of woman participants training with woman experimenters hampered the training outcomes of the participants. They observed no learning effect in this group. The influence of the participants' tension found in our results might partly explain this difference of results. In their article, they found a strong and significant positive correlation between the locus of control in dealing with technology, i.e., the level of control that people feel that they have over the control of a technology, and the performances of women participants training with women experimenters. We did not assess this trait for our participants, thus the difference in results might also arise from a difference in the locus of control of our women participants. We did not assess the locus of control of our participants. Though, we assessed the agentivity they felt toward the feedback their were provided with during the training. We did not observe any gender influence over the agentivity reported by our participants. Overall, our analysis of the user-experience metrics only revealed an influence of participants' gender on the evolution of the mindfulness metric. Men participants tended to have a decrease of mindfulness over the session, when women participants tended to increase their level of mindfulness. Wood and Kober do not report controlling for the prior acquaintanceship between their participants and experimenters [Wood and Kober, 2018]. [Rosenthal, 1963] found that this could modulate the bias induced by experimenters mostly between men experimenters and women participants. Another explanation of the differences found between our two studies would be that by asking their participants to fill a questionnaire regarding their locus of control in dealing with technology, Wood and Kober activated a stereotype bias that was not activated in our study. Finally, the protocol used by Wood and Kober was a neurofeedback one which could also contribute to the differences of results obtained.

Both our results and Wood and Kober's results might be explained by other factors. Indeed, inter-experimenter variability other than gender (e.g., psychological profile, teaching competence), intra-experimenter variability (e.g., appearance and outfit, fatigue, expectations), inter- and intra-participants variability (e.g. psychological profile, attractiveness, or motivation) - plus the interaction's characteristics (e.g. physical proximity, use of humour, familiarity, verbal and non-verbal communication, quantity of interaction, etc.) were not analysed. Future experiments might provide more insight on this interaction between participants' and experimenters' gender.

5.5 Conclusion and Prospect

We investigated the potential influence of the experimenters' gender depending on the participants' gender on MI-BCI performances and progression throughout one MI-BCI session. Six experimenters (3 men; 3 women) trained 59 participants (30 men; 29 women). The general observation emerging from this study is that women experimenters seemed to induce better progress of the Trial-wise Accuracy for both men and women participants. Men participants seemed to start with substantially lower performances when they were training with men experimenters compared to when they were training with women experimenters. Also, even though women participants started with higher performances when training with men experimenters, their performances decreased throughout the session when they overall increased when training with women experimenters.

While this study does provide first insights on the influence of the interaction between experimenters' and participants' gender, future studies are needed to further explore it. Studies with a larger number of experimenters and participants might provide more information regarding the underlying factors of this genders influence. For instance, it could confirm, or infirm, the influence of the level of tension of the participants. If confirmed, our hypothesis regarding the beneficial similarity between the level of tension of participants and experimenters could be assessed. Furthermore, the long term impact of the experimenters' and participants' bias on MI-BCI training remains unknown.

Our results highlight the need for research methods that explicit a greater amount of influencing factors (such as the experimenter) emerging from experimental protocol and context. For instance, the instructions that participants are provided with regarding the strategies they should adopt to perform mental-imagery tasks, are rarely formalized, or in any case they are not mentioned in papers. It is common practice for studies in the BCI field not to report experimenter-related information. Though, the literature as well as our results indicate that the influence of experimenters should be considered carefully while designing and reporting experimental protocols.

Double-blind methods, in which neither of the experimenters and participants know the group in which the participant is included, limit the experimenter related bias. They are already used in clinical research. It would be worth applying similar methods in non-clinical experiments. It should be noted that hiring research assistants to perform the experiments might not be a solution to limit experimenter-related bias. Indeed, it was shown that experimenters can unconsciously transmit their bias to their research assistants [Rosenthal, 1963]. The literature suggests several other solutions to limit the potential bias arising from the experimenter [Rosnow and Rosenthal, 1997, Miyazaki and Taylor, 2008]. These methods include: monitoring participant-experimenter interaction; increasing the number and diversity of data collectors; pre-testing the method and controlling expectancy; providing an extensive training for administrators/ data collectors; monitoring and standardizing the behaviour of experimenters with detailed protocol and pre-written instructions for the participant; and statistically controlling for bias.

Beyond the potential bias that could arise from the experimenters' presence, the social and emotional feedback that experimenters provide could be leveraged to improve MI-BCI learning and user-experience. Indeed, the use of social feedback in BCI has been encouraged [Sexton, 2015]. Social presence and trust relationship between the user and the experimenter are essential for maintaining training motivation, which has been shown to facilitate the BCI learning process [Kleih et al., 2011]. It may also be leveraged to reduce computer anxiety [Jeunet et al., 2017]. Taking experimenter-related factors into account might lead to a conjoint progress of the BCI performance and the validity and understanding of BCI experimental results.

General discussion

In this part, our aim was to improve the content of the feedback provided during MI-BCI training. After a review of the literature, we found that improving the supportive aspect of feedback was under-explored in the literature. First, we explored the influence of a learning companion, PEANUT, specifically designed and implemented to provide social presence and emotional feedback during MI-BCI training. We found that such a companion might have a differential impact on the training depending on the level of autonomy of the participants. Anxious participants, who are usually disadvantaged compared to non-anxious participants, had higher performances when training with PEANUT. PEANUT also tended to have a beneficial influence on the user experience. More specifically, the reported memorability/learnability and efficiency/effectiveness of the system were improved when PEANUT was present during the training. Second, we explored how experimenters, who are the main source of emotional feedback and social presence, impacted the MI-BCI training. We found that experimenters had a differential impact depending on their gender and both the gender and level of tension of their participants. Our results confirm the findings of Jeunet et al. who found that tensed participants tend to have lower performances than non-tensed participants [Jeunet et al., 2015a]. Non tensed and tensed participants had significantly higher performances respectively with women and men experimenters.

Those findings suggest that the content of the feedback, or at least the supportive aspect of it, should be leveraged and carefully adapted to the profile of the learner. As any type of feedback, social presence and emotional feedback can be detrimental. Though, it seems that non-autonomous and tensed people could particularly benefit from such feedback. This is particularly interesting for MI-BCI training as those participants were found to be disadvantaged when using MI-BCIs [Jeunet et al., 2015a]. In the field of education, social reward and praise can be considered detrimental to the learning as it can impede the intrinsic motivation [Hattie, 1999]. Our results suggest that the effect of social presence and emotional feedback might be modulated by the profile of the learner.

While providing supportive feedback, experimenters can unwillingly influence MI-BCI outcome. Such influence might impede the replicability and reliability of the results. Using an advanced conversational agent represents an interesting method to control and/or enhance the experimenter influence. However, Moreno et al., found that gender stereotypes could still be applied to animated agents and that those stereotypes affected learning [Moreno et al., 2002]. Gender-related differences were reported in several studies using learning companions. Baylor et al., 2004 revealed that, when provided with the choice, college students were more likely to choose to work with an agent of the same gender. They found no impact on learning outcome, though students were more satisfied with their performance and reported that the agent facilitated more self-regulation if the agent was male [Baylor and Kim, 2004]. However, the gender of the learner was not taken into account in the analysis. The design of the learning companion should be carefully considered to take into account the differential impact it might have depending on its characteristics, e.g., gender, race or age, and the characteristics of the learner, e.g., gender or cognitive profile.

Part III

How should the feedback be presented?

Research question

In the first background part of this thesis, we argued that a feedback can be defined by answering three main questions. In part II, we explored the information that the feedback should convey. In this third part, we explore another key element of the feedback: its modality of presentation. As Paul Tyson said in an article from 1982, "The success of biofeedback is not only due to what information the person receives, but how he receives it" [Tyson, 1982].

From our analysis of the literature, it seems that the modality chosen to provide feedback for BCI training is mostly selected depending on the context of learning and the sensorial abilities of the users (see Section 2.2 Feedback modality - How is the feedback presented?). The modality of feedback is often adapted to the sensory abilities of impaired patients. For example, patients in a complete locked-in state that cannot control any of their eye muscles anymore may benefit from auditory feedback instead of a visual one [Nijboer et al., 2008].

Following the beginning of a collaboration with Bertrand Glize from the post-stroke rehabilitation center of Bordeaux, we focused our research on post-stroke patients. The neuronal loss resulting from stroke forces 80% of the patients to undergo motor rehabilitation [Rathore et al., 2002]. When patients attempt or imagine performing a movement, Brain-Computer Interfaces (BCIs) can provide them with a synchronized sensory (e.g., tactile) feedback based on their sensorimotor-related brain activity [Cervera et al., 2018]. The co-activation of ascending (i.e., somatosensory) and descending (i.e., sensorimotor) networks enables significant functional motor improvement, together with significant sensorimotor-related neurophysiological changes [Grosse-Wentrup et al., 2011a]. Somatosensory abilities play an important role in motor rehabilitation [Kessner et al., 2016]. They are essential for the patients to benefit from the feedback provided by the BCI system. Yet, around half of post-stroke patients suffer from somatosensory deficits [Pumpa et al., 2015, Kessner et al., 2016]. We hypothesize that these deficits alter patients' ability to benefit from BCI-based therapies. The modality of feedback used during training might need to be adapted to the patients' somatosensory abilities. Functional somatosensory and motor rehabilitation seem to be interdependent [Pavlides et al., 1993, Turville et al., 2017]. The feedback modality might be leveraged to improve patients' somatosensory abilities as well as their functional motor abilities using a systemic approach.

An impaired perception of the feedback might not be the only reason why patients with somatosensory loss might not benefit as much as patients without such loss from BCI-based therapies. Indeed, post-stroke patients with somatosensory loss were shown to have deteriorated motor imagery abilities [Liepert et al., 2016]. We hypothesised that the modality of feedback might also need to be adapted depending on the visual and kinaesthetic imagery abilities not only for post-stroke patients but also for neurotypical people. Previous research regarding the impact of visual and kinaesthetic imagery abilities on MI-BCI performances are not conclusive (See Section 3.1 Influence of learners' traits). When participants perform visual imagery while monitoring a visual feedback, there might be an interference between the two tasks because both solicit visual related cognitive resources [Wickens, 2002]. The competition between the two tasks for the amount of cognitive resources might cause a decrease in performances. Depending on the type of motor imagery task, i.e., visual or kinaesthetic, that participants perform and on the modality of the feedback, e.g., visual or haptic, provided to the participants different sensorial resources can be solicited.

Our aim in this part is to assess potential characteristics of the neurophysiological and psychological profile of people that could influence the type of modality of feedback to favour for BCI training. First, we present the details of our theoretical contribution regarding the probable influence of somatosensory abilities on post-stroke motor rehabilitation in Chapter 6.

Second, in Chapter 7, we focused on an empirical comparison of two modalities of feedback, i.e., a realistic visual feedback and the same visual feedback associated with a vibrotactile feedback. We specifically focused on the influence of the profile of our neurotypical participants. Especially, we wanted to know if their kinaesthetic and visual imagery abilities had a differential impact on the performances and user-experience depending on the modality of feedback.

Chapter 6

Theoretical contribution 3 – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - A physical learning companion can be useful for MI-BCI user training depending on learners' autonomy
	5. **Contribution 2** – An interaction of experimenters' and participants' gender has an influence on MI-BCI training
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

Collaborators: Bertrand Glize (MD and PhD from the post-stroke rehabilitation center of Bordeaux), Pierre-Alain Joseph (MD and PhD from the post-stroke rehabilitation center of Bordeaux) and Camille Jeunet (PhD, Researcher at CLLE, Toulouse).

Related full papers: Pillette, L., Lotte, F., N'Kaoua, B., Joseph P.A., Jeunet, C., & Glize, B., « The influence of somatosensory abilities on BCI-based motor rehabilitation after stroke - A review », In preparation.

6.1 Introduction

In the section 1.1.1 Post-stroke motor rehabilitation, we presented how brain-computer interfaces could promote plasticity and functional motor recovery for post-stroke patients. Indeed, BCIs enable rewarding post-stroke patients with somatosensory feedback (i.e., bottom-up processes) when they perform motor imagery or attempted movement tasks (i.e., top-down processes) depending on the modifications that are observed in their neuronal activity [Grosse-Wentrup et al., 2011a]. It is assumed that this co-activation of sensorimotor networks by top-down and bottom-up processes induces Hebbian plasticity, which underlies functional improvement [Grosse-Wentrup et al., 2011a].

Hence, the efficiency of therapies in general and of BCI-based therapy in particular greatly depends on the integrity of top-down efferent processes, i.e., sensorimotor network, and bottom-up afferent processes, i.e., somatosensory sensations. The latter encompasses two types of information: exteroception, which represents the information arising from the skin, and proprioception, which encompasses information arising from the muscles and joint receptors [Kessner et al., 2016]. Both may be impaired after a stroke [Kessner et al., 2016]. More than half of the patients experience somatosensory loss [Pumpa et al., 2015, Kessner et al., 2016], which crucially interferes with post-stroke motor recovery. Indeed, somatosensory loss is known to have a negative effect on motor rehabilitation and daily use of the paretic arm [Kessner et al., 2016]. Also, the prevalence of extremity paresis is significantly higher for patients with abnormal somatosensations [Andersen et al., 1995].

Given the essential role of somatosensory afferences in motor rehabilitation, it seems important to assess the repercussion of somatosensory abilities on BCI therapy's efficiency. Yet, most of the studies reporting findings on motor rehabilitation using BCIs do not report any information on the matter. This somatosensory assessment would have two main advantages. First, it might enable a better adaptation of the BCI-based therapy to the patients and thereby foster motor rehabilitation. For instance, the modality of the feedback provided could be adapted to the somatosensory abilities of patients. Second, it might provide insights regarding the between-patients and between-studies variability in outcome after BCI-based motor rehabilitation therapy.

In the following paragraphs, the aim is to describe the involvement of somatosensory abilities on BCI therapy's outcome for post-stroke motor rehabilitation, and to promote the assessment of these abilities prior to BCI therapy. Because BCIs have proven promising for upper limb rehabilitation [Cervera et al., 2018], a focus on strokes affecting motor abilities of the upper limb, e.g., hemiplegia or hemiparesis, will be made. We will first briefly present the prevalence and characteristics of somatosensory loss after a stroke as well as tools to assess this somatosensory loss. Then, we will introduce how these deficits can influence neuroplasticity and motor rehabilitation. Finally, a focus on the interrelation between BCI therapy and somatosensory loss will be made.

6.2 Sensory impairments and assessment post-stroke

6.2.1 Sensory impairments post-stroke

It has been estimated that more than half of strokes lead to somatosensory deficits [Pumpa et al., 2015, Kessner et al., 2016]. Most often, i.e., in 75% of the case, the sensory loss impacts the upper limbs [Rathore et al., 2002]. Among the different types of somatosensory loss, exteroceptive impairments seem to be the most frequent. Indeed, most of the literature suggests that tactile impairments are for instance twice more frequent than proprioceptive impairments [Tyson et al., 2008], despite opposite findings [Connell et al., 2008]. Deficits in proprioception and elementary sensory modalities, such as touch, pressure, pain, vibration and temperature, are equally reported for 53 to 64% of patients [Connell et al., 2008, Tyson et al., 2008]. Moreover, discriminative sensations, such as stereognosis (i.e., ability to recognize objects using tactile sensations only), texture discrimination, position sense or two-point discrimination seem to be particularly affected [Klingner et al., 2012].

The amount of sensory loss is correlated to both the severity of the stroke and the extent of the lesion [Connell et al., 2008, Tyson et al., 2008]. Somatosensory submodalities can be differently affected in a given body part. For instance, at the level of the wrist, the light touch ability might not be as impacted as the proprioceptive one [Connell et al., 2008]. Nonetheless, adjacent body parts are likely to have similar amount of loss for a given somatosensory submodality, e.g., touch ability between wrist and hand are likely to be similar [Connell et al., 2008]. Stroke lesions can also result in somatosensory loss (notably deficits in tactile discrimination and position senses) to the ipsilesional hand, even though the impairment seems less important than for the contralesional hand [Carey and Matyas, 2011]. This phenomenon might be the consequence of damages in ipsilateral somatosensory pathways and bilateral networks processing somatosensory information [Connell et al., 2008]. This result is of the utmost importance as it implies that the ipsilesional limb, i.e., the 'unimpacted limb', cannot always be considered as a reference for the contralesional limb, i.e., the 'impacted limb'.

Different types of stroke have been associated with different somatosensory losses [Kessner et al., 2016]. Patients who have suffered from an ischemic stroke are more likely to experience sensory impairments than patients who have suffered from an hemorrhagic stroke [Rathore et al., 2002]. Also, right hemispheric strokes are more likely to be associated with somatosensory loss than left hemispheric strokes [Sullivan and Hedman, 2008]. Though, spatial neglect [1] is common for patients with right hemispheric strokes and could also explain this difference of somatosensory loss observed between right and left hemispheric strokes. Lesions affecting the thalamus, brainstem, lenticulocapsular, or parietal regions are known to induce somatosensory symptoms [Klingner et al., 2012]. The impairment of one somatosensory submodality or another (e.g. touch, pressure, pain, vibration and temperature) might be different depending on the lesion location.

Further investigations are needed to know which somatosensory submodalities are the most likely to be affected depending on the type of stroke [Kessner et al., 2016].

6.2.2 Sensory assessment post-stroke

The prevalence of somatosensory deficits in stroke is still difficult to estimate because the studied population is heterogeneous. Also, the assessment outcome depends on the time between the evaluation and the stroke onset, as well as on the spontaneous somatosensory recovery occurring in the first three months [Kwakkel et al., 2006]. Furthermore, the prevalence is probably under-estimated given the lack of standardized psychometric tools available to assess somatosensory impairments [Kessner et al., 2016].

Frequently, routine tests of patients after stroke consist in clinical tests and do not precisely assess all somatosensory submodalities [Kessner et al., 2016]. They mostly focus on light touch and proprioception assessment but often fail to assess other submodalities, e.g., two-point discrimination or point localization [Pumpa et al., 2015]. This limited scope in clinical somatosensory examination also contributes to the underestimation of the somatosensory loss [Sullivan and Hedman, 2008]. Indeed, using standardized assessment of discriminative sensations, Kim and Choi-Kwon [Kim and Choi-Kwon, 1996] found that around 90% of patients who were thought to suffer from pure motor stroke had somatosensory impairments. Clinical assessment can also be in contradiction with the results from standardized tests. Indeed, Carey et al. [Carey et al., 2002] have shown that one third of the patients identified as unimpaired by testing tactile discrimination and limb position assessment using quantitative measures (Tactile Discrimination Test [Carey et al., 1997] and Wrist Position Sense Test [Carey et al., 1996]) were classified as impaired using classic clinical tests, which results were subjective to the clinician's judgment (Naef Tastspiel material circles matching and Imitation Response and Verbal Response). On the contrary, two thirds of the patients with proprioceptive impairments detected using quantitative measures were not classified as such using clinical measures.

Several standardized test protocols dedicated to the assessment of somatosensory loss have been identified in the literature. Kessner et al. [Kessner et al., 2016] have summarized the different tools that assess different somatosensory modalities. In their review, the authors recommended to use the "Erasmus-modified Nottingham Sensory Assessment" for clinical use because of its fair compromise between robustness and usability. For research purposes, they recommended the "Rivermead

[1] Spatial neglect corresponds to a deficit of attention dedicated to somatosensory information arising from one side of the body.

Assessment of Somatosensory Performance" [Winward et al., 2002] (RASP) because it is highly standardized and provides measures related to interval scales which are easier for statistical use. Though, the RASP is not produced by any company at the moment. Promising research was recently led using robotic technology to create more reliable proprioceptive, kinesthesic and motor assessments [Semrau et al., 2015].

It is worth noting that cognitive impairments, e.g., aphasia or spatial neglect, might interfere with somatosensory assessment when assessed using clinical scales. For example, spatial neglect[1] could lead to an overestimation of somatosensory deficits of the left sided limbs and to a greater difference of somatosensory abilities between left and right sided limbs. Such cognitive impairments being frequent after a stroke, their influence on somatosensory tests should be assessed [Kessner et al., 2016]. Also, inclusion criteria should take into account such impairments when assessing somatosensory abilities using non-physiological measures.

In order to avoid potential bias arising from cognitive impairment, specific biomarkers, such as the somatosensory evoked potentials (SSEP)[2], could be used in addition to standardized tools. Indeed, SSEP correlates to sensory abilities [Giblin, 1964]. However, the relevance of such a biomarker remains unclear. Indeed, previous results found that two thirds of patients with abnormal SSEPs had somatosensory loss and four out of five patients with normal SSEP had normal sensations [Zeman and Yiannikas, 1989]. Finally, other biomarkers, such as diffusion tensor imaging measures of fractional anisotropy seem to be well correlated with clinical symptoms [Yamada et al., 2003].

6.3 Somatosensory and motor recovery

Motor function is the main focus of sensorimotor assessment and rehabilitation considering both clinical management and research [Kessner et al., 2016]. However, sensory and motor improvements are not specific but interrelated. Somatosensory impairment due to cortical lesion is almost always associated with motor impairment [Sullivan and Hedman, 2008, Kessner et al., 2016]. Somatosensory improvement spontaneously occurs in the acute phase and/or after a dedicated therapy [Kwakkel et al., 2006, Carey et al., 2011]. Interestingly, somatosensory training seems to have an impact on motor function and vice versa [Byl et al., 2003].

6.3.1 Somatosensory recovery

It is now acknowledged that spontaneous motor recovery reaches a plateau 3 months after the stroke onset for most of patients. This is due to the spontaneous cortical reorganization of the motor system which mostly occurs during this period of time [Kwakkel et al., 2006, Kessner et al., 2016]. Just like motor recovery, somatosensory function spontaneously improves [Klingner et al., 2012]. The amount of somatosensory recovery correlates positively with the severity of the stroke. Moreover, the somatosensory assessment on admission is a main predictor of recovery after 6 months

[2]Somatosensory evoked potentials are spontaneous electrical potentials from the nervous system following a tactile stimulation.

[Connell et al., 2008]. The recovery is highly variable between individuals, though results indicate a functional and structural plasticity occurring in the primary and secondary somatosensory cortices after stroke regardless of the sensorimotor therapy followed [Schaechter et al., 2006]. Such influence of motor rehabilitation on somatosensory network is to be expected in view of the role that somatosensory inputs play in motor rehabilitation.

The time course of somatosensory recovery has been much less studied than the motor one. Nonetheless, the literature indicates that somatosensory recovery occurs for a majority of patients. It takes place within the first 3 months following the stroke [Kessner et al., 2016, Julkunen et al., 2005], even though somatosensory functions can sometimes decrease and fluctuate over time [Julkunen et al., 2005]. During the chronic phase, the tactile detection threshold, graphesthesia and two-point discrimination might still improve [Julkunen et al., 2005]. Lesion location also has an influence on the recovery from somatosensory impairment. One could hypothesize that cortical redundancy would lead to greater recovery of cortical lesions compared to subcortical ones [Sullivan and Hedman, 2008]. Nonetheless, recent studies on proprioception have shown that persistent proprioceptive loss was associated with both subcortical and cortical lesions [Findlater et al., 2018].

Some research has been led to foster the recovery of somatosensory abilities. They focused on somatosensory discrimination tasks or on sensory stimulation involving tactile, electrical, thermal and magnetic stimulation. For an overview of the different somatosensory feedback investigated, see the review from Sullivan and Hedman [Sullivan and Hedman, 2008]. Therapies based on repetitive electrical peripheral nerve stimulation have proven efficient to enhance excitability of the motor cortex, improve motor functions and daily activities [Conforto et al., 2018]. Influence of peripheral somatosensory stimulation has however been questioned by Grant et al. [Grant et al., 2018]. Recent reviews [Conforto et al., 2018, Grant et al., 2018] concur on the need for further investigation with qualitative randomized controlled trials.

6.3.2 Influence of somatosensory abilities in motor recovery

Motor skill learning is crucial for motor recovery, and somatosensory inputs are involved in this learning [Krakauer, 2006]. Motor learning requires neuroplasticity, especially in the primary motor cortex [Pavlides et al., 1993], which has dense connections with the primary somatosensory cortex. Compared to neurotypical people, post-stroke patients with somatosensory deficits present lower amplitude of ERDs in alpha and beta frequency bands during both movement preparation and execution [Platz et al., 2000]. The conjoint activation of somatosensory afferences and motor cortical circuits affects the neural mechanisms of plasticity associated with skills learning [Pavlides et al., 1993]. Hence, the primary somatosensory cortex is crucial in motor skill learning. Ablation of the area dedicated to the hand in the primary sensory cortex of monkeys does not interfere with motor tasks learned before but impedes new learning [Pavlides et al., 1993]. Moreover, larger networks that involve the cerebellum, the pontine nucleus, the ventrolateral nucleus of the thalamus and both motor and somatosensory primary cortices play an important role in motor skills acquisition [Pavlides et al., 1993].

This influence of the somatosensory afferences on motor skill learning is also supported by post-stroke upper extremity motor rehabilitation studies.
First, somatosensory loss is associated with more paresis of the distal parts of the limbs [Andersen et al., 1995], greater motor and functional impairments, as well as less independence in daily living in chronic stage [Carey et al., 2018]. Also, somatosensory loss, and especially proprioceptive loss, has a negative influence on the rehabilitation's efficiency, assessed though functional outcome, but also on the length of the rehabilitative treatment and on the participation in daily activities [Kessner et al., 2016]. Abnormal SSEPs are biomarkers of poor motor recovery. Zeman and Yiannikas [Zeman and Yiannikas, 1989] found that the pattern of the SSEPs, i.e., the amplitude of the negative and positive peaks, correlates with the functional rehabilitation outcome measured using the length of the stay at the rehabilitation center and the daily living abilities, e.g., the ability to dress. Authors also hypothesized that the correlation between SSEPs and motor recovery could be influenced by the location of the lesion. Abnormal SSEPs due to cortical lesions resulted in poorer motor outcomes than abnormal SSEPs due to subcortical lesions. This negative influence of somatosensory loss on post-stroke motor rehabilitation could also originate from the non-use mechanism, which is the rarefied use of the plegic limb occurring in the absence of relevant proprioceptive and exteroceptive feedback [Kessner et al., 2016].
Second, the use of a constant sensory stimulation (mechanical vibration on the wrist) during motor rehabilitation has proven efficient in improving the motor function both at short and long terms, and in increasing motor related brain activity [Fleming et al., 2015].

The rehabilitation of somatosensory perception requires taking into account motor abilities. For instance, such therapies could increase the daily use of the impacted limb, but only if the motor abilities are not too damaged [Turville et al., 2017]. Motor therapies might have variable effects depending on the somatosensory deficiencies of the patients [Van der Lee et al., 1999]. The feedback might also need to be adapted with regards to the somatosensory deficiencies of patients. For instance, Jeannerod et al. [Jeannerod et al., 1984] described a patient with pure somatosensory impairment following stroke. The patient was able to perform complex tasks using visual feedback, but not without. Therefore, future research should provide more information about which therapies are the most beneficial depending not only on the motor deficits but also on the type of somatosensory loss [Sullivan and Hedman, 2008].

6.4 BCI-based therapy for motor rehabilitation post-stroke

Evidence of BCIs' effectiveness for improving plasticity and motor rehabilitation post-stroke has only recently started to arise from the different research that have been led on the topic [Cervera et al., 2018]. We provide here a review of 14 papers focusing on Randomized Clinical Trials (RCT) of BCI based on sensorimotor rythms for post-stroke motor rehabilitation [Ang et al., 2009, Ang et al., 2010, Ang et al., 2014, Ang et al., 2015, Biasiucci et al., 2018, Frolov et al., 2017, Li et al., 2014, Mihara et al., 2013, Pichiorri et al., 2015, Ramos-Murguialday et al., 2013, Rayegani et al., 2014, Várkuti et al., 2013, Wada et al., 2019, Young et al., 2016]. The tables provided in this section summarize the procedure, the results and the interpretation of these studies, particularly focusing on sensorimotor abilities and the potential related biases.

The literature indicates that using a BCI to provide visual feedback (e.g., a virtual representation of the patient's hands movements) when motor imagery was detected by the BCI, enables a significantly higher improvement of motor functions than motor imagery alone [Pichiorri et al., 2015]. When providing somatosensory feedback (e.g., exoskeleton moving the impacted limb [Frolov et al., 2017, Ramos-Murguialday et al., 2013, Ang et al., 2009] or functional electrical stimulation [Biasiucci et al., 2018]), BCIs have proven more effective than proprioceptive stimulation alone [Biasiucci et al., 2018, Frolov et al., 2017, Ramos-Murguialday et al., 2013, Ang et al., 2009]. Compared to traditional therapies, such as motor imagery or muscle and proprioceptive stimulation alone, BCIs enable the co-activation of both top-down processes (i.e., motor imagination or attempt) and bottom-up processes (i.e., coherent somatosensory afferences from visual or somatosensory stimulation of the affected limb). Studies on participants without neurological impairments have shown that the BCI ability to recognize the activation of top-down processes through brain activity patterns is modulated by numerous factors. For example, it is modulated by the type of algorithm used to process the data [Lotte and Jeunet, 2018], the psychological profile of the participants [Jeunet, 2016] or the characteristics of the feedback (e.g., modality of presentation, accuracy or latency) [Grosse-Wentrup et al., 2011a]. Though, the impact of these factors on BCI-based post-stroke motor rehabilitation outcome remains mostly unknown. Furthermore, post-stroke BCI-based therapy might also have comparable limitations than the other post-stroke motor therapies. This might be particularly true for those arising from the somatosensory abilities of post-stroke patients. Patients with somatosensory loss might benefit less from BCI-based motor rehabilitation than patients without somatosensory loss (see Section 6.3.2 Influence of somatosensory abilities in motor recovery). Interestingly, the central role that sensory feedback plays in BCIs might also be harnessed and used for somatosensory rehabilitation.

6.4.1 Somatosensory abilities for BCI-based rehabilitation

Somatosensory abilities interfere with motor rehabilitation. Such influence might be dependent of the therapy followed by the patients. BCI efficiency is assumed to result from timely somatosensory feedback in regards to motor imagination or attempt. Therefore, somatosensory abilities most probably interfere with the use of BCI tools and/or the efficiency of BCI rehabilitation post-stroke. Hence, it seems crucial to either describe exclusion criteria that refer to somatosensory abilities or assess these abilities a priori. When reviewing the literature on BCI for post-stroke motor rehabilitation, all studies report using inclusion/exclusion criteria known to potentially influence motor rehabilitation outcomes (Table 6.2 reports somatosensory-related inclusion/exclusion criteria only). For example, the time since the stroke onset, that correlates with recovery [Kwakkel et al., 2006], has been used as an inclusion criterion by 71% of the studies included in this review. These criteria limit the bias that could arise from comparing patients that do not have the same potential for recovery. Table 6.2 summarizes the information on somatosensory-related inclusion/exclusion criteria used in previous studies. Surprisingly, only 14% of these studies report checking the somatosensory abilities of the included patients. Rayegani et al. [Rayegani et al., 2014] and Mihara et al. [Mihara et al., 2013] used somatosensory deficits or sensory loss as exclusion criteria. Mihara et al. [Mihara et al., 2013] were the only ones to provide somatosensory abilities of their patients. Though, they did not report how they assessed these abilities and provided only subjective scales, i.e., 'None', 'Mild', 'Moderate', which limits the reliability and reproducibility between studies. Another exclusion criteria that involve somatosensory abilities is pain, used by Ang et al. [Ang et al., 2014, Ang et al., 2015] and Ramos-Murguialday et al. [Ramos-Murguialday et al., 2013]. Somatosensory impairments might provide insights regarding the variability in the therapeutic outcome observed between-patients [Ang et al., 2009, Ang et al., 2015, Frolov et al., 2017, Young et al., 2016] and between-studies.

6.4.2 Providing somatosensory feedback: a promising approach that remains under-exploited

Hebbian plasticity, i.e., the reinforcement of the synaptic connection induced by the conjoint activation of pre and post synaptic neurons, is currently used to explain how BCIs foster plasticity and improve motor functions. It has been shown that Hebbian-like learning occurred in the context of somatosensory rehabilitation. Indeed, Ingemanson [Ingemanson, 2017] was the first to directly support the concept of somatosensory-induced Hebbian-like learning within the context of robot-assisted motor rehabilitation for chronic stroke. Somatosensory abilities are improved by robot-assisted rehabilitation and BCI therapy often used such robotic tools to improve motor control without assessing the impact on somatosensory abilities. Several authors have suggested that motor improvement observed using BCI therapy together with robotic proprioceptive feedback might be due to the involvement of timely somatosensory afferences (see Table 6.1). However, these studies have not explored the possible biases that could arise from somatosensory loss (see Table 6.2 for more details). Hence, future research, taking into account the somatosensory loss for randomization and/or inclusion/exclusion criteria, have to further investigate the mechanisms that would explain the neural bases of BCI therapy's efficiency. Investigating potential predictors, including somatosensory abilities, could provide explanations for the inter-patients and inter-study variability of BCI-based post-stroke motor rehabilitation outcome found in the literature.

Just as it is the case for robotic proprioceptive feedback, BCI using motor imagery and visual feedback should take into account somatosensory deficits. Somatosensory loss might interfere with motor imagery, which is the basis of various BCI studies. Indeed, the severity of a somatosensory deficit affects the temporal aspects of motor imagery, i.e., the ability to estimate the time required to perform a motor imagery task [Liepert et al., 2016]. Spatial aspects, i.e., the ability to visualize a 3D object, do not seem to be compromised [Liepert et al., 2016]. Hence, such influence might interfere with the neural mechanisms that underlie improvement due to motor imagery. The type of feedback, i.e., extrinsic (information originating from an external source, e.g., a screen or a person) or intrinsic (somatosensory sensations felt by the person during the training), should also be adapted depending on the type and amount of somatosensory loss. While both extrinsic and intrinsic feedback have proven efficient [Mihara et al., 2013, Biasiucci et al., 2018], somatosensory deficits might impede the relevance of some types of feedback more than others and thereby have a negative impact on the BCI therapy.

6.5 Conclusion and Prospect

BCI therapy has proven efficient in improving motor functions post-stroke [Cervera et al., 2018]. The therapy is based on the co-activation of top-down pathways, resulting from either motor imagery or motor attempt, and bottom-up pathways, resulting from visual and/or somatosensory feedback provided by the BCI. Based on the Hebbian theory, this co-activation should foster plasticity and improve motor abilities [Grosse-Wentrup et al., 2011a]. Hence, the integrity of the ascending sensory pathways, such as somatosensory pathways, should be assessed.

A crucial challenge for research is thus to better describe all the abilities of the patients that could interfere with or influence the BCI therapy, particularly somatosensory abilities, which are often forgotten or assessed using non-standardized tests. Such rigorous and standardized assessments now need to be performed. Doing so would allow us to improve our understanding of what makes BCI-based post-stroke motor rehabilitation successful. It would also enable us to optimize this rehabilitation approach possibly much further, by adapting it to each patient.

Table 6.1: Characteristics of the studies selected for this review. Main elements of the studies (columns 1 to 8), then mechanisms quoted by the authors to explain their results (column 9) and finally our analysis of the potential factors (intrinsic to the patients, e.g., somatosensory loss, or extrinsic to the patients, e.g., design issues) that could arise from the inclusion/exclusion criteria presented in table 6.2 (column 10) are introduced. During the studies, patients were either asked to perform motor-imagery (MI) or motor-attempt (MA) tasks. If they were stated in the article for both the experimental (exp) and control (contr) groups the number of patients included, chronicity and motor impairment of are reported in such order and separated by a slash. If not, the average is provided. Chronicity is defined as the time between the stroke and the inclusion in the study such as: Acute≤1 month, Subacute≤3 months and Chronic≥3 months. Mean and standard deviation of time from stroke for each group distinctly or globally are provided either in days or months. When provided in the article, minimal and maximal values are also reported, i.e., (min-max). Mean and standard deviation of motor impairment at inclusion are provided using the Fugl-Meyer Assessment of Upper Extremity (FMA-UE), Jebsen Hand Function Test (JHFT), Action Research Arm Test (ARAT) and Brunnstrom recovery stage. Indication regarding the motor capacity of the patients are provided depending on the FMA-UE scores, i.e., no: 0-22, poor: 23-31, limited: 32-47, notable: 48-52, full: 53-66, or on the ARAT scores, i.e., no: 0-10, poor: 11-21, limited: 22-42, notable: 43-54, full: 55-57. Following is a list of the abbreviations used in the table and their signification: Classification Accuracy (CA), Blood Oxygen Level Dependent effect (BOLD), Diffusion Tensor Imaging (DTI), ElectroEncephaloGraphy (EEG), ElectroMyoGram (EMG), European Stroke Scale (ESS), Event Related Desynchronization (ERD), functional Magnetic Resonance Imaging (fMRI), Goal Attainment Scale (GAS), Hand Grip Strength (HGS), Lateralization Index (LI), Medical Research Council (MRC), Modified Ashworth Scale (MAS), Motor Activity Log (MAL), Motor Evoked Potential (MEP), NASA Task Load Index (NASA-TLX), National Institute of Health Stroke Scale (NIHSS), Near InfraRed Spectroscopy (NIRS), Nine Hole Peg test (9-HPT), Power Spectral Density (PSD), Resting State Connectivity (RSC), revised Brain Symmetry Index (rBSI), SensoriMotor Cortex (SMC), Stroke Impact Scale (SIS), Transcranial Magnetic Stimulation (TMS).

Table 6.1

Study	Aim	Design of the study, Patients number (exp/contr), Chronicity (time to stroke)	Motor impairment at inclusion	BCI intervention	Control group	Outcome measures	Results	Mechanisms discussed supposedly underlying the results	Potential bias due to inclusion/exclusion criteria (detailed in table 6.2) for mechanisms supposedly underlying the results
Ang et al., 2009	Compares the effect of MI-BCI with robotic feedback to standard robotic rehabilitation on functional improvement	Blindness not described, 18 (8/10), Subacute and chronic (Days, 385,5±293,5 (57-1053))	No capacity to full capacity (FMA-UE, 29,7±17,7 (4-61))	MI-BCI (EEG) to drive robotic orthosis to move the shoulder and elbow of the impaired arm with gamified visual feedback	Standard robotic rehabilitation	FMA-UE	Significant functional improvement post-rehabilitation and at the 2-months follow-up when groups are combined. Significant greater improvement in MI-BCI group for the 2 months follow-up after removal of the non-responders in both groups and correction for age and gender.	No hypothesis regarding underlying neurophysiological mechanisms.	Non-responders might have been due to abnormal abilities (visual, somatosensory, etc.) but not described. No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria. Possible randomization bias.
Ang et al., 2010	Compares the effect of MI-BCI with robotic feedback to standard robotic rehabilitation on functional improvement	Blindness not described, 25 (11/14), Subacute and chronic (Days, 383±291 (71-831) / 250±184 (37-668))	No capacity to limited capacity (FMA-UE, 26,3±10,3 (14-47) / 26,6±18,9 (4-57))	MI-BCI (EEG) to drive robotic orthosis to move the shoulder and elbow of the impaired arm with gamified visual feedback	Standard robotic rehabilitation	FMA-UE	Significant functional improvement in both groups post-rehabilitation and at the 2-months follow-up. Slightly less functional improvement in the MI-BCI group but not significant.	"Ipsilesional motor cortex activation from motor imagery is effective in restoring upper extremities motor function in stroke."	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria. Possible randomization bias.

Study	**Aim**	**Design, Patients nbr, Chronicity**	**Motor impairment at inclusion**	**BCI intervention**	**Control group**	**Outcome measures**	**Results**	**Mechanisms discussed supposedly underlying the results**	**Potential bias**
Ang et al., 2014	Compares the effect of MI-BCI with robotic feedback to standard robotic rehabilitation and standard motor rehabilitation on functional improvement	Blinded assessment, 21 (6/8/7), Chronic (Days, 285,7±64 / 398,2±150,9 / 455,4±109,6 (191-651))	No capacity to notable capacity (FMA-UE, 33±16,2 / 25,5±11,5 / 23,4±14,5 (10-50))	MI-BCI (EEG) to drive robotic orthosis for fingers extension and wrist rotation with visual feedback	Standard robotic rehabilitation / Standard Arm therapy	FMA-UE	Significant functional improvements in all groups 6 weeks post-rehabilitation still significant at 12 and 24 weeks follow-up for the MI-BCI and standard robotic groups. Significantly greater functional improvement for the MI-BCI group compared to the standard therapy group at 3, 12 and 14 weeks follow-ups.	"[...] performance of MI in the [experimental] group [...] facilitated neuroplasticity"	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria except pain and spatial neglect. Possible randomization bias.
Ang et al., 2015	Compares the effect of MI-BCI with robotic feedback to standard robotic rehabilitation on functional and physiological improvement	Blinded assessment, 25 (11/14), Chronic (Days, 383±290,8 / 234,7±183,8)	No capacity to limited capacity (FMA-UE, 26,3±10,3 / 26,5±18,2 (4-40))	MI-BCI (EEG) to drive robotic orthosis to move the shoulder and elbow of the impaired arm with gamified visual feedback	Standard robotic rehabilitation	FMA-UE, EEG (rBSI)	Significant functional improvement for both groups post-rehabilitation. Slightly less functional improvement in the BCI group close to significant post-training that could be caused by reduced arm exercise repetitions in BCI group. Negative correlation of rBSI over the sessions and functional improvement for the experimental group. Higher asymmetry in spectral power between the 2 cerebral hemispheres associated with less motor recovery in the BCI group.	"[...] possible role for BCI in long-term cortical plasticity."	Non-responders might have been due to abnormal somatosensory abilities but not described. No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria except pain and spatial neglect. Possible randomization bias.

Study	Aim	Design, Patients nbr, Chronicity	Motor impairment at inclusion	BCI intervention	Control group	Outcome measures	Results	Mechanisms discussed supposedly underlying the results	Potential bias
Biasiucci et al., 2018	Compares the effect of MA-BCI with FES feedback to MA-BCI with sham FES feedback on functional and physiological improvement	Double blinded, 27 (14/13), Chronic (Months, 39,79±45,9 (10-176) / 33,46±30,51 (11-121))	No capacity to limited capacity (FMA-UE, 21,6±10,8 (7-37) / 19,9±11,2 (4-40))	MA-BCI (EEG) to trigger FES for fingers and wrist extension	Sham (random FES feedback)	FMA-UE, MRC, MAS, ESS	Significant functional recovery (FMA-UE, MRC) sustained at the 6 to 12 months follow-up correlated with significant increase in functional connectivity between motor areas in the affected hemisphere in favor of the BCI group	"BCI-FES therapy can drive significant functional recovery and purposeful plasticity thanks to contingent activation of body natural efferent and afferent pathways"" through ""somatosensory input, in the form of peripheral nerve stimulation"	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria except spatial neglect. Possible randomization bias.
Frolov et al., 2017	Compares the effect of MI-BCI with robotic feedback to sham robotic feedback on functional improvement	Blinded assessment, 74 (55/19), Subacute and chronic (Median Months, 8 [4-13] / 8 [1-13])	No capacity to limited capacity (Median FMA-UE, 24 [12-14] / 12 [11-49])	MI-BCI (EEG) to drive robotic orthosis for fingers extension and simple visual feedback	Sham without MI but with EEG (random robotic feedback)	FMA-UE, ARAT, MAS	Significant functional recovery (ARAT, FMA-UE) for both groups. More patients from the experimental group than the control group reached the MCID threashold (ARAT, FMA-UE). Correlation between CA and rehabilitation outcome (ARAT, FMA-UE).	"The kinesthetic imagination of both affected and unaffected limbs and even transition to the motor relaxation are related to motor functions and generally influence the mechanisms of neuroplasticity resulting in motor recovery."	Worst motor impairments in the control group which could be due to greater somatosensory impairments. No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria. Possible randomization bias.

Study	Aim	Design, Patients nbr, Chronicity	Motor impairment at inclusion	BCI intervention	Control group	Outcome measures	Results	Mechanisms discussed supposedly underlying the results	Potential bias
Li et al., 2014	Compares the effect of MI-BCI with FES feedback to standard FES therapy on functional and physiological improvement	Blindness not described, 14 (7/7), Subacute and chronic (Months, 2,21±1,8 (1-6) / 2,79±2 (1-6))	No capacity to poor capacity (FMA-UE, 13,57±4,72 (9-22) / 11,71±2,63 (9-16))	MI-BCI (EEG) to trigger FES for wrist extension with gamified visual and auditory feedback	Standard FES therapy	FMA-UE, ARAT, EEG (ERD)	Significant functional improvement for both groups (ARAT, FMA-UE). Significant functional improvement (ARAT) of the experimental group compared to the control group at the 6 week follow-up. Significantly stronger ERD of the affected sensorimotor cortex for the experimental group post-training but not significantly different than the control group. Significant negative correlation of the ERD value and functional improvement (ARAT, FMA-UE). CA of the experimental group significantly improved and was significantly higher than the one from the control group.	"BCI training [using MI task and FES feedback] may enhance the activation of the affected SMC to prime the motor functional reorganization"	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria. Possible randomization bias.
Mihara et al., 2013	Compares the effect of MI-BCI with visual feedback to MI-BCI with sham visual feedback on functional and physiological improvement	Double blinded, 20 (10/10), Chronic (Days, 146,6±36,2 (94-190) / 123,4±38,27 (89-194))	No capacity to notable capacity (FMA-UE, 22,5±14,14 (9-50) / 24±13,8 (4-50))	MI-BCI (NIRS) to provide visual feedback	Sham (random visual feed-back)	FMA-UE, ARAT, MAL, NIRS (BOLD)	Significant functional improvement for the experimental group (FMA-UE hand/finger subscale). Greater functional improvement for the experimental group associated with significantly greater motor imagery-related cortical activation (ipsilesional premotor area).	"[...] modulation of the excitability in the premotor area and related networks augments the functional recovery."	No description of the precise sensory assessment limiting the reproductibility of the study.

Study	Aim	Design, Patients nbr, Chronicity	Motor impairment at inclusion	BCI intervention	Control group	Outcome measures	Results	Mechanisms discussed supposedly underlying the results	Potential bias
Pichiorri et al., 2015	Compares the effect of MI to MI-BCI with realistic visual feedback on functional and physiological improvement	Double blinded, 28 (14/14), Subacute, (Months, 2,7±1,7 / 2,5±1,2)	~No to limited capacity (FMA-UE, 23,4±17,3 / 24,2±18,2)	MI-BCI (EEG) to provide realistic visual feedback (finger extension of a virtual hand)	Standard MI therapy	FMA-UE, MRC, NIHSS, MAS, NASA-TLX, TMS (MEP), EEG (RSC, PSD)	Significant functional improvement for both groups (FMA-UE, MRC, NIHSS). Significantly higher functional improvement for the experimental group (FMA-UE, MRC, NIHSS) correlated with intrahemispheric connectivity increase at rest in the affected hemisphere (FMA-UE). Probability of reaching the MCID for FMA-UE significantly higher for the experimental group. Significantly higher working memory involvment for the BCI group (NASA-TLX). Significantly more robost desynchronisation for the experimental group than for the control group post-training.	"[...] it is plausible that the BCI promoted the activity of sensorimotor areas (the ipsilesional parietal area and mesial premotor and supplementary motor areas) other than the primary motor cortex that are stimulated during MI implying that the better clinical outcomes in the BCI group were mediated by compensatory changes rather than the restoration of primary motor cortex activity."	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria except spatial neglect. Possible randomization bias.
Ramos-Murguialday et al., 2013	Compares the short term effect of MA-BCI with robotic feedback to MA-BCI with robotic sham feedback on functional and physiological improvement	Double blinded, 32 (16/16), Chronic (Months, 66±45 / 71±72)	~No to poor capacity (cFMA-UE, 11,15±6,92 / 13,28±10,71)	MA-BCI (EEG) to drive robotic orthosis to move the upper limb forward and for finger extension	Sham (random robotic feedback)	FMA-UE, GAS, MAL, Ashworth scale, fMRI (LI), EMG	Significant functional improvement (FMA-UE, EMG) in the BCI group not present for the control group correlated with LI for patients with subcortical lesions (FMA-UE). Significant functional improvement (GAS, MAL) for both groups. Significant physiological improvement (LI) for the experimental group not found for the control group.	"BMI training, involving proprioceptive positive feedback and reward that is time-contingent upon control of ipsilesional sensorimotor brain oscillations, may prime and thus improve the beneficial effects of physiotherapy on motor function."	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria except pain. Possible randomization bias.

Study	Aim	Design, Patients nbr, Chronicity	Motor impairment at inclusion	BCI intervention	Control group	Outcome measures	Results	Mechanisms discussed supposedly underlying the results	Potential bias
Rayegani et al., 2013	Compares the effect of occupational therapy with MI-BCI using gamified feedback or with EMG biofeedback or alone on functional and physiological improvement	Blinded assessment and statistics, 30 (10/10/10), Chronic (Months, 8,5±6 / 8,7±10,8 / 8±8,8)	N.A. (JHFT, 169±66 / 167±83 / 175±78)	Occupational therapy and MI-BCI (EEG) to control a game (visual and auditory feedback)	Occupatic therapy and EMG biofeedback, Occupational therapy alone	JHFT, EEG (PSD)	Similar funtional improvement in all the groups (JHFT). Significant increase of the PSD of the SMR band in the BCI group. Significant increase of mean and maximum contraction values of electrical activities of the paretic hand in the biofeedback group. Improved satisfaction for the biofeedback groups.	MI enables to increase or decrease SMR which was shown to be correlated with motor improvement post-stroke.	No description of the precise sensory assessment limiting the reproductibility of the study.
Varkuti et al., 2013	Compares the effect of MI-BCI with robotic feedback to standard robotic rehabilitation on physiological change	Blindness not described, 9 (6/3), Subacute and chronic (Months, 11,67±13,51 (3,9-8,8) / 6,8±6,5 (3,2-35,1))	Moderate to severe impairments (FMA-UE, 17,67±16,28 (4-23) / 14,67±9,71 (4-39))	MI-BCI (EEG) to drive robotic orthosis to move the shoulder and elbow of the impaired arm with gamified visual feedback	Standard robotic rehabilitation	fMRI (resting state), FMA-UE	Difference in resting state fMRI pre-post training are predictor of functional improvement (FMA-UE).	"MI-BCI training presumably strengthens the reassociation of neural representations of the paretic limb and the experienced afference, which could lead to better recovery."	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria. Possible randomization bias.
Wada et al., 2019	Compares the effect of MI-BCI with robotic feedback to MI-BCI with sham robotic feedback on functional and physiological improvement	Crossover study, Blindness not described, 9, Subacute and chronic (Days, 104±24)	N.A., Brunnstrom recovery stage from II to IV	MI-BCI (EEG) to drive robotic orthosis for finger extension and congruent visual feedback	Sham (random robotic feedback)	EEG (ERD), MAS, FMA-UE	Strong tendendy of increase of the ERD strength on the affected side and significant improvement of the spasticity (MAS) after BCI training none of which is observed in the control condition. Significant improvement of the spasticity after the BCI training which is not observed in the control condition.	"[...] promotion of remaining motor neurons on the affected hemisphere and the suppression of the hyperactivity of the unaffected hemisphere [...] leading to better prognosis."	No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria reported. Possible randomization bias.

Study	Aim	Design, Patients nbr, Chronicity	Motor impairment at inclusion	BCI intervention	Control group	Outcome measures	Results	Mechanisms discussed supposedly underlying the results	Potential bias
Young et al., 2016	Compares the effect of MA-BCI with multimodal feedback (Visual, FES and tongue stimulation) to customary care on functional and physiological improvement	Crossover study, Blindness not described, 19 (17/10), Subacute and chronic (Months, 34,53±44,14 (2-168))	No capacity to full capacity (ARAT, 30,06±25,37 (0-57) / 32,1±24,96 (0-57))	MA-BCI (EEG) to trigger visual feedback, FES for finger extension and tongue stimulation	Customary care	ARAT, SIS, 9-HPT, DTI	No significant neurophysiological difference between the control and experimental group (ARAT, SIS, 9-HPT, DTI). Fractional anisotropy values are significantly correlated to functional improvement (ARAT, SIS, 9-HPT).	N.A.	Non-responders might have been due to abnormal somatosensory abilities but not described. No prior assessment of somatosensory-related abilities for inclusion/exclusion criteria. Possible randomization bias.

Table 6.2: Inclusion and exclusion criteria related to somatosensory abilities of the studies selected for this review. When reported by the authors, the test or questionnaire associated with the criteria are stated in parentheses after the later. Following is a list of the abbreviations used in the table and their signification: Abbreviated Mental Test (AMT), Fugl-Meyer Assessment of Upper Extremity (FMA-UE), Intelligence Quotient (IQ), Kinaesthetic and Visual Imagery Questionnaire (KVIQ), Medical Research Council (MRC), Mini-Mental State Examination (MMSE), Modified Ashworth Scale (MAS), Montreal Cognitive Assessment (MoCA), Upper Extremity (UE), Visual Analogue Scale (VAS).

Table 6.2

Study	Instructions to use kinesthetic MI	Inclusion/Exclusion criteria related to somatosensory assessment							
		Time to stroke onset	**Spasticity, dystonia, movement disorders**	**Visual abilities**	**Pain**	**Somatosensory abilities**	**Cognitive Abilities**	**Language**	**Unilateral spatial neglect**
Ang et al., 2009									
Ang et al., 2010									
Ang et al., 2014	Yes	>4 months	No capacity to notable capacity (FMA-UE≥10 and ≤50), Motor power controlled (MRC), No severe spasticity (MAS≤2)	No severe visual impairement	No pain (VAS≤ 4)		Able to understand simple instructions, No inattention, No severe depression, No psychiatric disorder	No severe aphasia	No hemispatial neglect
Ang et al., 2015	Yes	>3 months	No capacity to limited capacity (FMA-UE≤45), No severe spasticity (MAS≤2), No fixed joint contractures	No severe visual impairement	No pain (VAS≤4)		Able to understand simple instructions (AMT>6), No cognitive deficits, No severe depression	No severe aphasia	No hemispatial neglect
Biasiucci et al., 2018		≥10 months	No capacity to limited capacity (FMA-UE≤40), No severe dystonia/involontary movements, No other neurological disorders (e.g., Parkinson's disease)	Good or corrected eyesight			Able to understand simple instructions, No cognitive deficits preventing to perform the rehabilitation task (Raven's Test), No patients under heavy medication affecting the central nervous system (including vigilance)		No hemispatial neglect
Frolov et al., 2017	Yes	≥1 month	Hand paresis (MRC, mild to plegia), No spasticity (MAS<4)	No severe vision impairment			No severe cognitive impairment (MoCA>10)	No sensory aphasia, No severe motor aphasia	
Li et al., 2014	Yes (with KVIQ assessment)	1 to 6 months	Affected UE (Brunnstrom period level between I and III)				No cognitive impairment (MMSE>27), Able to perform MI tasks evidenced by KVIQ, Able to understand the experimental commands	No speech disorders	

Study	Instructions to use kinesthetic MI	Inclusion/Exclusion criteria related to somatosensory assessment							
		Time to stroke onset	**Spasticity, dystonia, movement disorders**	**Visual abilities**	**Pain**	**Somatosensory abilities**	**Cognitive Abilities**	**Language**	**Unilateral spatial neglect**
Mihara et al., 2013	Yes (with KVIQ assessment)	$\geq$12 weeks	Motor hemiparesis (FMA-UE$\leq$50)	No hemianopia		No sensory loss	No cognitive impairment (MMSE$\geq$23), No depression	No moderate to severe aphasia	No spatial neglect
Pichiorri et al., 2015	Yes	6 weeks to 6 months	Hemiplegia or hemiparesis, No spasticity (MAS<4), No apraxia				No cognitive impairment (MMSE>24)	No severe aphasia	No severe hemispatial neglect
Ramos-Murguialday et al., 2013		>10 months	Paresis of one hand, No active finger extension, No cerebellar lesion or bilateral motor deficit		No severe pain		Able to follow and understand instruction, No psychiatric or neurological condition other than stroke, No depression, IQ above 80	No severe aphasia	
Rayegani et al., 2013	Yes	3 to 12 months	Good trunk balance, Good motor recovery (stage 4 to 5 of Brunnstrom's stage of motor recovery), Partial ability to grasp and release			No sensory impairment in the upper limbs		No cognitive disorders making communication difficult	
Varkuti et al., 2013		$\geq$1 month	No capacity to limited capacity (FMA*leq*45)						
Wada et al., 2019 (No criteria mentioned)	Yes								
Young et al., 2016			Persistent UE motor impairment				No other known neurologic, psychiatric or developmental disabilities		

Chapter 7

Contribution 4 – Which modality of feedback for BCI training?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - A physical learning companion can be useful for MI-BCI user training depending on learners' autonomy
	5. **Contribution 2** – An interaction of experimenters' and participants' gender has an influence on MI-BCI training
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Somatosensory abilities post-stroke probably influence BCI-based motor rehabilitation
	7. **Contribution 4** – Which modality of feedback for BCI training?
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

Supervision: Romain Sabau (Master student at the time).

Related full papers: Pillette, L., Sabau, R., Lotte, F. & N'Kaoua, « The influence of feedback modality on MI-BCI user training », In preparation.

7.1 Introduction

In the chapter 6, we stated that somatosensory abilities were important to benefit from post-stroke motor rehabilitation therapies. We also argued that, given the central role of somatosensory feedback for BCI-based therapies, somatosensory deficits would limit the benefice of BCI-based motor rehabilitation therapies. There are various types of somatosensory losses depending on the modalities that were impacted by the stroke. For example, a patient can have preserved tactile sensations but a loss of proprioception. We hypothesis, that depending on the modality of the feedback that is provided and on the type of somatosensory loss that patients have, BCI-based therapies would not have the same therapeutic impact. The literature indicates that somatosensory losses are associated with a deterioration of motor imagery abilities [Liepert et al., 2016].

As we have seen in Section 3.2 Influence of learners' states, an impact of mental imagery abilities was found on MI-BCI performances of neurotypical persons when classifying right versus left hand motor imagery [Vuckovic and Osuagwu, 2013, Marchesotti et al., 2016]. Though, Rimbert et al. did not find any influence of mental imagery abilities on MI-BCI performances when classifying resting state versus right hand motor imagery [Rimbert et al., 2017]. Further studies are required to assess the influence of those abilities on MI-BCI performances [Rimbert et al., 2017]. It would be important to have a better understanding their influence to (1) better understand the underlying mechanisms of BCI user training (2) limit the bias that could arise if they are not evaluated (3) adapt the user training accordingly.

In addition, we hypothesise that the modality of feedback might benefit participants differently depending on their visual and kinaesthetic imagery abilities. Indeed, if participants rely on visual or kinaesthetic imagery, then providing them respectively with visual or tactile feedback might disrupt their performance of the task. Both the monitoring of the feedback and the performance of mental imagery task would solicit similar sensory cognitive resources. This might lead to an overtaxing of the sensory cognitive resources and lead to a decrease of the BCI performances and the user-experience [Wickens, 2008]. Compared to a visual feedback alone, a multimodal feedback composed of both a visual feedback and a proprioceptive feedback, e.g., an orthosis, was found to increase MI-BCI performances and ERD/ERS modulation in the beta frequency range of neurotypical participants [Gomez-Rodriguez et al., 2011, Darvishi et al., 2015]. Using a feedback provided distinctly from the interactive application forces users to split their attention between the two. For example, controlling a video game on one screen while receiving the instruction for that game on another screen would force players to split their attention. This might lead to an increase of cognitive resources [Jeunet et al., 2015b]. It was not reported that such an increase in cognitive resources impacted MI-BCI performances or the user-experience in previous articles comparing visual and vibrotactile feedback over a single session [Cincotti et al., 2007, Gwak et al., 2014, Lukoyanov et al., 2018, Jeunet et al., 2015b]. The literature does not provide any information regarding characteristics of the learner that would impact the benefice of the modality of feedback during MI-BCI user training.

We also aimed at evaluating the long term influence of a vibrotactile feedback on MI-BCI performances, which remained unknown. Previous experiments compared the performances of visual versus vibrotactile performances during one session only (see Section 2.2.2 Tactile to somatosensory feedback). However, the long term use of such feedback could lead to a desensitisation and a decrease of performances [Jeunet et al., 2015b]. If a desensitisation occurs, we expect the performances of the visual and vibrotactile feedback to progressively become comparable to the ones of the visual feedback alone.

To summarize, our goal for this experiment was to test the long term influence of two modalities of feedback, one visual and one vibrotactile and visual, on BCI performances and user-experience.

7.2 Materials & methods

The participants participated in 10 sessions, 5 for each modality of feedback. A within participant comparison for the influence of the modalities of feedback was chosen. Participants were divided into two groups depending on the laterality of the hand that they imagined or moved. The order of presentation of the feedback modalities and the laterality of the tasks were balanced over our participants (see Table 7.1).

7.2.1 Participants

Sixteen MI-BCI naïve participants were included in this study (8 women; age 18-27; $\bar{X}$=22.31; SD=2.33). None of them had any history of neurological or psychiatric disorder. Participants were randomly assigned to one of four groups depending on (1) the type of feedback they started practising with, i.e., visual or visual and vibrotactile, and (2) the laterality of the hand they should imagine or execute movements with (see Table 7.1).

Groups		Group VR	Group VL	Group TR	Group TL
Modality of feedback	First 5 sessions	Visual FB		Tactile and visual FB	
	Last 5 sessions	Tactile and visual FB		Visual FB	
Tasks to perform	Motor imagination	Right	Left	Right	Left
	Motor execution	Left	Right	Left	Right

Table 7.1: Type of feedback provided and tasks to perform during the sessions depending on the group.

Our study was conducted in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki. Participants gave informed consent before participating to the study. The study has been reviewed and approved by Inria's ethics committee, the COERLE (approval number: 2019-04).

7.2.2 Experimental protocol

To control the BCI, participants were asked to perform three tasks, i.e., one resting task, one motor imagery task of either their right or left hand and one motor execution task of their opposite hand. Participants were instructed to kinaesthetically imagine or execute an opening and closing movement of their hand. The laterality of the hand that participants were asked to imagine or execute movements with depended on the group they were included in. Feedback was only provided for the motor-related tasks. The feedback represented how well the system recognized the modification occurring in the brain activity of the participants when they performed motor-related tasks compared to their brain activity when they were in a resting state. It lasted 6 seconds and was updated at 16Hz, according to the last 1 second of EEG signals.

A realistic visual feedback representing arms was displayed on a screen and placed over the arms of the participants to give the impression of embodiment (see Figure 7.1). Participants were asked to place their hands on the table in front of them in a supine position (palms facing upwards) below the screen. Virtual hands performed opening and closing movements depending on the classifier output. The more confident the system was in its recognition of the task, the faster the hand was opening and closing. Only positive feedback was displayed, i.e., the feedback was provided only when there was a match between the instruction and the task recognized by the system. In addition to the visual feedback, a tactile feedback was provided during the 5 first sessions for half of the participants and during the last 5 sessions for the other half. This tactile feedback consisted in vibrations on the wrist provided using vibro-tactile motors contained in gloves worn by the participant. The system of vibro-tactile motors embedded in gloves was used in a previous MI-BCI experiment aiming at comparing a visual and an equivalent tactile feedback in a high cognitive load situation [Jeunet et al., 2015a]. The intensity of the vibration depended on the output of the classifier. The better the classifier recognized the task performed by the participant, the stronger the vibration got. The minimal and maximal vibration frequencies were adjusted at the beginning of the first session. Participants were presented with the lowest, i.e., 50Hz, and highest, i.e., 200Hz, intensities of vibrations and asked if they felt the vibrations and if feeling them repetitively during 6 seconds would be painful. None of the participants asked to change these default intensities. Their were five thresholds separating uniformly six different intensities of vibration. The discriminability between two successive intensities of vibrations was tested as well. Participants were asked to recognize the highest intensity of vibration between each pair of consecutive intensities presented successively in a random order. Each of our participants distinguished consecutive vibrations for at least three of the five thresholds. The intensity of vibration and the discriminability were tested independently for each hand.

Participants were asked to perform or imagine performing the movements as fast as the maximum speed of the feedback, i.e., one opening and closing movement per second. A demonstration of the maximum speed was made at the beginning of the session. We chose to give these instructions to maximize the similarity between the realistic feedback presented on the screen and the mental imagery task that the participant would perform to promote the sense of agency.

Participants took part in 10 MI-BCI sessions, each lasting between 1.5 and 2 hours, spread over a month with 2 to 3 sessions per week and no more than one session per day. The sessions were organized as follows. First, depending on the session, participants were asked to complete one validated psychometric questionnaire (see Section 7.2.3 Questionnaires) assessing some aspects of their personality and/or cognitive profile (∼10 to 20min). Then, the EEG headset was installed as well as the gloves containing vibrotactile motors (∼10 to 20min). Two baselines were recorded. One to assess the brain activity of the participants while being at rest with eyes opened (∼3min) and one to assess the brain activity of the participants while they only perceived sham vibrotactile and/or visual feedback without performing any motor-related task (∼6min). Next, participants performed 7 runs, each lasting 5.33 minutes (∼45min containing 5 minutes of break). The first three runs were used to calibrate the system if necessary. Finally, the cap was uninstalled, one or two questionnaires were filled depending on the session and a quick debriefing was made.

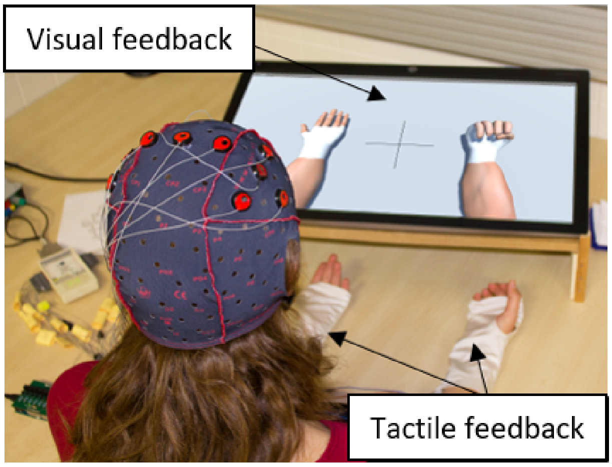

Figure 7.1: Type of feedback provided and tasks to perform during the sessions depending on the group.

During the runs, participants had to perform 20 trials, half of motor execution and half of motor imagery. Tasks were presented in a random order and each trial lasted 15 seconds. Trials unfolded as described in the following sentences (see Figure 7.2). At t=0s, a cross was displayed in the center of the screen. At t=1s, a "beep" announced the coming instruction and half a second later, at t=1.5s, the participant was asked to rest for 3s. Then, at t=4.5s an arrow pointing left or right indicated which task, left or right hand movement execution or imagery, the participants had to perform in loop until the end of the trial. Finally, at t=5.250s, either visual feedback only or both visual and tactile feedback were provided. A gap lasting between 3.5s and 4.5s separated each trial.

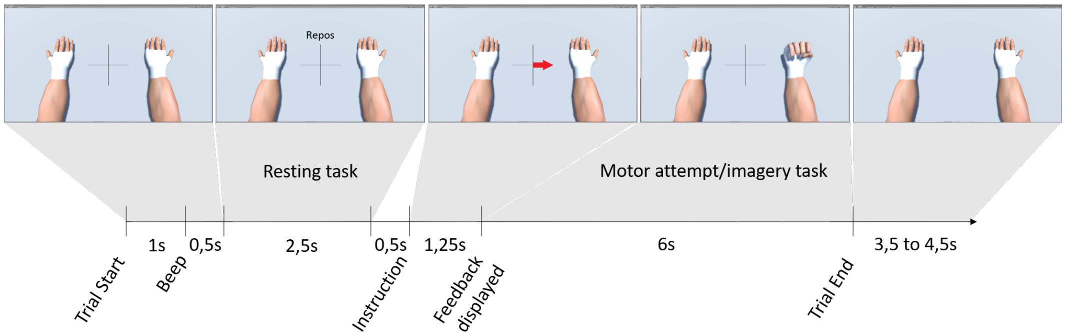

Figure 7.2: Timing of a trial.

7.2.3 Questionnaires

Throughout the sessions, participants were asked to fill or carry out the following questionnaires or tests:

- 1st Session - General questionnaire - To assess general information of the participant, such as age, eyesight or if they practice meditation.

- Every session - Pre and post session questionnaires – To assess general information regarding the state of the participant, such as physiological state (tiredness / alertness, stimulants consumption, etc.) or emotions (Self-Assessment Manikin scale).

- Every session - Pre and post session UX questionnaires – To assess participants' states and user-experience. The questionnaires were developed by Aurore Hakoun, Samy Chikhi and François-Benoît Vialatte (in process of validation, see Annexe) [Jaumard-Hakoun et al., 2017]. Based on validated questionnaires, it determines five dimensions of user-state and/or user-experience. Three of them are assessed pre and post training and evaluate the mood, mindfulness and motivational states of the user. Two of them assess the user-experience post-training through the cognitive load, i.e., amount of cognitive process required to control the MI-BCI system, and the agentivity, i.e., feeling of control of the participant over the feedback provided by the MI-BCI. The evolution of the participant's states also provides an information regarding the user-experience.

- 1st, 6th and last sessions – Kinesthetic and Visual Imagery Questionnaire (KVIQ) [Malouin et al., 2007] – To determine participants' ability to visualize and feel an imagined movement.

- 2nd session - Mental Rotation Test [Vandenberg and Kuse, 1978] - To determine participants' ability to visualize a 3D object rotating in space.

- 3rd session – Edinburgh lateralization questionnaire [Oldfield, 1971] – To determine the laterality of the participants, i.e., how dominant each hand is.

- 4th session – Index of Learning Styles [Felder and Spurlin, 2005] – to determine the participants' preferred learning styles according to four dimensions: visual / verbal, active / reflective, sensitive / intuitive and sequential / global.

7.2.4 EEG Recordings & Signal Processing

The electrophysiological data was recorded with 16 active EEG electrodes, using a g.USBAmp EEG amplifier (g.tec, Austria). Two electrodes placed 2.5cm below the skinfold of both wrists recorded electromyographic activity from both hands. Three were placed respectively below, above and beside the left eye to record the electrooculogram. Finally the rest of the electrodes were placed on the scalp of the participant over the sensorimotor area (at locations FC3, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CP4 in the 10-20 system). The electrodes were referenced to the left earlobe and grounded to AFz. The data was sampled at 256 Hz, and processed online using OpenViBE 2.1.0 [Renard et al., 2010].

We used two participant-specific classifiers to compare the data acquired during the resting task to the data acquired during motor execution (ME) tasks or mental imagery (MI) task. We used the following pipeline to classify the data. First, two Laplacian spatial filters were computed over C3 and C4 [Blankertz et al., 2008]. Then, EEG signals were band-pass filtered in 8-10Hz, 10-12Hz, 12-16Hz, 16-20Hz and 20-24Hz using Butterworth filters of order 5. The band power of the 5 frequency filtered EEG signals were then computed by squaring the signals, averaging them over the last 1 second time window (with 15/16s overlap between consecutive time windows) and log-transforming them. This resulted in 10 different band-power features that were fed to two shrinkage Linear Discriminant Analysis (LDA), i.e., one LDA for the MI vs rest tasks and one for the ME vs rest task.

LDA classifiers were calibrated on the data from the three first runs on the 1st and 6th sessions, when the participants started training with a new feedback. These classifiers were then applied on the subsequent runs to provide online feedback. The calibration data from the three first runs of the 1st and 6th sessions were also used to compute the median and mean absolute deviation of both MI and ME LDA classifier outputs (distance to the separating hyperplane) to normalize the classifier output. MI and ME classifiers' normalised outputs were then computed online by subtracting the median value to the LDA classifier outputs (distance to the separating hyperplane) and dividing it all by twice the value of the mean absolute deviation.

Consistent feedback could not be provided from the 1st to the 3rd run of the session when participants were using a new feedback, i.e., 1st and 6th sessions. Indeed, the classifiers were not yet trained to recognize the changes of brain activity associated with the mental tasks performed by the participant. In order to limit biases with the other runs, e.g., EEG changes due to different visual processing between runs, the participant was provided with a sham feedback, i.e., the hands moved similarly to what could happen if there were classifiers but randomly, as in [Jeunet et al., 2015b]. Participants were aware that this feedback during the calibration runs was a fake feedback.

The MI and ME classification accuracy, or performances, were computed online and corresponded to the percentage of epochs (1s long time windows) from the feedback and resting state periods that were correctly classified.

For the sessions when participants were not using a new feedback (2nd to 5th and 7th to 10th sessions), the classifiers were trained and centered on the data from all the runs of the previous session. After the third run, the average MI and ME performances over the three first runs were checked to verify the adequacy of the classifiers. The performances of a classifier were considered as low if they were below the chance level of 62.5% [Müller-Putz et al., 2008] and/or below the minimal performances across runs of the last session. If the performances of a classifier were low, then the median and mean absolute deviation used to normalize the data of the given classifier were changed for the ones computed on the data from the first three runs of the day. The performances obtained during the first three runs were then recalculated with the new centering data. If the new performances were not low anymore, then the centered classifier was kept for the last four runs of the session. If new performances were still low, then the classifiers were trained on all the available runs from the current session, i.e., the first three runs. If the cross validation accuracy on the first three runs minus 5% (estimated optimism of the cross validation score [Thomas et al., 2013]) was not considered as low, then the new classifiers were kept. Otherwise, the classifiers allowing the best performances over the first three runs were kept.

7.2.5 Variables & Factors

The first aim of our analysis was to test the influence of the modality of feedback on MI or ME classification accuracy as well as their evolution. The measures of performances used for the analysis were the online MI or ME classification accuracy (see Section above 7.2.4 EEG Recordings & Signal Processing) averaged over each runs of the different sessions. Participants had two performances, one per classifier. One corresponds to the percentage of recognition of the mental imagery task, i.e., MI classification accuracy. The other corresponds to the classification accuracy in discriminating the movement execution task from the resting state, i.e., ME classification accuracy.

Second, we wanted to assess the potential impact of the modalities of feedback on the user experience and its evolution. The user experience is defined by the two percentages provided by the questionnaire of Aurore Hakoun et al. [Jaumard-Hakoun et al., 2017] regarding the amount of cognitive load and agentivity felt during the training. It is also defined by the evolution of mood, mindfulness and motivation, assessed in percent, of the participants between the beginning and end of the training. This evolution is assessed by subtracting the measure post training to the measure pre training per session. The higher the percentage, the more participants increased their reported levels of positive emotions and calm, mindfulness, motivation, cognitive load and sense of agency.

Finally, we wanted to know if characteristics of the participants' profile could provide first elements of comprehension regarding the potential differences in MI or ME classification accuracy or user-experience. We focused on traits and states that were shown to have an influence on MI-BCI performances in previous studies, i.e., mental rotation scores (MRS)[Vandenberg and Kuse, 1978], tensed and/or non-autonomous (both measured using the 16PF5 questionnaire [Cattell and P. Cattell, 1995]), mood, motivation and mindfulness [Jeunet et al., 2015a, Nijboer et al., 2008, Tan et al., 2014]. We also assessed how well our participants could kinaesthetically and visually imagine the side of the body for which they had to perform the mental imagery task [Malouin et al., 2007]. The Kinaesthetic and Visual Imagery Questionnaire (KVIQ) provided us with two scores, one for the visual imagery abilities and one for the kinaesthetic imagery abilities. This questionnaire was answered three times, before and after each training with a feedback modality.

7.3 Results

7.3.1 Comparability of the groups

Before it all, we verified if the distribution of the data collected was normal using Shapiro-Wilk tests. The variables describing the mental rotation scores ($p=0.52$) and tension ($p=0.36$) of our participants could be considered as having a normal distribution. Most of the mean classification accuracy of the sessions could be considered as having normal distributions. Only the fourth sessions of the ME classification accuracy with both the visual and the multimodal feedback did not have a normal distribution (respectively, $p=0.05$ and $p=0.04$). The autonomy ($p=0.02$) of the participants did not follow a normal distribution either. The measures of visual and kinaesthetic imagery had a normal distribution for the 1st and 6th sessions. Though, the repartition of the scores can not be considered as normal for the visual imagery of the 1st session and for all the scores of the 10th session ($p\in[0.01, 0.04]$). In the following results, we report performing ANOVAs using these variables. Even though the normality of the data is a pre-requisite of an ANOVA, the ANOVA is considered as robust against the normality assumption and, to the best of our knowledge, no other non parametric test enabled to perform the analysis that we were interested in.

To make sure that our results would not be biased, we also verified if some of our participants could be considered as outliers. A performance was considered as an outlier if it was superior (or inferior) to the mean performances of all the participants by more (or less) than two standard deviation. We did not find any outlier for both modalities of feedback, whether it was the MI or ME performances.

We also verified if there were significant differences in the groups depending on the modality of feedback that they started training with, i.e., *"1stModality"*, and the laterality of the hand with which they imagined or executed movements, i.e., *"HandTask"*. We focused on mental rotation scores (MRS), tension, autonomy and the visual and kinaesthetic abilities, mood, motivation and mindfulness on the first session. To check if the groups were comparable, we ran 2-way ANOVAs with *"1stModality*HandTask"* as independent variables and either mental rotation scores, tension, autonomy, kinaesthetic imagery abilities or visual imagery abilities as dependent variable. Results indicate that groups were comparable in terms of mental rotation scores, tension, autonomy and kinaesthetic imagery. Though, scores of visual imagery on the first session were not comparable between the groups depending on the hand they were imagining moving [$F(1,16)=6.84$; $p=0.02$, $\eta^2=0.36$] and depending on the first modality of feedback they were training with [F(1,16)=7.43; p=0.02, η^2=0.38]. Participants that imagined moving their left hand and participants that first trained with visual feedback had lower initial visual imagery abilities that participants that respectively imagined moving their right hand and started training with both visual and tactile feedback (see Figure 7.3).

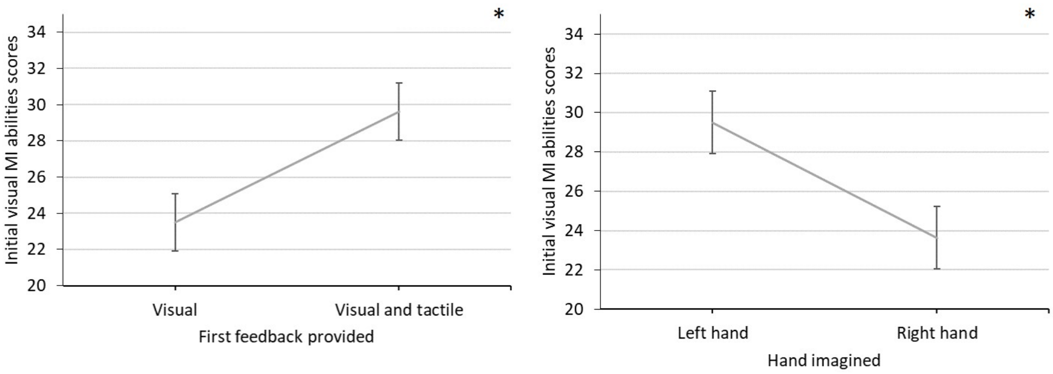

Figure 7.3: Scores of visual imagery on the first session depending on the first modality of feedback provided or on the laterality of the imagined hand.

7.3.2 Influence of the modality of feedback on movement execution and imagery performances

7.3.2.1 Main analyses

The first aim of our analyses was to test the influence of the modality of feedback, i.e., *"Modality"*, on the evolution of MI and ME classification accuracy over the sessions, i.e., *"Session"*. To do so, we performed a 2-way repeated measures ANOVA with *"Modality*Session"* as independent variables and the repeated measures of MI or ME classification accuracy as dependent variable.

When using the MI classification accuracy as dependent variable, we found single effects of *"Modality"* [F(1,15)=8.57; p=0.01, η^2=0.36] and *"Session"* [F(2.33,34.96)= 3.68; p=0.03, η^2=0.2] (specificity corrected using the Greenhouse-Geisser method (epsilon=0.58)). No significant impact of *"Modality*Session"* [F(4,60)=2.42; p=0.06, η^2=0.14] was found.

Overall, our participants seemed to have decreasing MI classification accuracies until the third session and then retrieved similar MI classification accuracies to those of the first session during the last session (see Figure 7.5). The MI classification accuracy of participants was significantly higher when they trained with multimodal feedback compared to when they trained with visual feedback only (see Figure 7.4).

When using the ME classification accuracy as dependent variable, we found no single impact of *"Modality"* [F(1,15)=0.03; p=0.86, $\eta^2<10^{-2}$] and *"Session"* [F(2.41, 36.19)=2.5; p=0.09, η^2=0.14] (specificity corrected using the Greenhouse-Geisser method (epsilon=0.6)) and no impact either of *"Modality*Session"* [F(4,60)=1.54; p=0.2, η^2=0.09].

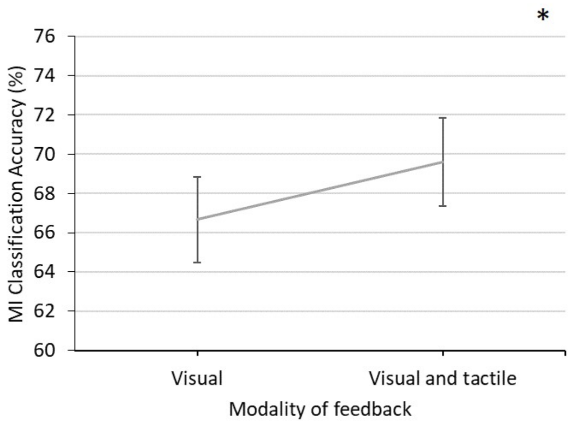

Figure 7.4: MI classification accuracy depending on the modality of feedback.

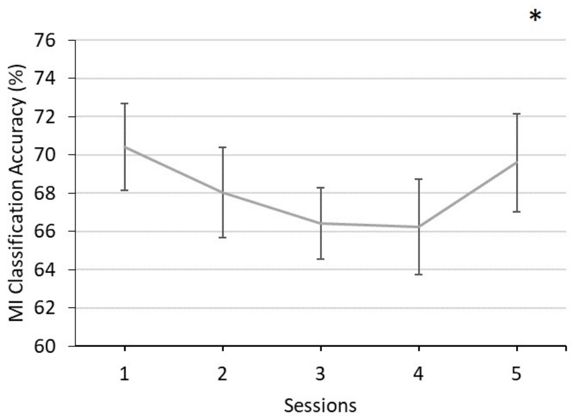

Figure 7.5: Evolution of the MI classification accuracy over the sessions.

7.3.2.2 Potential bias from the initial visual imagery ability

As we found a significant difference of initial visual imagery abilities, i.e., *"InitVI"*, among our groups of participants, we verified if these differences had an impact on our results. We performed the same analysis than in the previous section, i.e., 2-way repeated measures ANCOVAs with *"Modality*Session"* as independent variables and the repeated measures of MI or ME classification accuracy as dependent variable, with *"InitVI"* as covariate.

First, we used the MI classification accuracy as dependent variable. No significant influence of the initial visual imagery abilities on any simple effect or interaction was found. *"InitVI"* [F(1,14)=2.57; p=0.13, η^2=0.16] did not have a significant impact on the MI classification accuracy.

Second, we used the ME classification accuracy as dependent variable. No significant influence of the initial visual imagery abilities on any simple effect. Though, a significant impact of the initial visual imagery abilities was found on the interaction of *"Modality*Session*InitVI"* [F(4,60)=3.58; p=0.01, η^2=0.2]. The corresponding effect of *"Modality*Session"* [F(4,60)=4.14; p<10^{-2}, η^2=0.23] was significant. ME classification accuracy seemed quite stable over the first three sessions and decreased on the fourth session when participants trained with multimodal feedback. ME classification accuracy decreased over the first three sessions and increased on the last sessions when participants trained with visual feedback only. See Figure 7.6.

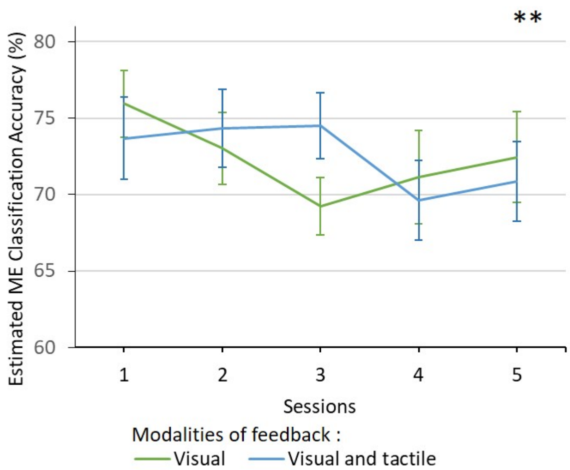

Figure 7.6: Evolution of the estimated ME classification accuracy depending on the modality of feedback with the initial visual imagery abilities taken into account.

7.3.2.3 Influence of the order of presentation on the performances

Experiments comparing different modalities of feedback often present the participants with the different feedback with a controlled order of presentation, sometimes with a few number of participants [Gwak et al., 2014]. [Jeunet et al., 2015b] hypothesised that the order of presentation of the feedback might have an impact. Therefore, we tested if the order of presentation of the modalities of feedback, i.e., *"Order"*, influenced our results. We led our same main analyses as in the previous sections, i.e., 2-way repeated measures ANCOVAs with *"Modality*Session"* as independent variables and the repeated measures of MI or ME classification accuracy as dependent variable, with *"Order"* as covariate.

First, we used the MI classification accuracy as dependent variable. No significant influence of the order on any simple effect or interaction was found. Though, *"Order"* [F(1,14)=7.02; p=0.02, η^2=0.33] had a significant impact on the MI classification accuracy. The mean MI classification accuracy depending on the order of presentation of the modalities of feedback was computed to have a better understanding of this influence. The mean MI classification of participants that started training with the visual feedback only ($\bar{X}$visualFB=72.95; SD=2.57) was higher than the mean MI classification accuracy of the participants that started training with the visual and tactile feedback ($\bar{X}$visualTactileFB=63.32; SD=2.57) (see Figure 7.7).

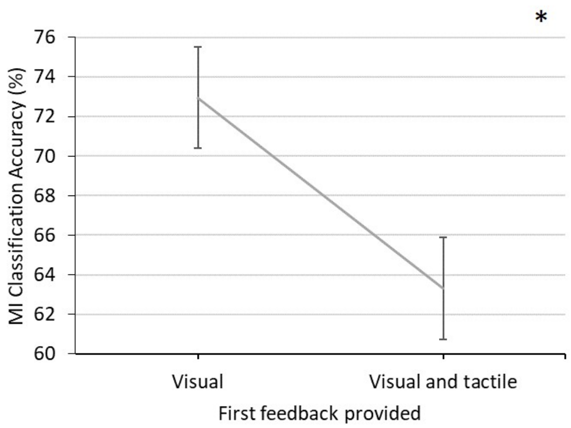

Figure 7.7: MI classification accuracy depending on the order of presentation of the modalities of feedback.

The corrected simple effects of the modality and session found in 7.3.2.1 were not robust to the correction for the order of presentation. No other effects were revealed when using the order as covariate.

Second, we used the ME classification accuracy as dependent variable. No significant influence of the order on any simple effect or interaction was found. Though, *"Order"* [F(1,14)=4.65; p=0.05, η^2=0.25] had a significant impact on the ME classification accuracy. Once again, the mean ME classification accuracy depending on the order of presentation of the modalities of feedback was computed to have a better understanding of this influence. Similarly to the results found for MI classification accuracy, the mean ME classification of participants who started training with the visual feedback only ($\bar{X}$visualFB=77.09; SD=3.02) was higher than the mean ME classification accuracy of the participants who started training with the visual and tactile feedback ($\bar{X}$visualTactileFB=67.87; SD=3.02) (See Figure 7.8).

No other effects were revealed when using the order as covariate.

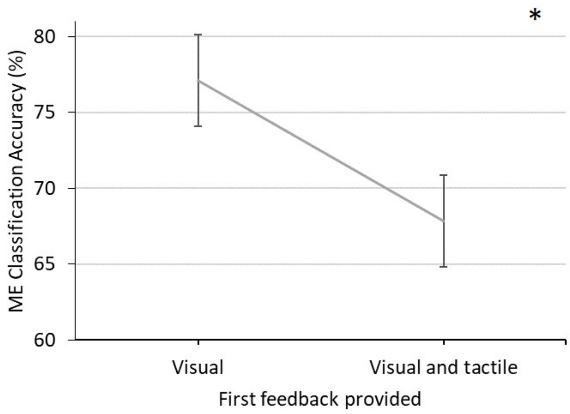

Figure 7.8: ME classification accuracy depending on the order of presentation of the modalities of feedback.

7.3.2.4 Influence of the laterality on the performances

Half of the participants imagined movements of the right hand and performed the movement with their left hand and the other half did the opposite. Therefore, we checked if the laterality of the imagined hand, i.e., *"Laterality"*, had an impact on the MI and ME classification accuracy. We led our main analyses, i.e., 2-way repeated measures ANOVAs with *"Modality*Session"* as independent variables and the repeated measures of MI or ME classification accuracy as dependent variable, with *"Laterality"* as covariate.

First, we used the MI classification accuracy as dependent variable. No significant influence of the laterality on any simple effect or interaction was found. *"Laterality"* [F(1,14)=1.24; p=0.28, η^2=0.08] did not have a significant impact on the MI classification accuracy.

Second, we used the ME classification accuracy as dependent variable. No significant influence of the laterality on any simple effect or interaction was found. *"Laterality"* [F(1,14)=0.31; p=0.59, η^2=0.02] did not have a significant impact on the ME classification accuracy.

7.3.2.5 Influence of participants' traits and states

We also analysed if the autonomy, tension, mental rotation abilities or initial kinaesthetic imagery abilities of our participants had impacted their mean MI or ME classification accuracy. Their was no correlation between the mean MI classification accuracy over the sessions and the autonomy [Spearman correlation, r=0.16, p=0.55], tension [Pearson correlation, r=-0.41, p=0.12], mental rotation abilities [Pearson correlation, r=0.03, p=0.92] and initial kinaesthetic imagery abilities [Pearson correlation, r=-0.26, p=0.33]. There was no correlation either between the ME classification accuracy and the autonomy [Spearman correlation, r=-0.08, p=0.77], tension [Pearson correlation, r=-0.37, p=0.16], mental rotation abilities [Pearson correlation, r=-0.17, p=0.53] and initial kinaesthetic imagery abilities [Pearson correlation, r=-0.06, p=0.82].

7.3.3 Influence of the modality of feedback on the user-experience

7.3.3.1 Evolution of the user-experience depending on the modality of feedback

Finally, we analysed the influence of the modality of feedback on the five dimensions of the user-experience, i.e., mood, mindfulness, motivation, cognitive load and agentivity.

We performed five 2-way ANOVAs with *"Modality*Session"* as independent variables and the difference of mood, mindfulness or motivation between the end and the beginning of the sessions or the measures of agentivity or cognitive load post training as dependent variables.

We first used the measure of cognitive load post training as dependent variable. No influence was found of *"Modality"* [$F(1,15)=1.14$; $p=0.3$, $\eta^2=0.07$], *"Session"* [$F(4,60)=0.79$; $p=0.53$, $\eta^2=0.05$] and *"Modality*Session"* [$F(4,60)=1.16$; $p=0.34$, $\eta^2=0.07$].

A second ANOVA with the measure of agentivity post training as dependent variable was then performed. No simple effects of *"Modality"* [$F(1,15)=0.96$; $p=0.34$, $\eta^2=0.06$] and *"Session"* [$F(4,60)=1.73$; $p=0.16$, $\eta^2=0.1$] were found. Though, a significant influence of the interaction *"Modality*Session"* [$F(4,60)=4.07$; $p<10^{-2}$, $\eta^2=0.21$] was found. The agentivity was increasing over the three first sessions, decreased drastically on the fourth and increased on the fifth with the multimodal feedback. The agentivity was decreasing over the three first sessions, and increased over the rest of the sessions with the visual feedback only. The agentivity seemed higher for the participants with a multimodal feedback during the second and third sessions. Though, the agentivity seems higher for the visual feedback than the multimodal on the fourth session. See Figure 7.9.

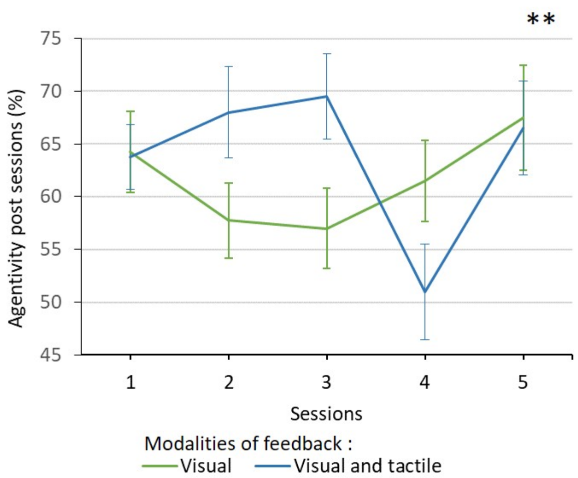

Figure 7.9: Evolution over the sessions of the mean percent of agentivity post training depending on the modality of feedback.

We then performed a third ANOVA with the difference of mood between the end and the beginning of the session as dependent variable. No single effects of *"Modality"* [F(1,14)=2.48; p=0.14, η^2=0.14] and *"Session"* [F(4,60)=0.3; p=0.88, η^2=0.02] were found. Though, a significant impact of *"Modality*Session"*[F(4,60)=3.81; p<10^{-2}, η^2=0.2] was found. Figure 7.10 represents this effect.

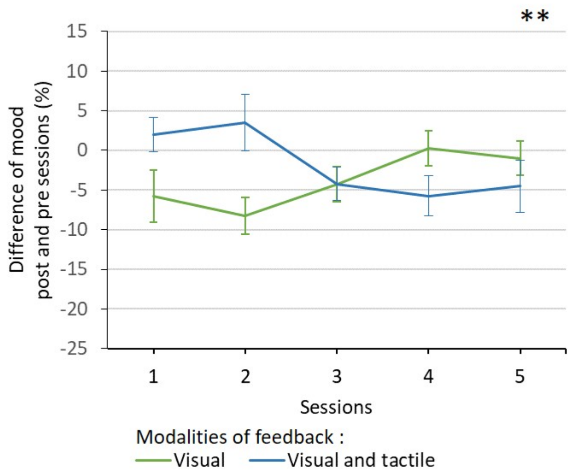

Figure 7.10: Mean difference of positive mood between the end and the beginning of session over the sessions depending on the type of feedback.

The evolution of difference in amount of positive and calm emotions between the beginning and end of the sessions over the sessions seems to be negative with a visual and tactile feedback and positive with a visual feedback only. During the first two sessions, when participants were training with visual feedback, they felt more positive emotions at the end of the session compared to the beginning of the session. It was the opposite when participants trained with multimodal feedback. During the last two sessions, whether participants trained with visual or multimodal feedback, they felt less positive emotions at the end of the training compared to the beginning of the training. Though, the decrease in positive emotions seemed greater when participants were training with a multimodal feedback compared to when they were training with a visual feedback only.

A fourth ANOVA with the difference of measure of mindfulness between the end and the beginning of the session as dependent variable was then performed. No single influence of *"Session"* [F(2.32,34.73)=1.67; p=0.2, η^2=0.1] (specificity corrected using the Greenhouse-Geisser method (epsilon=0.58)) was found. Though, significant impacts of *"Modality"* [F(1,15)=5.97; p=0.03, η^2=0.3] and *"Modality*Session"* [F(4,60)=2.94; p=0.03, η^2=0.16] were found. Figure 7.11 represents these effects.

Mindfulness seems to decrease more over the session when participants were training with a visual feedback than when they were training with a multimodal feedback. This difference is particularly visible during the first two sessions. During these sessions, the mindfulness increases between the beginning and the end of the session when the participants were training with multimodal feedback but greatly decreases when they were training with visual feedback. Overall, the mindfulness

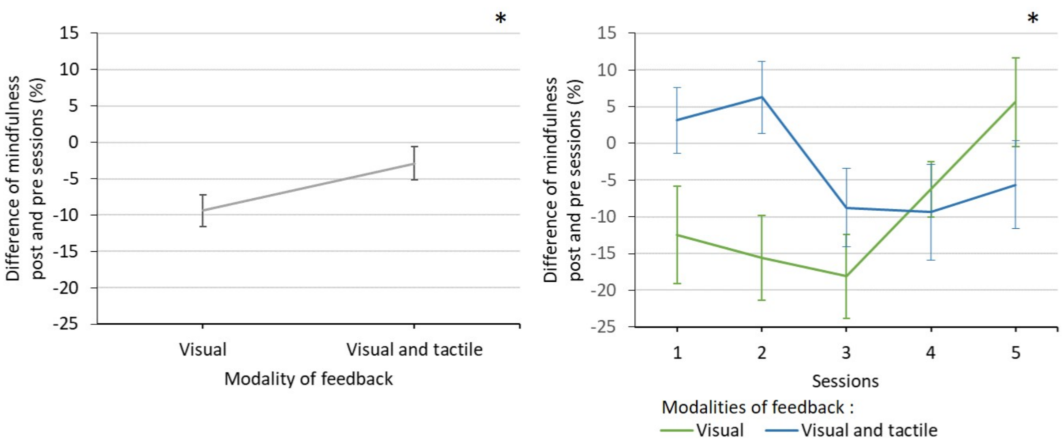

Figure 7.11: Mean difference of mindfulness between the end and the beginning of session over the sessions depending on the type of feedback.

seems to decrease over the sessions when participants were training with a multimodal feedback whereas a large increase is visible between the third and the last sessions when participants were training with a visual feedback.

Finally, a fifth ANOVA with the difference of measure of motivation between the end and the beginning of the session as dependent variable was performed. No influence was found of *"Modality"* [F(1,15)=0.32; p=0.58, η^2=0.02], *"Session"* [F(4,60)=1.86; p=0.13, η^2=0.11] and *"Modality*Session"* [F(4,60)=0.53; p=0.71, η^2= 0.03].

7.3.3.2 Influence of the order of presentation on the user-experience

To have a better understanding of the main influence we found on the performances by the order of presentation of the feedback, we led the same main analyses than in the previous section, i.e., five 2-way ANCOVAs with *"Modality*Session"* as independent variables, the repeated measures of user-experience, i.e., mood, mindfulness, motivation, cognitive load or agentivity, as dependent variable, and *"Order"* as covariate.

No significant influence of the order on any simple effect or interaction was found for the mood, mindfulness, agentivity and cognitive load. Though, *"Session*Order"* [F(4,56)=2.71; p=0.04, η^2=0.16] had a significant impact on the motivation. Regardless of the modality of feedback that they were training with, and apart from the fourth session, participants' motivation increase more when they started training with a visual feedback than when they started training with a multimodal feedback. Overall, the difference of motivation between the end and the beginning of the session seems to increase over the sessions. Figure 7.12 represents the evolution of motivation depending on the order of presentation of the modalities of feedback.

The resulting impact of the *"Session"* [F(4,56)=1.76; p=0.15, η^2=0.11] on the motivation was not significant.

The corrected effects of the modality and session found in 7.3.3.1 were not robust

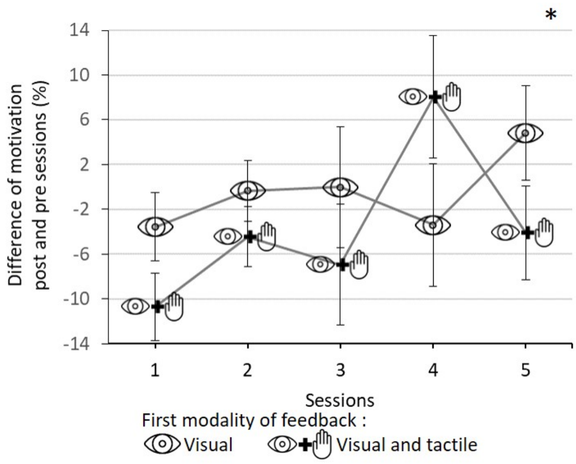

Figure 7.12: Evolution of the motivation over the sessions depending on the order of presentation of the modalities of feedback.

to the correction for the order.

An very close to significant effect of the *"Modality"* [F(4,56)=4.6; p=0.05, η^2=0.25] on the cognitive load was revealed after a correction for the order of presentation of the modality of feedback. When the order of presentation of the modalities of feedback are taken into account, the visual feedback seems to induce a higher level of cognitive load (see Figure 7.13).

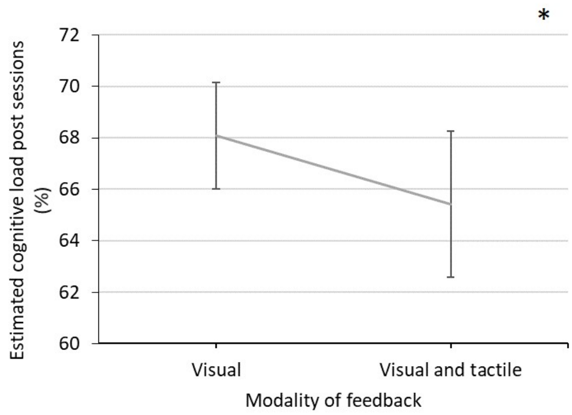

Figure 7.13: Cognitive load depending on the modality of feedback with the order of presentation of the modality of feedback taken into account.

No other effects were revealed when using the order as covariate.

7.4 Discussion

Performances seem higher when the movement is executed compared to when it is imagined, which is consistent with the existing literature [Toriyama et al., 2018]. Our participants seemed to have decreasing MI performances until the third session and then retrieved similar MI performances to the first session during the last session. The lack of feedback regarding the resting state performances might have biased participants' perception of their performances. Without negative feedback, learners that do not know how BCIs work might not understand that the machine has not recognized their task. Also, the fact that participants were only provided with feedback regarding the recognition of the motor related tasks might have led them to learn how to maximise the motor task recognition (i.e., true positive recognition) even if it was at the expense of the recognition of the resting task. Future analysis on the number of false and true positive recognition of the motor-related tasks might provide more information regarding the learning. The choice of not providing a feedback regarding the resting state was made because our long term goal was to use a similar protocol for post-stroke motor rehabilitation. As the aim of the feedback for post-stroke rehabilitation is to enable a co-activation between motor efferent systems and sensory afferent systems, we thought that not providing feedback regarding the recognition of the resting tasks would not be an issue. The alternative was to have dedicated trials for the resting state, which is time consuming and explains why we made this choice. Though, given our current results, in the future we will use dedicated trials with feedback regarding the resting state.

The mean MI classification accuracy was higher when participants were training with a visual and vibrotactile feedback than when they were training with a visual feedback only. This result is in accordance with the literature indicating that a multimodal feedback, with somatosensory and visual stimulations, has a better influence on BCI training than a unimodal visual one [Gomez-Rodriguez et al., 2011, Darvishi et al., 2015, Barsotti et al., 2017]. Similar results were obtained by Barsotti et al. who found that proprioceptive stimulation, based on vibration patterns, in addition to a realistic visual feedback led to higher classification accuracy and more stable ERDs than a realistic visual feedback alone [Barsotti et al., 2017]. Our results indicate that the positive difference of performances between the multimodal feedback composed of vibrotactile and visual stimulations and the visual feedback alone seems quite robust over time. Also, previous studies had tested multimodal feedback using proprioceptive feedback and not tactile feedback. Difference of ME performances evolution depending on the modality of feedback could only be found when taking into account the initial visual mental imagery abilities of participants. The positive influence of a multimodal feedback could be caused by the redundancy and congruency of the information provided on different modalities of feedback. This could have resulted of an increase of the sense of agency, i.e., the subjective feeling of being able to control one's own action (body agency), and through it, external events (external agency) [Leonardis et al., 2012]. Indeed, we found that the evolution of participants' agentivity depended on the modality of feedback. It seems that overall participants felt more in control of the visual and tactile feedback than of the visual feedback alone during the first sessions. This difference is inverted for the fourth session and inexistent for the last.

The difference of mindfulness pre and post sessions also provides an interesting insight that might explain why a visual and vibrotactile feedback seemed more effective than a visual feedback alone. The training seems to have a negative impact on the reported state of mindfulness. Though, the decrease of mindfulness is more important when participants were training with a visual feedback only. Our results suggest that feedback has a differential impact on the mindfulness depending on its modality of presentation. As mindfulness was associated with better MI-BCI performances, we can assume that this decrease in mindfulness could have had a detrimental impact on the performances [Botrel and Kübler, 2019, Wood and Kober, 2018]. This decrease in mindfulness could be related to the higher cognitive load found with a visual feedback only compared with a visual and vibrotactile feedback found when taking into account the order of presentation of the modalities of feedback.

The long term beneficial influence of a visual and vibrotactile feedback compared to a visual one tends to be modulated by the evolution of the difference of mood and mindfulness reported pre and post session. During the first sessions, the visual and vibrotactile feedback tended to have a better influence on the mood and mindfulness reported by our participants than the visual feedback alone. Though, these tendencies seem to be reversed during the last sessions. Given the user-experience results, it can be hypothesised that a visual feedback could be more efficient than a visual and vibrotactile feedback over a longer period of training.

Interestingly, a significant and strong impact of the order of presentation was found for both MI and ME performances. Participants had better performances when they started training with visual feedback only. The cognitive load originating from the processing of the feedback might explain, at least in part, the differences of performances observed. This is in accordance with previous research (see Section 2.2.2 Tactile to somatosensory feedback). Integrating information arising from two modalities of feedback while performing the task could be particularly challenging for a novice learner. Thus, starting with a single modality can let the participant learn how to process that modality before transitioning to a more complex feedback with two modalities. Starting with both modalities at once could indeed be overwhelming to the participant. Vibrotactile feedback could also have a disruptive effect on mental imagery [Cincotti et al., 2007]. This result needs further investigation to be confirmed, in particular because it results from a between-participants comparison. It can not be excluded that our participants had pre-existing abilities that would explain such result.

The use of a vibrotactile feedback raises the question of its level of influence on the sensorimotor cortical areas activation and thereby on the performances. The study of Shu et al. addresses this question [Shu et al., 2018]. It demonstrates that classification of EEG signals acquired during a vibrotactile stimulation without motor attempt enabled a classification accuracy close to but below chance level (54,6% with chance level at 55.8%). Classification of EEG signals acquired during motor attempt tasks without vibrotactile feedback enabled a classification accuracy of 74.5%. Similar analysis should be performed on our data in the future using the EEG signals acquired during resting task with either visual or visual and vibrotactile stimulation.

Finally, our results indicate a significantly different evolution of ME performances depending on the initial visual imagery abilities of the participants and the modality of feedback. No influence of the initial visual and kinaesthetic imagery was found on the MI performances. This result is in accordance with the ones of Rimbert et al. [Rimbert et al., 2017], who found that the kinaesthetic and visual abilities might not be a predictor of performances when classifying resting task versus a hand movement imagery task. Both Rimbert et al. and us have used a realistic visual feedback. Previous experiments indicating an impact of visual and kinaesthetic imagery abilities on MI-BCI performances used either no feedback or an abstract feedback [Marchesotti et al., 2016, Vuckovic and Osuagwu, 2013]. Further studies taking into account the modality of feedback are required to investigate the influence of initial visual and kinaesthetic imagery on BCI performances. An analysis of the strategies that the participants use to perform the mental imagery tasks might also provide more insight on these results.

7.5 Conclusion and Prospect

In this experiment, the participants trained with both a realistic visual feedback only and a vibrotactile feedback on their wrist in addition to this same visual feedback. They performed the target movement, i.e., opening and closing their hand, with one of their hand and imagined the same movement with their other hand. The order of presentation of the modalities of feedback and the lateralisation of the hand imagined were balanced over our participants. Our goal was to assess the impact of the modality of feedback over the evolution of the performances and the user-experience. We also wanted to assess if characteristics of the profile of participants, particularly the visual and kinaesthetic imagery abilities, modulated the influence of the modality of feedback.

We found that using a vibrotactile feedback in addition to a realistic visual feedback seems to have a beneficial influence on MI performances. This result is in accordance with previous results on neurotypical participants demonstrating that a multimodal feedback seems to be preferable to a unimodal one for short term performances [Gomez-Rodriguez et al., 2011, Darvishi et al., 2015, Barsotti et al., 2017]. The results from this experiment indicate that this beneficial impact remains true for long term training, which had not been tested before. They also indicate that the multimodal feedback can include tactile stimulation instead of proprioceptive stimulations and still remain more efficient that a visual feedback only. To our knowledge, only Shu et al. used vibrotactile feedback for post-stroke motor rehabilitation [Shu et al., 2018]. It might represent an acceptable and less expensive alternative to FES or orthesis.

However, the results obtained for the user-experience, i.e., the evolution of mood and mindfulness over the sessions, seem to progressively be in favour of the visual feedback alone in long term. This could relativize the results obtained for the MI performances. An experiment with a longer period of training could be of interest. The order of presentation of the modalities of feedback was found to have an influence on the MI and ME performances. Using only a visual feedback at the beginning of the training seems to be beneficial.

Our work presents limits, in particular, the number of participants included in the study. Furthermore, numerous statistical analyses were performed to obtain the results that we presented. The results would not be sustained with a correction for multiple comparison. This should be taken into consideration when reading our results. Future experiments with a greater number of participants are necessary to confirm the results, particularly the one regarding the impact of the order of presentation of the modalities of feedback, as the latter is the results of a between-participants comparison. Another limit could arise from the number of training session per modality of feedback, while such a number of sessions is relatively high compared to previous BCI studies comparing feedback modalities. Our goal was to assess the long term impact of different modalities of feedback. As our participants trained with both modalities of feedback, they only trained during five sessions with each modality. A higher number of sessions per modality might provide more insight on the long term impact of both modalities. The number of participants included and the number of sessions per modalities are related issues. Both of them arise from a compromise between the relevance of the results and time needed to perform the experiments.

Other limits emerge from the combination of instructions and feedback that participants were provided with. Using a realistic feedback and providing the participants with the instruction to imagine a similar movement as the one performed by the virtual hand during feedback aimed at eliciting a greater sense of agency from the participants [Sollfrank et al., 2015]. Though, the temporal and spatial asynchrony occurring when the arms were not perfectly aligned with the participants' arms and when task was not perfectly recognized by the MI-BCI system might have decreased the sense of agency of our participants [Brugada-Ramentol et al., 2019]. Low performers had the larger discrepancy between their mental imagery and the visual feedback they received. This might have particularly impeded their learning.

In summary, for future studies we would recommand the use of a visual feedback for naive users and then of a multimodal feedback, once the learners have acquired some skills to interpret the feedback. The use of a vibrotactile feedback seems to be an acceptable and less expensive alternative to a proprioceptive feedback. Future studies are necessary to assess the potential differential impact of a proprioceptive feedback compared to an exteroceptive one. The modality of feedback to favour might be impacted by the initial visual abilities of the learners when considering performances associated with executed movements.

General discussion

In this part, we mostly focused on improving the training through the adaptation of the modality of feedback depending on the profile of the learner. In a first theoretical section, we discussed the important role that somatosensory abilities play in motor rehabilitation. These abilities seem essential for the patients to benefit from the feedback provided by the BCI system. Yet, around half of post-stroke patients suffer from somatosensory deficits. We hypothesized that these deficits alter their ability to benefit from BCI-based therapies. We reviewed the literature on post-stroke BCI-based motor rehabilitation (14 randomized clinical trials) and investigated how somatosensory abilities were reported and considered with regards to therapy efficiency. Our review indicates that somatosensory abilities are rarely considered and/or reported in the literature on BCI-based motor rehabilitation post-stroke. Only a few studies have assessed them or used them as inclusion/exclusion criteria. Somatosensory abilities certainly have a strong influence on the perception of BCI feedback. Failure to assess them will most likely cause biases in the reported results. Moreover, somatosensory abilities' assessment might improve (1) our understanding of the mechanisms underlying motor recovery (2) the therapy's adaptation to the patients' abilities and (3) our understanding of the between-subject and between-study variability of therapeutic outcomes mentioned in the literature.

In the second section, we designed a protocol to compare the impact of two modalities of feedback, one visual and vibrotactile and one only visual. This experiment provided further proof that a multimodal feedback has a beneficial impact on MI-BCI performances. Though, it also indicated that the order of presentation of the modality of feedback could influence BCI performances as well. A unimodal feedback might be easier to interpret for BCI beginners. The future and longer term goal (not addressed in this thesis) was to adapt it to test the influence of somatosensory abilities and visual and kinaesthetic imagery abilities on post-stroke motor rehabilitation. In this thesis, we tested the protocol on neurotypical people to improve and validate it.

Most of the studies on post-stroke motor rehabilitation focus on visual and somatosensory feedback (see Table 6.1). Contingent to the activation of the sensorimotor cortex, a peripheral somatosensory stimulation seems more effective to improve motor functions than a visual feedback alone [Ono et al., 2014]. Ramos-Murguialday et al. found that proprioceptive feedback improves BCI performances significantly compared to a sham proprioceptive stimulation [Ramos-Murguialday et al., 2012]. To our knowledge, only Shu et al. used vibrotactile feedback for post-stroke motor rehabilitation [Shu et al., 2018]. The results that we present in this chapter indicate that it might represent an acceptable and less expensive alternative to existing proprioceptive feedback such as FES or orthesis.

The experiment also provided us with useful insights on how to improve the protocol. First of all, we designed the protocol with the aim of having sessions lasting less than an hour to limit the potential tiredness of the patients. Though, the duration of the sessions was underestimated, particularly for the 1st, 6th and 10th sessions when participants had to fill questionnaires and perform tests. Providing a feedback regarding the recognition of the resting task by the classifier seems necessary to train our participants to have more distinguishable patterns of activity for the BCI and thereby a better classification accuracy.

Other improvements were also considered specifically for post-stroke rehabilitation. For example, the movement of opening and closing the hand might not be the most appropriate for post-stroke rehabilitation. Training with movements of proximal (upper arm in our case) muscles induces distal (lower arm or hand in our case) muscles recovery but training with movements of distal muscles does not produce proximal muscles recovery unless it uses coordination movements, implying distal and proximal joint control [Tyc and Boyadjian, 2006]. Therefore, coordination movements and/or movements of the upper arm would be more adapted for post-stroke motor rehabilitation.

We believe that verifying the probable impact of somatosensory loss on post-stoke motor rehabilitation outcome is necessary to improve the reliability of the therapy. We argue that future experiment assessing the impact of somatosensory ability post-stroke should take into account the modality of feedback.

Part IV

When should the feedback be provided?

Research question

In the last two Parts, we have explored the content and modality of presentation of the feedback. In this fourth part, we explore another key element of the feedback: its timing of presentation. Our review of the literature (see Section 2.3 Feedback timing - When and how often is the feedback be provided?), we found that a continuous feedback, i.e., provided when the person performs the mental imagery task, is recommended by the theoretical literature and by experimental results [McFarland et al., 1998, Neuper et al., 1999]. However, there is little information on the frequency of presentation that feedback should have. Studies in other fields reveal that the frequency of feedback may have an influence on the attention state of people [Magill, 1994]. The more frequent the feedback is, the more attentional resources are required to analyse the feedback. Also, the BCI literature indicates that both the attention traits and states have an influence on the ability to control a BCI (see Section 3.2 Influence of learners' states). Indeed, it was shown that results from attentional tests, such as the digit span, are correlated with MI-BCI performances [Daum et al., 1993, Hammer et al., 2012]. Furthermore, both spectral (i.e., alpha and theta) and spatial (i.e. attentional networks) neural correlates of attention were correlated with MI-BCI performances [Ahn et al., 2013, Grosse-Wentrup, 2011, Grosse-Wentrup and Schölkopf, 2012].

Though, "Attention" is a generic word which encompasses a set of different states. The number and characterisation of these different states differ between the different models that were developed over the years [Knudsen, 2007, Petersen and Posner, 2012]. We chose to focus on the model of van Zomeren and Brouwer [Zomeren and Brouwer, 1994] because an extensive literature exist regarding each of the types of attention in this model. The literature in general, and more specifically the literature regarding localised brain damages, indicates that each type of attention has specific neurophysiological components [Zomeren and Brouwer, 1994]. Also, there are enough information in the literature to build a protocol accordingly and assess the different types of attention stated in the model. The model states four types of attention, i.e., alertness, sustained attention, selective attention and divided attention. **Alertness** and **Sustained attention** are referring to the intensity of attention, i.e., its strength. In addition, **Selective Attention** and **Divided Attention** are related to its selectivity, i.e., the amount of information that is monitored.

Alertness, which can also be called arousal, is considered to be the most basic intensity aspect of attention. It is probably necessary for the other types of attentional processes to take place. It represents the preparedness to respond to a stimulus [Sturm et al., 1997, Sturm et al., 1999]. Two types of alertness can be distinguished.

Tonic, or intrinsic, alertness, is the most stable of the two. It changes only slowly and involuntarily throughout the day. *Phasic* alertness, or extrinsic alertness, is the most dynamic of the two. It represents the augmentation of attentional process following the perception of a warning preceding the appearance of a monitored target.

Sustained attention is involved when monitoring the non predictable appearance of frequent stimuli over a long period of time [Sturm et al., 1997]. If the target appears very infrequently then, *Vigilance*, a different type of attention is involved. Both types of attention are often mistaken for one another.

Selective Attention, which can be considered as a synonym for focused attention [Chang and Dean, 2011], requires that participants focus their attention on one aspect of the sensory information they receive while inhibiting the others.

Divided attention differs from selective attention by the number of monitoring tasks the participants have to perform. Instead of focusing their attention on one particular sensory cue, they have to attend to several of them. Sensory cues can potentially be displayed in different sensory modalities. Due to the limited amount of cognitive resources, an increase in workload is expected when the different stimuli are provided in the same modality [Wickens, 2002].

These different attentions were demonstrated in several experimental and clinical neurophysiological studies [Gunstad et al., 2006]. Each of these different types of attention is well documented in the literature and has been studied in different contexts. For example, sustained attention has particularly been studied in the aviation field [Molloy and Parasuraman, 1996].

The types of attention involved in BCI training remain unclear. Assessing which types of attention are involved and should be involved during BCI user training might provide information to improve the latter. Indeed, attention is necessary for memorization to occur [Fisk and Schneider, 1984]. Given the central role that attention has on training, the level of attention might be leveraged to adapt the training. For instance, in the chapter 7 Contribution 4 – Which modality of feedback for BCI training? we hypothesised that a multimodal feedback might impede the performances of novice learners. Maybe paying attention to the feedback arising from two modalities as well as performing the motor imagery task requires too many attentional resources for a novice participant. The training should enable the learner to automatise the performance of the task and to free some attentional resources [Kluger and DeNisi, 1996]. If we were able to assess the attentional states of our participants, we might be able to know when to provide a unimodal or multimodal feedback. Also, if we could detect when the participants are in an attentional state that do not benefit BCI training, maybe the training should be paused or postponed. Also, little is known regarding the frequency of feedback that should be used (see 2.3 Feedback timing - When and how often is the feedback be provided?). We can hypothesis that when the attention could be informative regarding the adaptability of the feedback frequency. For instance, when the attentional resources of the users are not overloaded, they can process the information conveyed by the feedback. However, if the quantity of information that the learner receives is too high, then the attentional resources of the users would be overloaded and all the information might not be taken into account.

Therefore, our long term goal was to continuously assess the different types of attentional state during the MI-BCI user training. Using EEG signals to distinguish these different attentional state seemed fitting as attentional correlates were already found in EEG [Mulholland, 1969, Rowland et al., 1985]. Also, some EEG correlates of attention have already been associated with MI-BCI performances [Grosse-Wentrup et al., 2011b, Grosse-Wentrup and Schölkopf, 2012]. In the following chapter, we present the first step toward assessing the different types of attentional states involved in BCI user training using EEG data in the future.

Chapter 8

Contribution 5 - Can attentional states be reliably distinguished using electroencephalographic data?

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - A physical learning companion can be useful for MI-BCI user training depending on learners' autonomy
	5. **Contribution 2** – An interaction of experimenters' and participants' gender has an influence on MI-BCI training
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Somatosensory abilities post-stroke probably influence BCI-based motor rehabilitation
	7. **Contribution 4** – Modality of feedback might need to be adapted to learners' skills
IV. When should the feedback be provided?	8. **Contribution 5** - Can attentional states be reliably distinguished using electroencephalographic data?
V. Discussion & Prospects	9. Discussion & Prospects

Collaborators: Professor Andrzej Cichocki (Head of the Advanced Brain Signal Processing laboratory at RIKEN BSI in Tokyo, Japan at the time) and Aurélien Appriou (PhD student).

Related full papers: Pillette, L., Appriou, A., Cichocki, A., N'Kaoua, B., & Lotte, F., « EEG correlates of the components of attention ». In preparation.

8.1 Introduction

As stated above, the aim of this chapter is to comprehensively study the different attentional states described in the model of van Zomeren and Brouwer using EEG data [Zomeren and Brouwer, 1994]. All the different frequency bands, i.e., Delta, Theta, Alpha, Beta and Gamma have been associated with the different attentional states. The Theta, Alpha and Beta frequency bands are the most frequently related to attention. We will focus on these three frequency bands for the rest of this chapter.

The theta band (4-7Hz) seems to play a role in focused attention particularly in the frontal area [Gevins et al., 1979a, Gevins et al., 1979b, Gundel and Wilson, 1992, Miyata et al., 1990, Yamamoto and Matsuoka, 1990]. A positive correlation has been shown between the amplitude of the signal Theta and the amount of Selective attention required, the difficulty of the task as well as the workload [Schacter, 1977]. It is also related to Sustained attention during which Theta power increases with both the length and difficulty of the task and the amount of workload it involves [Gevins et al., 1997, Parasuraman, 1985, Wickens, 1991].

The alpha band (8-12Hz) has been associated with attention for a long time [Mulholland, 1969, Rowland et al., 1985]. High power in Alpha band has been considered an ideal state [Gevins et al., 1997, Steriade, 1981, Van Winsun et al., 1984]. Both task difficulty and task load stray from this ideal state and therefore lower the Alpha power. It is mostly related to Alertness [Klimesch et al., 1998] and Selective attention [Ward, 2003]. Studies have shown that the lower Alpha band (8-10Hz) would be the one modulated by attentional demands whereas the upper Alpha band (10-12Hz) would be related to the processing of sensorial and/or semantical information [Klimesch et al., 1998]. Alpha bands dropout in early stage of drowsiness.

The beta band (12-30 Hz) is associated with Alertness, Selective attention and Sustained attention. In particular, low frequency Beta waves (12-15Hz) are associated with Selective attention and high frequency Beta waves (18-30Hz) are more related to Alertness. Sustained attention has been assessed by focusing on Beta activity in the frontal and temporal regions [Arruda et al., 1999, Arruda et al., 2007, Arruda et al., 2009]. The increase of power during Selective attention could be explained by the presence of Beta waves in the parietal area for cognitive related processes [Rowland et al., 1985].

Even though each of these results offer a valuable insight into attentional components, none of them offered a comparable overview of the attentional components. Nor do we know if they can be decoded using EEG signals. So the aim of this study was to fill this gap in the literature and to develop a protocol to decode the different attentional states described in the model of van Zomeren and Brouwer in EEG signals.

8.2 Methods

8.2.1 Participants

After providing written informed consent, 17 persons (5 women; mean age = 32.8 y.o. SD=7.16) participated in the experiment. All of them had normal or corrected sight and audition. None of them had past or present history of traumatic brain injury, neurological disorder, and other medical conditions (e.g. hypertension, diabetes, cardiac disease, thyroid disease). Nor did they have family history of attention deficit hyperactivity disorder, schizophrenia, bipolar disorder, or genetic disorder.

The experimental protocol is in accordance with the relevant guidelines for ethical research according to the Declaration of Helsinki and was reviewed and approved by the RIKEN Brain Science Institute ethical committee (Approval number: Wako3 29-2(2)).

8.2.2 Experimental protocol

The experiment was composed of only one session of 2 hours. The participants were equipped with an EEG-cap and were asked to perform different attention related tests seated on a chair and facing a computer screen. All the tasks assessed one of the types of attention of the van Zomeren and Brouwer model, i.e., Tonic, Phasic, Sustained, Selective and Divided attentions [Zomeren and Brouwer, 1994]. A baseline of 20 seconds was performed before every task. During each task, participants had to react as fast as possible – by pressing the space bar of a keyboard – to the appearance of 80 target stimuli. The frequency of target appearance was the same for every task to have a similar motor response for each task and therefore a comparable amount of electromyographic activity. We also chose not to use letters or words as stimuli to limit the amount of semantical treatment.

During each task, the participants had to monitor the appearance of a white visual stimulus displayed for 120ms on a black screen (see Figure 8.1). Participants were situated 80cm from the screen. The target stimulus was either a circle or a square (8cm*8cm $\sim 3°$ of visual angle). Each task beside the Sustained attention task was divided into two runs of 3.5min, which enabled counterbalance of the type of target that the participant had to monitor, i.e., square or circle. It also limited the fatigue effect.

Alertness is considered to be the most basic intensity aspect of attention. It is assessed using simple reaction paradigms, with or without using a warning prior to the appearance of the target stimulus to respectively assess the Phasic or the Tonic attention [Zimmermann and Fimm, 2002]. During the Alertness tasks, i.e., Phasic and Tonic, only one type of simple target (see Figure 8.1) was used per run, i.e., circle or square. In the Phasic attention task, a sound was provided 100ms to

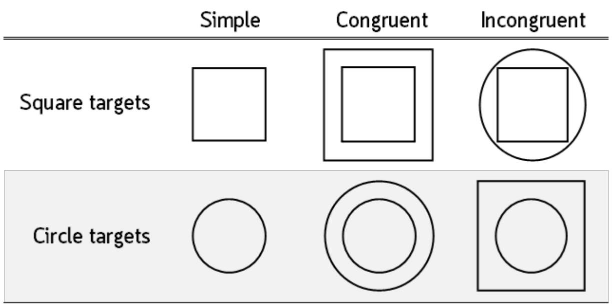

Table 8.1: The different visual stimuli used in the experiment. Simple ones were used in the Alertness tasks. Congruent and Incongruent ones were used in the other tasks.

1000ms before the appearance of the target. The target stimulus was alternatively either a square or a circle.

Selective attention represents the ability to focus on certain stimuli and suppress voluntary responses to irrelevant stimuli [Sturm et al., 1997]. It is assessed using choice reaction paradigms were the participant must attend to one of several competing sensory inputs [Styles, 2006]. Therefore, for this task, we used complex shapes (see Figure 8.1, 12cm*12cm $\sim 4.5°$ of visual angle) which were either congruent (the inner form matching the surrounding one) or incongruent (the inner form not matching the surrounding one). This task is a non-letter equivalent of the flanker task of Eriksen and Eriksen (1974) [Eriksen and Eriksen, 1974] proposed by Leeuwen et al. (2004) [Van Leeuwen and Lachmann, 2004]. It involves more inhibitory process than a go-nogo task [Zimmermann and Fimm, 2002]. The target stimuli were alternatively the shapes with circles or squares inside, regardless of their congruency. The rest of the stimuli presented are considered as distractors.

Sustained attention is involved when monitoring the appearance of non predictable and frequent stimuli over a long period of time [Parasuraman, 1985]. Therefore, we used a similar task as the one presented above for the selective attention. However, the participants had to monitor the appearance of the target stimuli continuously during 14 min. The number of distractors was 2.5 times higher than for the Selective attention task. Just as the Selective attention task, the target stimuli were alternatively the shapes with circles or squares inside, regardless of their congruency. The rest of the stimuli presented are considered as distractors.

Finally, Divided attention occurs when participants are dividing their attention to monitor the appearance of target stimuli on several sensorial modalities or types of information [Styles, 2006]. It is assessed using dual task paradigms [Zimmermann and Fimm, 2002]. We chose to present target stimuli on the visual and auditory modalities. We wanted to have comparable visual and auditory tasks for the assessment of the Divided attention, where the participants have to monitor the appearance of target stimuli presented either on the visual or auditory modality. There are examples of auditory equivalent of the flanker task. Though, to our knowledge, all of them are using semantical cues [Chan et al., 2005, Francis, 2010]. This is why we chose to use four types of non auditory cues (see Figure 8.1). Just like the other auditory flanker task, we used spatial cues by presenting different sounds in each ear. People were asked to react when they heard a loud high pitched sound in a given ear. The loud high pitched sound presented in the other ear were considered as distractors. The ear participants had to focus on was counterbalanced between the different runs.

	Left Ear	Right Ear
Target Left - Congruent	2000Hz (+0 dB)	2000Hz (-10 dB)
Target Left - Incongruent	2000Hz (+0 dB)	1000Hz (-10 dB)
Target Right - Congruent	2000Hz (-10 dB)	2000Hz (+0 dB)
Target Right - Incongruent	1000Hz (-10 dB)	2000Hz (+0 dB)

Table 8.2: The different auditory stimuli used in the Divided attention task.

To summarize, the tasks and types of attention were differentiated by the type of sensorial modality of the stimuli, number of distractors, presence of a warning before the stimuli and the length of the task. Table 8.3 summarizes the characteristics of the different tasks which were chosen based on the literature [Van Leeuwen and Lachmann, 2004, Francis, 2010, Sturm and Willmes, 2001, Schmidt, 1968].

	Duration (sec)	Modality of targets	Number of target	Number of distractor	Warning before stimuli
Alertness - Tonic	2 * 210		80	0	-
Alertness - Phasic	2 * 210		80	0	120ms tone
Sustained attention	1 * 840		160	400	-
Selective attention	2 * 210		80	80	-
Divided attention	2 * 210		40 + 40	40 + 40	-

Table 8.3: Characteristics of the tasks that aimed at eliciting five types of attention. Each task differs from the others depending on its duration, the modality of presentation of the stimuli, the number of targets and distractors and finally the presence or absence of a warning preceding the appearance of a stimulus.

Before every task, instructions were provided to the participants. Then, each time a type of task was performed for the first time, participants had to perform a short version of it (30sec) to become familiar with the task. We considered that the instructions were understood if the participant had a success rate above 85% at the pre-task test. If they did not reach this threshold, they were offered to take a new look at the instructions and do the pre-task again until they reached the threshold. People were still offered to do a pre-test even if they had already performed a similar task previously but it was not mandatory.

8.2.3 Questionnaires

During this session, participants first had to fill the following questionnaires:

- A general information questionnaire that assesses the different characteristics which can have an impact on attention, such as coffee consumption or the amount of sleep [Lorist et al., 1994].
- The Edinburgh lateralization questionnaire which assesses the tendency to use either the right or the left hand for daily tasks [Oldfield, 1971].
- Pre-task version of the Short Stress State Questionnaire which gives an indication about the current distress, engagement and worry states [Helton and Näswall, 2015].

After every task, participants were asked to fill Hart and Staveland's Nasa Task Load Index to assess workload [Hart and Staveland, 1988]. At the end of the session, they filled a post-task version of the Short Stress State Questionnaire [Helton and Näswall, 2015].

8.3 Materials

8.3.1 Program

We used OpenViBE 1.3.0 [Renard et al., 2010] to record the EEG data, display the stimuli and record each time the space-bar was pressed. Several scenarios were created and will be submitted and available on OpenViBE git repository.

8.3.2 EEG Recordings & Signal Processing

The brain activity was recorded using BioSemi 64 active scalp electrodes (AF7, AF3, F1, F3, F5, F7, FT7, FC5, FC3, FC1, C1, C3, C5, T7, TP7, CP5, CP3, CP1, P1, P3, P5, P7, P9, PO7, PO3, O1, Iz, Oz, POz, Pz, CPz, Fpz, Fp2, AF8, AF4, AFz, Fz, F2, F4, F6, F8, FT8, FC6, FC4, FC2, FCz, Cz, C2, C4, C6, T8, TP8, CP6, CP4, CP2, P2, P4, P6, P8, P10, PO8, PO4, O2 ; 10-20 system) and BioSemi Active Two Amplifier. Data was sampled at 2048 Hz. Electrodes were referenced using their average activity.

During a first phase of offline preprocessing of the data using EEGlab, we applied a high-pass Hamming windowed sinc FIR filter to remove linear trends below 1Hz. During the experiment, the EEG channels that were visibly noisy were reported in a separate text file. We also replayed the different EEG recordings of our participants to take note of the different channels that were noisy. The electrodes that were considered as visibly noisy were removed. The Kurtosis method (from EEGlab) for removing bad channels was used as well with a trim percentage of 5%. On average 11.18 ± 3.03 electrodes per subject were removed. The data was then filtered between

48 and 52 Hz using Hamming windowed sinc FIR filter to reject line noise. Data was resampled at 128 Hz.

For each task, 80 targets stimuli were presented. We used one second prior to target presentation as the analysis window. Only data from targets that were at least one second apart from a motor response were analysed to prevent motor-related artefacts. Before each task, a baseline of 20 seconds was performed. The data from this baseline was used as the corresponding resting state to the following task. The baseline was divided into 20, 1s analysis windows.

We wanted to know which were the neurophysiological differences between the resting state and the different attentional states of our participants, depending on the frequency band, i.e., Theta, Alpha and Beta. The distribution of the band power for each participant, frequency band and electrode did not have a normal distribution. Therefore, for each participant, each frequency band and each electrode (depending on the electrodes remaining after the rejection of the noisy ones), we performed two-sided Wilcoxon rank sum tests to compare the data between each pair of tasks among Tonic, Phasic, Sustained, Selective, Divided and Rest. The p-values obtained for all the tests were corrected for multiple comparisons using the Benjamini & Hochberg procedure with a false discovery rate of 5%. For each band and electrode, we defined an activation index $I_{c,f}$, computed as follows: $I_{c,f} = sign(BP_{c,f}^{rest} - BP_{c,f}^{task}) * -log(p)$

The median activation index obtained across the participants for each electrode and for a given band are presented in the form of topographies in Section 8.4.2. We chose to use the median activation index over our participants to avoid taking into account any potential activation index outlier.

Finally, we were interested in the possibility for classifying the five different attentional states using only electroencephalographic data. We did not include the resting state in this classification as each attentional state had its own resting state reference (see Section 8.3.2 EEG Recordings & Signal Processing). The participant-specific discriminability (one classifier per participant) of the EEG patterns between each of the five attention tasks was assessed using the tangent-space classifier described in [Yger et al., 2016], with 5-fold cross-validation, using the BCPy software [Appriou et al., 2018]. The 5-classes classification was performed twice with EEG data either filtered in the Theta or Alpha band. We did not perform any classification with EEG data filtered in Beta to limit the potential influence of motor-related artefacts on our classification accuracy. The results of this classification are presented in Section 8.4.3.

8.3.3 Variables & Factors

For each of the tasks the behaviour of the participants was analysed through:

- Their response time (RT): time between the appearance of targets stimuli and the response of the participant (space bar pressed).
- Their percentage of accuracy ($Accuracy$): number of targets which elicited a response depending on the number of targets presented.
- Their percentage of anticipations ($Anticipations$): number of targets which elicited an anticipated response depending on the number of target presented.

An answer was considered as anticipated when the response time was below 133ms according to the review of Schmidt [Schmidt, 1968].

- Their number of error (*Errors*): number of non-target stimuli which elicited a response. The percentage was not used as the number of non-target is intentionally higher for the Sustained task.

8.4 Results

8.4.1 Behavioural data assessment

During a first part of the analyses, we focused on the behavioural data to assess if the different types of attention that we aimed at eliciting are associated with different behavioural reactions. We performed four 1-way repeated measures ANOVA, one for each of the four measures of performances, i.e., *RT*, *Accuracy*, *Anticipations* and *Errors* as dependent variable and the different tasks, i.e., *"Tonic"*, *"Phasic"*, *"Sustained"*, *"Selective"* and *"Divided"*, as repeated measures.

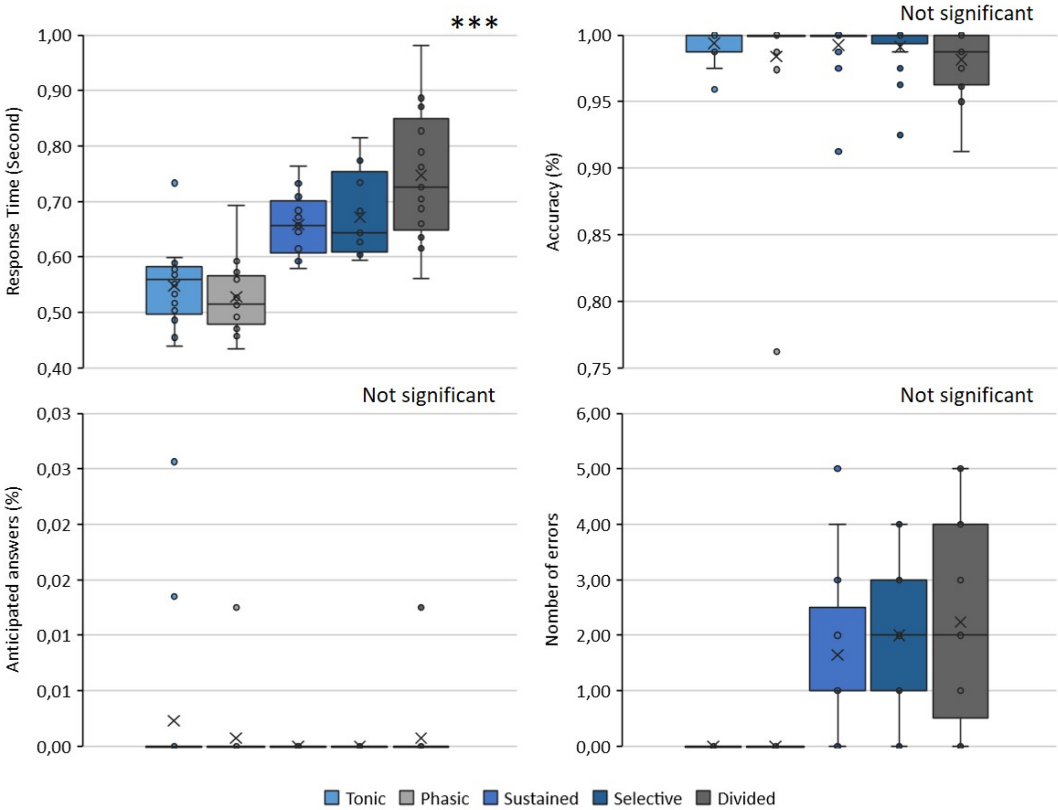

Figure 8.1: Difference of performances in terms of mean response time, percentage of accuracy, percentage of anticipation and percentage of error depending on the task.

For the *RT*, the ANOVA revealed a strong influence of the type of task [D(2.02,32.3) =53.36; p$\leq 10^{-3}$, η^2=0.77]. A pairwise comparisons with Bonferroni adjustment revealed a significant difference of *RT* between *"Tonic"* and *"Sustained"* [$p \leq 10^{-3}$], *"Tonic"* and *"Selective"* [$p \leq 10^{-3}$], *"Tonic"* and *"Divided"* [$p \leq 10^{-3}$], *"Phasic"* and *"Sustained"* [$p \leq 10^{-3}$], *"Phasic"* and *"Selective"* [$p \leq 10^{-3}$], *"Phasic"* and *"Divided"* [$p \leq 10^{-3}$], *"Sustained"* and *"Divided"* [$p < 10^{-2}$] and *"Selective"* and *"Divided"* [$p < 10^{-2}$]. No significant difference in *RT* was found between *"Tonic"* and *"Phasic"* [p=1] and between *"Sustained"* and *"Selective"* [p=1].

No influence of the task was revealed for the *Accuracy* [D(1.48,23.69)=0.75; p=0.44, η^2=0.05], *Anticipations* [D(1.69,26.95)=1.12; p=0.33, η^2=0.07] and *Errors* [D(1.48,23.7)=0.9; p=0.39, η^2=0.05].

Both of the Alertness tasks, i.e., Tonic and Phasic, have a significantly lower response time than the rest of the attentional tasks. No difference of response time was found between both tasks. A slight but non significant decrease in the accuracy for the Tonic task and a slight decrease in the response time for the Phasic task might suggest that different attentional states were still elicited during these tasks.

The Sustained task does not seem to be significantly different from the Selective task. Despite the longer period of training and the higher amount of distractors for this task than for the Selective task, the participants seem to have a comparable number of errors and response time.

The response time for the Divided task is significantly the highest. The percentage of accuracy was also the lowest and the number of errors the highest but these differences were not significant.

8.4.2 Neurophysiological characteristics of the components of attention

We also wanted to know which where the neurophysiological differences between the resting state and the different attentional states of our participants, depending on the frequency band, i.e., Theta, Alpha and Beta. The method used to compute the topographies is presented in Section 8.3.2. First, we will focus on the topographies representing the differences between the resting state and the tasks. Then, we will focus on the topographies representing the differences between the tasks depending on the frequency band, i.e., Theta, Alpha and Beta.

8.4.2.1 Characteristics of the components of attention compared to the resting state

The topographies on the **Theta frequency band** reveal an overall decrease over the frontal area for all the tasks but the Sustained one. The laterality of this decrease is difficult to interpret. No significant effects are visible for the Sustained task.

From the topographies on the **Alpha frequency band**, we can distinguish an increase of activation for the tasks related to the intensity of attention, i.e., Tonic, Phasic and Sustained, and a decrease for the tasks related to the selectivity of attention, i.e., Selective and Divided. The increase for both of the Alertness tasks, i.e., Tonic and Phasic, was in the parietal area and might be slightly lateralized on the right. For the Sustained task, the increase was in the occipito-parietal area. The decrease of activation index for the Selective and Divided attention tasks was lateralized respectively on the right and on the left of the frontal area.

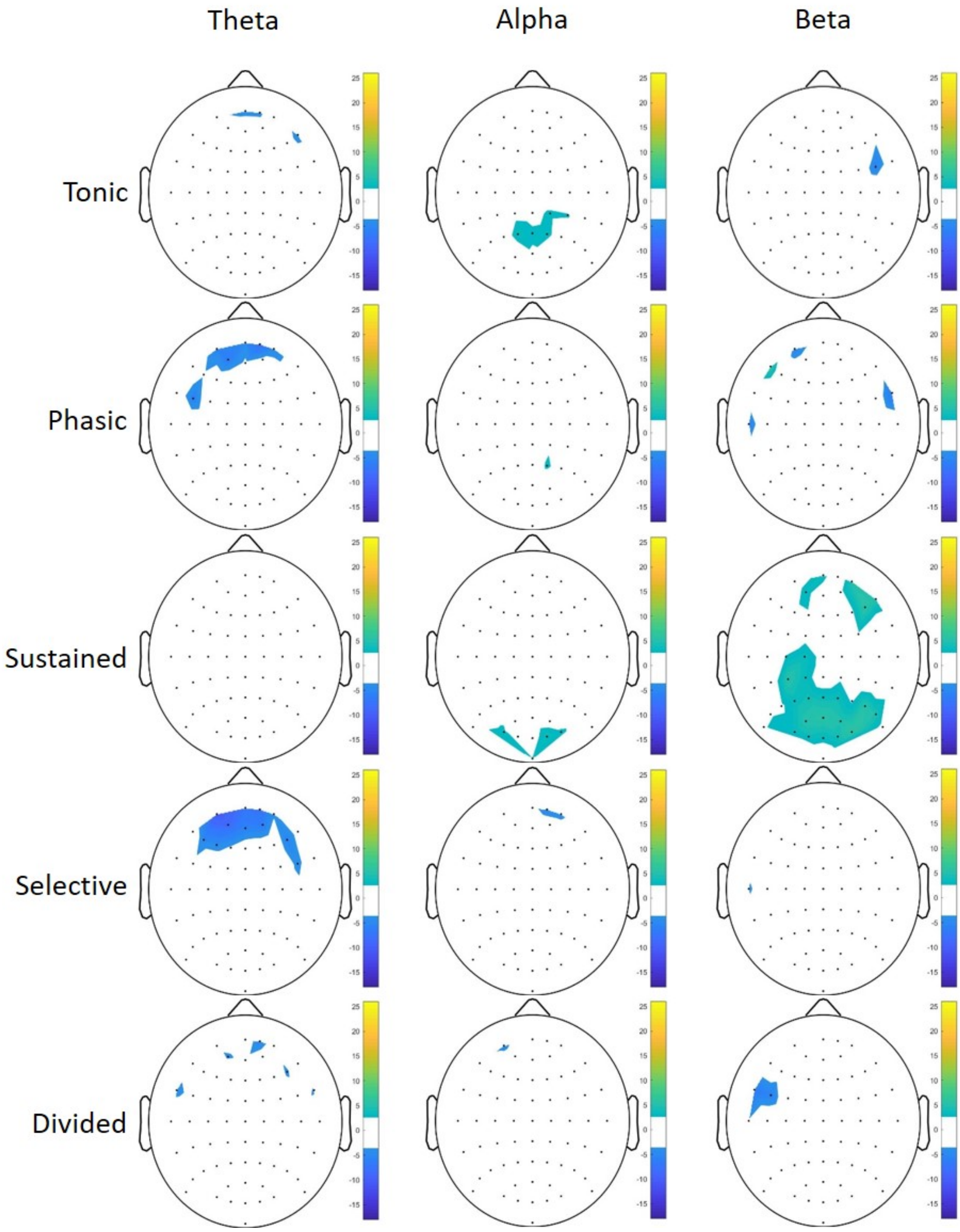

Figure 8.2: Topographies representing the median intra-participant difference of band power between each task and the resting state for the Alpha, Beta and Theta frequency band. If a significant positive difference is observed, then the activation indexes of the task represented in the row was more important than the one from the resting task. On the contrary, if a significant negative difference is observed, then the activation index of the task represented in the raw was less important than the one from the resting task. Only the significant index are displayed (corrected p-values>0.05).

Finally, the topographies on the **Beta frequency band** reveal some decrease of activation index in the fronto-temporal for all the tasks besides the Sustained one. The decrease seems lateralized on the right for the Alertness tasks, i.e., Tonic and Phasic and on the left for the Divided, Selective and Phasic tasks. Increases of activation index can be observed in the right of the frontal area, in the right of the occipito-parietal area and on the left of the centro-parietal area for the Sustained task.

8.4.2.2 Characteristics differentiating the components of attention from one another

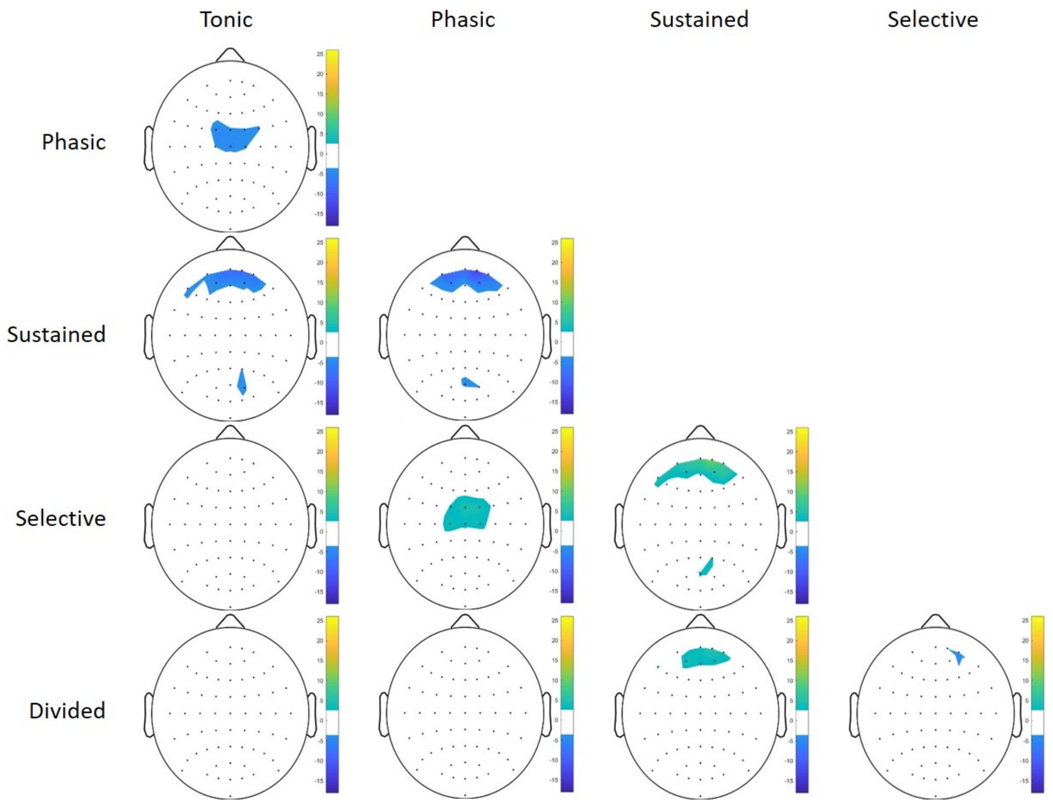

Figure 8.3: Topographies representing the median intra-participant difference of Theta band power between each task and the resting state. If a significant positive difference is observed for a topography, then the activation index of the task represented in the column was more important than the one from the task represented in the raw. On the contrary, if a significant negative difference is observed for a topography, then the activation index of the task represented in the column was less important than the one from the task represented in the raw. Only the significant indexes are displayed (corrected p-values>0.05).

The topographies in the **Theta frequency band** indicate that the main differences between the different tasks in the Theta frequency band are localised in the frontal and central areas. An increase of activation index in the frontal area seems to distinguish the Sustained tasks from the others. An increase in occipito-parietal area could also be found between the Sustained task and the Tonic, Phasic and Selective tasks. A diminution in the centro-frontal activation index seems to discriminate the Tonic and Selective tasks from the Phasic one. Finally, it seems that there is a slight diminution of the right frontal activation index in the Selective task compared to the Divided one.

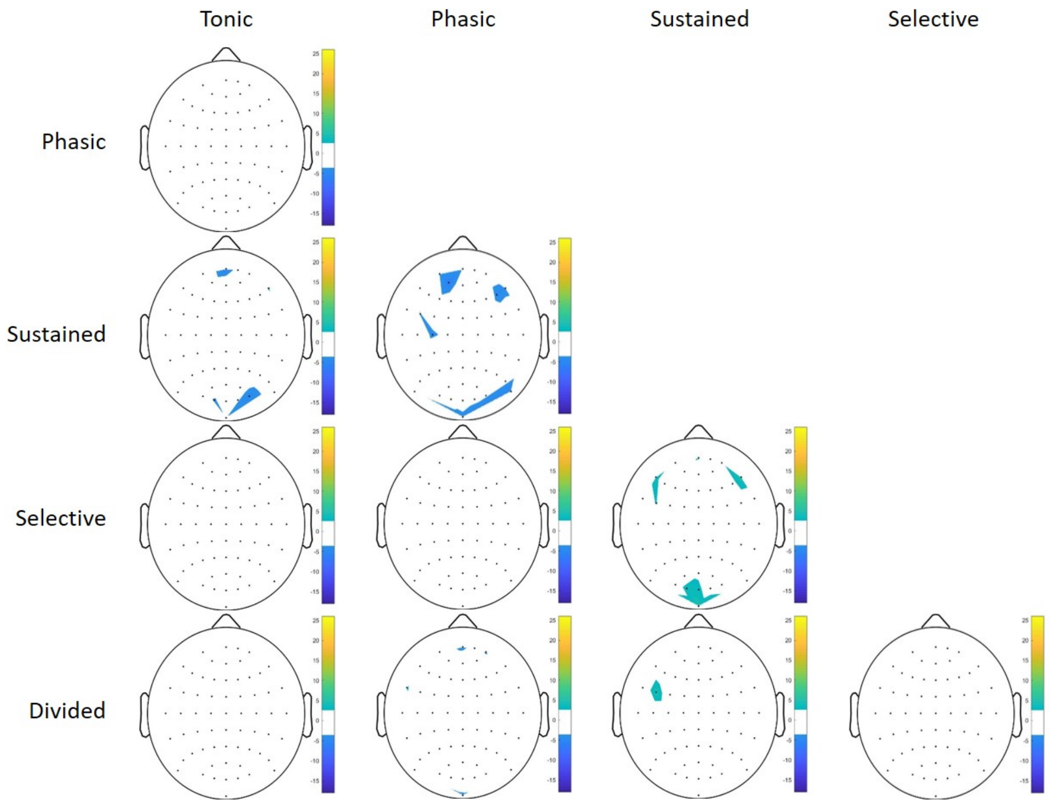

Figure 8.4: Topographies representing the median intra-participant difference of Alpha band power between each tasks. If a significant positive difference is observed for a topography, then the activation index of the task represented in the column was more important than the one from the task represented in the raw. On the contrary, if a significant negative difference is observed for a topography, then the activation index of the task represented in the column was less important than the one from the task represented in the raw. Only the significant indexes are displayed (corrected p-values>0.05).

The **Alpha frequency band** seems to particularly discriminate the Sustained task from the others. There seems to be an increase of activation index in the frontal area during the Sustained task compared to the other tasks. An increase in the occipital area can also be found for the Tonic, Phasic and Selective tasks. A decrease in the frontal and occipital areas enables to distinguish the Tonic task from the Divided one.

The **Beta frequency band** also seems to be particularly involved in the distinction of the Sustained task from the other tasks. An increase in the fronto-temporal and the parieto-occipital areas distinguishes the Sustained task from the others. The increase is particularly located in the right occipito-parietal area for the Tonic and

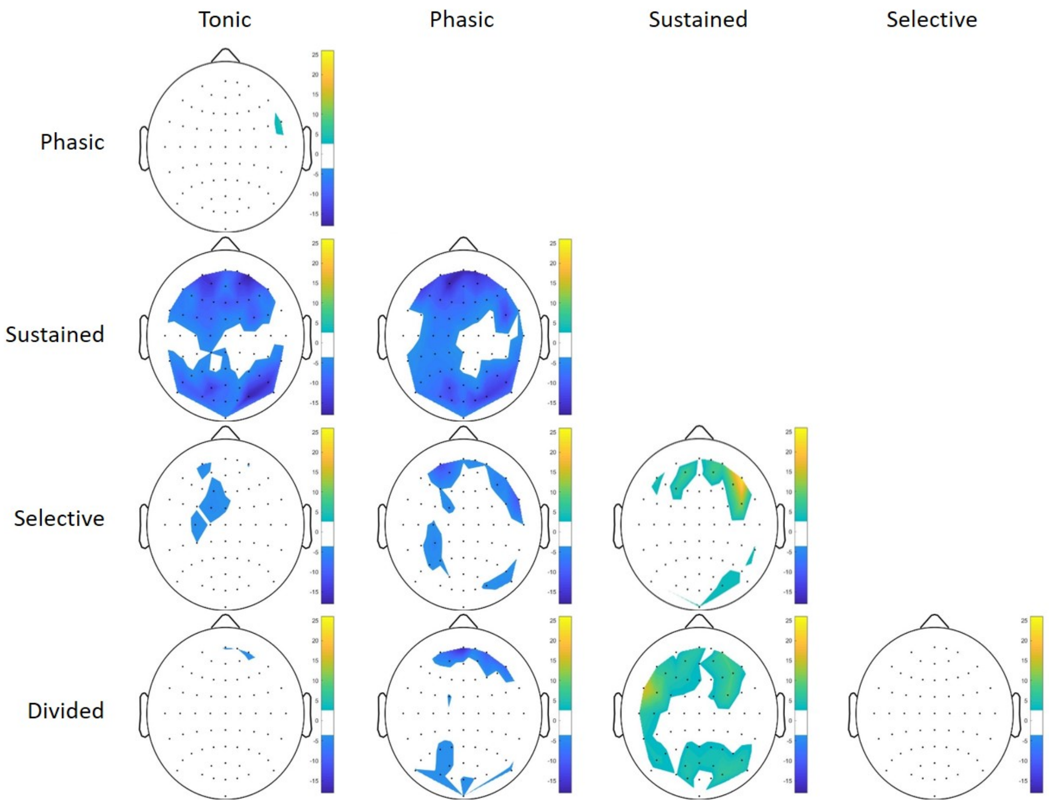

Figure 8.5: Topographies representing the median intra-participant difference of Beta band power between each task and the resting state. If a significant positive difference is observed for a topography, then the activation index of the task represented in the column was more important than the one from the task represented in the raw. On the contrary, if a significant negative difference is observed for a topography, then the activation index of the task represented in the column was less important than the one from the task represented in the raw. Only the significant indexes are displayed (corrected p-values>0.05).

Phasic tasks, in the right frontal area for the Selective task and the left fronto-temporal area for the Divided task. A fronto-central increase of activation of the Tonic task compared to the Phasic one can be observed. The activation index in the left fronto-central area seems to distinguish the Selective task from the Tonic and Phasic tasks. Left parietal activation index also seems to play a role in the differentiation of the Phasic and Selective tasks. A difference of activation index in the frontal area also seems to discriminate the Divided task from the Tonic and Phasic tasks. A diminution of activation index in the Phasic task compared to the Divided one is also present.

8.4.3 Offline classification

Finally, we wanted to know if we could classify the five types of attentional states using only electroencephalographic data. The method of classification used is presented in Section 8.3.2.

The average ratio of trials recognized over the total number of trials tested when using either data filtered in Theta or Alpha band were respectively of $\bar{X}$theta=0.66; SD=0.08 and $\bar{X}$alpha=0.67; SD=0.11 (see Figure 8.6). We calculated that the chance level is around 29% [Müller-Putz et al., 2008]. The accuracy does not seem to be significantly higher using data filtered in Theta or Alpha.

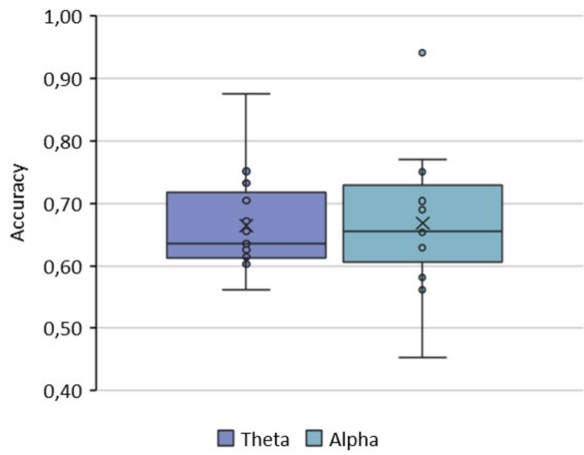

Figure 8.6: Average ratio of trials recognized over the total number of trials tested when using either data filtered in Theta or Alpha band.

The confusion matrix, representing for each class the ratio of trials that where accurately or wrongfully associated with it over the total number of trial were then computed. The average confusion matrices over all participants for the classification in Theta and Alpha bands are displayed in Figure 8.7. Overall, the Alertness, i.e., Phasic and Tonic attentional states, seem to be particularly well recognized both using data filtered in the Theta and the Alpha band. The Sustained attention seems to be the class that is the least correctly recognized. It is mistaken the most with the Tonic attention in the Theta band and with the Divided attention in the Alpha band.

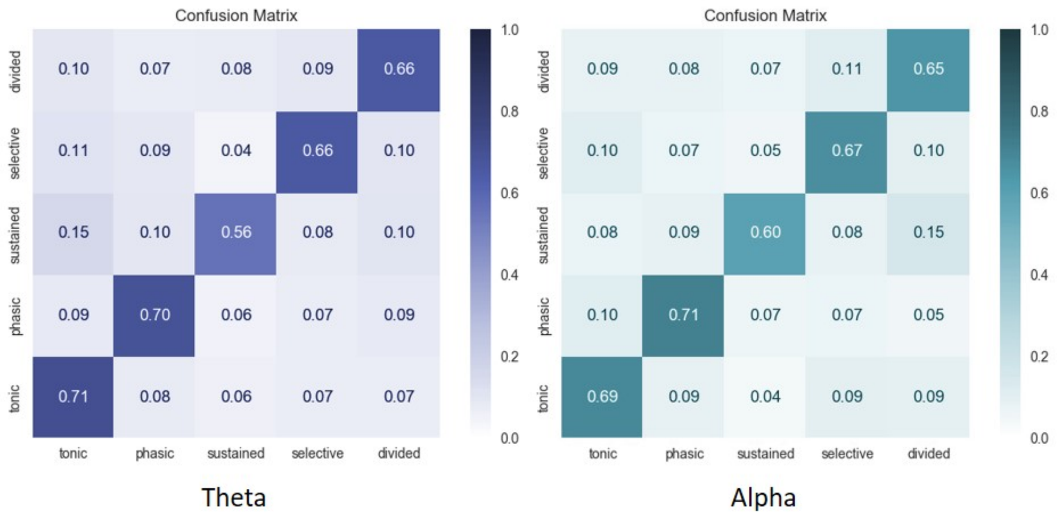

Figure 8.7: Mean confusion matrix over all the participants for the classification performed with the data filtered in either the Theta or Alpha band.

We also included the confusion matrices of all the participants in Annexe A.

8.5 Discussion

The behavioural results that we obtained seem coherent with the literature. The response times were the lowest for the Alertness tasks, i.e., Tonic and Phasic, and the highest for the Divided task [Wyart et al., 2015]. We did not observe any significant differences in behavioural response between the Tonic and Phasic tasks and between the Sustained and Selective tasks. Despite the presence of a higher number of distractors and a longer performance time in the Sustained task than in the Selective task, the response time and the number of errors for the Sustained task were not higher than the ones of the Selective task. We can hypothesize that the length of the task was not long enough. Previous experiments on Sustained attention could last several hours [Shepherd, 1982]. It is also possible that, in comparison with the other tasks, the increase of difficulty for the Sustained task has enhanced the motivation of our participants to preform the task. The theory of flow states that, when performing a task, people enter an "ideal" state of mind when they feel challenged enough but not too much to feel stressed [Csikszentmihalyi, 1975]. Maybe by increasing the number of distractors and thereby the level of difficulty of the task, our participants felt more motivated.

In terms of neurophysiology, our results are in accordance with the literature indicating a main involvement of the Theta frequency band in the frontal area [Gevins et al., 1979a, Gevins et al., 1979b, Gundel and Wilson, 1992, Miyata et al., 1990, Yamamoto and Matsuoka, 1990]. They are also in accordance with previous results indicating a role of Theta for the Selective attention [Schacter, 1977]. Adversely, previous results found that attention is related to an increase in Theta power. In our results we found a decrease in Theta power for all of the different tasks. The differences may be explained by the time window selected to perform the analysis. For this study, we chose to select one second before the appearance of the target to limit the influence of motor artefacts and visual inputs on the brain activity [Gale et al., 1969]. Previous study seem to have analysed the brain activity over all the time of the experiment or over a time window selected after the appearance of the target. Also, the Theta power is usually related to the Sustained attention. It should increase with the length of the task and the amount of workload that it involves [Gevins et al., 1997, Parasuraman, 1985, Wickens, 1991]. Though, we did not find a significant difference in Theta between the resting state and the attentional state during the Sustained task. However, we did find an significant increase of the Theta band in the frontal area to be distinctive of the Sustained attention compared to all the other attentional states [Gevins et al., 1997, Parasuraman, 1985, Wickens, 1991].

The Alpha band, which is strongly associated with attention in the literature, did present significant differences for each type of attention compared to the rest. The parietal activation in the Alpha band found for the Alertness tasks is consistent with previous results from the literature [Anzolin et al., 2017]. Previous results on connectivity found strong links between frontal and parietal areas in the Alpha band for Alertness [Anzolin et al., 2017]. The direction, i.e., increase or decrease, of the difference of activation compared to the resting state seems to discriminate attentional states related to the intensity of attention, i.e., Tonic, Phasic and Sustained attentions, from the ones related to its selectivity, i.e., Selective and Divided attentions. An overall decrease was found for the attentional states related to the intensity of the attention and an increase for the attention related to the selectivity of the attention. Further research distinguishing the lower (6.5-10.5Hz) from the upper (10.5-12.5Hz) Alpha band might provide more insights. Indeed, the lower Alpha seems to be the most discriminant of attentional processes [Klimesch et al., 1998].

We found more complex patterns of activation in Beta which is in accordance with the results from the literature [Anzolin et al., 2017]. Left temporal activation in presence of a warning, i.e., for the Phasic task, could be related with previous results that found an activation in the left temporal area in Gamma band [Anzolin et al., 2017]. The increase observed in parietal area for the Sustained attention might be related to inhibitory process [Rowland et al., 1985]. However, analysis using data filtered in Beta should be interpreted with caution as they could have potentially been influenced by motor-related artefacts.

We classified the data from the five classes using a Riemannian geometry based classifier. The accuracies obtained seem encouraging. On average, to discriminate the 5 different types of attention, a little more than two thirds of the different trials were correctly recognized. Data from the Sustained task were the least correctly recognized. This is in accordance with the results found for the behavioural data indicating that the duration of the task might not have been long enough. Even though we did not observe a significant difference in behavioural response for the Tonic and Phasic tasks, the two tasks were well recognized for both of the classification performed with either data filtered in Theta or Alpha band.

8.6 Conclusion and Prospect

In this chapter, we presented a first step towards distinguishing attentional states involved in the BCI user training. We found that attentional states described in the model of van Zomeren and Brouwer seem to have distinct electroencephalographic spatial and spectral patterns of activation. These results are in accordance with previous results from the literature which indicate that Posner's theoretical model of attentional states have distinct spatial and temporal patterns of activation [Anzolin et al., 2017]. Using a graph theory approach and studying the connectivity between neuro-physiological indices obtained through electroencephalography could provide temporal information in addition to the spatial information reported in this chapter. Anzolin et al. performed such an analysis with EEG data on Posner's theoretical model of attentional states [Anzolin et al., 2017].

Future analyses could investigate the differences in amplitude of involvement for each attentional state. The behavioural accuracies associated with the different tasks seem quite high to be able to find generalizable electroencephalographic characteristics for the targets that the participants did not respond to. Maybe by separating the trials of a task using the median response time, we could observe differences in the amplitude of the attentional states.

The next step would be to design a protocol to assess the different attentional states involved in BCI user training. It is expected that the attentional state of the learner should evolve throughout the BCI user training [Kluger and DeNisi, 1996]. Unspecific to BCI training, models of the different emotional states of learners exist [Kort et al., 2001]. Kort et al. argued that expert teachers excel at adapting to their students' emotional state [Kort et al., 2001]. Assessing attentional state of the learner might contribute to the modelling of the learning process occurring during BCI user training. This model could then be used to adapt the training to the attentional states of the learners and potentially to their learning phase. Though, assessing the different attentional states implicated in BCI user training represents some challenges.

First, a long time is currently required to acquire sufficient data to train a classifier adapted to the participants that detects their different attentional states. Participants who were included in our study informally reported being tired at the end of the session. Therefore, participants might not be at their best if they performed a BCI training after a first phase dedicated to the acquisition of the data required to train a classifier that would differentiate the attentional states. This tiredness could bias the results obtained during the experiment. Also, studying the evolution of the attentional states over several sessions of training might imply that the classifier would need to be trained before each session. Several methods might limit the time necessary to be able to distinguish the different attentional states of a person. First, depending on how transferable the classifiers are from one participants to another, we could consider using or adapting the classifier from one person to assess the attentional states from another. Second, depending on how transferable the classifiers are from one session to another, we could consider using or adapting a classifier trained on data from a previous session to assess the attentional states from a new session. Such adaptability of the classifier should be the subject of future analyses or experiment. Finally, other biometric measures, such as eye movements, could be used to improve the classification and reduce the time for calibration [Glaholt, 2014].

Second, the differences in brain activity induced by the performance of the mental imagery tasks might interfere with the recognition of the different attentional states. It would probably be more relevant to assess the attentional state of the user in-between the different trials or at the beginning and end of the session.

General discussion

We believe that assessing the state of the learner during BCI user training might represent real opportunities to improve BCI user training. As already stated in the last chapter, modelling the state of the learner during BCI training might be informative of the different learning phases that the learners go through during BCI user training. Such model might enable us to predict and maybe explain the outlying performances of participants in general or during specific sessions or trials. Even though further investigations are required on the matter, neurophysiological markers of attention were already found to be correlated with BCI performances [Grosse-Wentrup et al., 2011b, Ahn et al., 2013]. It could also provide more insights on the time required between two sessions or trials to improve the learning. Finally, when comparing different feedback, assessing the attentional state of the participants with each of the feedback might provide insights on their adaptability. For example, the salience and effectiveness of a feedback might be assessed through the measures of attentional state of the participants. Assessing the different types of attention involved in BCI user training and how they evolved with the performances of the learner represents a first step toward gaining a more systematic view of the learning process that occur during BCI user training.

Part V

Discussion & Prospects

Chapter 9

Discussion & Prospects

Guideline:

I. Theoretical background	1. Why should we use feedback?
	2. Which feedback has been used?
	3. Who benefits from the feedback?
II. What information should feedback convey?	4. **Contribution 1** - A physical learning companion can be useful for MI-BCI user training depending on learners' autonomy
	5. **Contribution 2** – An interaction of experimenters' and participants' gender has an influence on MI-BCI training
III. How should the feedback be provided?	6. **Theoretical contribution 3** – Somatosensory abilities post-stroke probably influence BCI-based motor rehabilitation
	7. **Contribution 4** – Modality of feedback might need to be adapted to learners' skills
IV. When should the feedback be provided?	8. **Contribution 5** - Attentional states be reliably distinguished using electroencephalographic data
V. Discussion & Prospects	9. Discussion & Prospects

In the last three parts of this thesis, we have explored several possibilities to improve the content (see Part II What information should feedback convey?), modality of presentation (see Part III How should the feedback be presented?) and timing (see Part IV When should the feedback be provided?) of the feedback provided during

BCI user training. In this chapter, we will first make a summary of the different contributions that we made. Then, different recommendations and challenges will be presented regarding each characteristic of feedback. Potential solutions will be proposed to meet these recommendations in the future.

9.1 Summary of the different contributions

Throughout this thesis, we have explored different potential sources of improvements to adapt the feedback to the learners' traits and states. We argued that a feedback is defined by three main characteristics, i.e., its content, its modality of presentation and its timing. Our contributions are related to each of these three main characteristics.

In Part II, we focused our effort on emotional feedback and social presence. Such feedback have been theoretically supported by the literature of the field [Sexton, 2015]. Though, their use is still under-explored for MI-BCI training (see Section 2.1.2). Only simple forms of social presence and emotional feedback, i.e., smileys, were tested [Zapała et al., 2018]. We argued that tensed and non-autonomous people, who are usually disadvantaged when controlling MI-BCIs, would probably benefit the most from a social presence and an emotional feedback (see Section 3.1). Therefore, we investigated the influence of two complex forms of social presence and emotional feedback for MI-BCI user training.

First, we designed, implemented and tested PEANUT, the first learning companion dedicated to providing social presence and emotional feedback during MI-BCI user training (see Chapter 4). PEANUT provided social presence and emotional support, depending on the performance and progress of the user, through interventions combining both pronounced sentences and facial expressions. It was designed based on the literature, data analyses and user-studies. We notably conducted several online user surveys to identify the desired characteristics of our learning companion in terms of appearance and supporting speech content. From the results of these surveys we notably deduced which should be the characteristics (personal/non-personal, exclamatory/declarative) of the sentences to be used depending on the performance and progression of a learner. We also found that eyebrows could increase expressiveness of cartoon-like faces. Then, once this companion was implemented, we evaluated it during real online MI-BCI use. We found that non-autonomous people, who are more inclined to work in a group and are usually disadvantaged when using MI-BCI, were advantaged compared to autonomous people when PEANUT was present with an increase of 3.9% of peak performances. Furthermore, in terms of user experience, PEANUT seems to have improved how people felt about their ability to learn and memorize how to use an MI-BCI by 7.4%, which is a dimension of the user experience we assessed.

These results, as well as the literature on augmented feedback, tend to indicate a differential impact of social presence and emotional feedback [Hattie, 1999]. Experimenters are the main source of social presence and emotional feedback in MI-BCI user training. Extensive literature in other fields exist regarding the influence, especially gender-related, they can have on participants' responses, behaviour and performances (see Section 2.1.2). However, experimenters' influence had never been studied for MI-BCI user training. Therefore, in Chapter 5, we assessed the impact of the interaction between experimenter and participant gender on MI-BCI performances and progress throughout a session. Our results revealed an interaction between participants gender, experimenter gender and progress over runs. It seems to suggest that women experimenters may positively influence participants' progress compared to men experimenters. Indeed, men participants seem to start with significantly lower performances when they start training with men experimenters compared to when they trained with women experimenters. Also, the learning-curve of women participants seems positive when they are training with women experimenters and negative when they are training with men experimenters. The level of tension of the participants had a significant impact on the influence of the experimenter. Tensed and non-tensed participants preferred training respectively with men and women experimenters. This might be explained by the fact that a similarity of experimenters' and participants' psychological profiles could lead to higher experimenter-related bias in the results [Rosenthal, 1963].

These results confirm that a social presence and emotional feedback could be leveraged to improve BCI user training. However, as any feedback, its effect can be detrimental. If not carefully assessed and taken into account in the design of the protocol, experimenters might bias the results of the experiments. We argue that the traits of the learners, especially their level of tension and autonomy, should be assessed and taken into account when designing such feedback.

In Part III, we investigated how the modality of the feedback could be adapted to the learners. Our review of the literature indicated that the visual abilities of the end-users have been taken into account to adapt the modality of the feedback. For instance, the influence of auditory feedback on the user-training has been investigated for locked-in patients, who often have visual deficits [Nijboer et al., 2008]. In chapter 6, based on a review of the literature, we argued that somatosensory abilities of post-stroke patients have not, but should be, taken into account for BCI-based motor therapies. Indeed, somatosensory abilities play an important role in motor rehabilitation in general, and in BCI-based therapies in particular. It is assumed that during BCI based therapies the co-activation of ascending (i.e., somatosensory) and descending (i.e., sensorimotor) networks enables significant functional motor improvement, together with significant sensorimotor-related neurophysiological changes. Somatosensory abilities seem essential for the patients to benefit from the feedback provided by the BCI system. Yet, around half of post-stroke patients suffer from somatosensory deficits. We hypothesize that these deficits alter their ability to benefit from BCI-based therapies. Our review of the literature on BCI-based motor rehabilitation post-stroke of 14 randomized clinical trials indicates that somatosensory abilities were rarely considered and/or reported. Only two studies over the fourteen reported using them as inclusion/exclusion criteria. Though, none of these two studies reported how they assess the somatosensory abilities, which limits the reproducibility of their results. We argued that assessing the somatosensory abilities of the patients is necessary to avoid any bias and enable reliable comparison between-subject and between-study. It could also be leveraged to improve our understanding of the underlying mechanisms of motor recovery and adapt the therapy to the patients' abilities.

Our review of the literature also informed us that a multimodal feedback composed of both somatosensory and visual feedback enables better performances than an unimodal visual feedback (see Section 2.2). Though, the long term influence of such feedback remained unknown. Also, only comparisons of multimodal interoceptive somatosensory feedback, e.g., orthosis, and visual feedback were made (see Section 2.2). The difference between a multimodal exteroceptive feedback, e.g., vibrotactile, and a visual feedback remained unknown. Another debated question is the influence of kinaesthetic and visual imagery abilities on BCI performances. We hypothesized that the kinaesthetic and visual imagery abilities of the participants could influence the modality of feedback they should be provided with. Our hypothesis was that depending on the visual and kinaesthetic abilities of the participants and the modality of feedback provided, the performance of mental imagery task could solicit similar sensory cognitive resources than the ones required to monitor the feedback. For instance, a participant could solicit visual cognitive resources to both perform visual imagery and monitor a visual feedback. This might lead to an overtaxing of the sensory cognitive resources, and thereby to a decrease of the BCI performances. Therefore, in Chapter 7, we tested the influence of visual and kinaesthetic abilities on the long term effects of a multimodal feedback composed of both vibrotactile and realistic visual stimulations, and a unimodal feedback with only realistic visual stimulations. We found that the beneficial impact of a multimodal feedback composed of both visual and somatosensory stimulation compared to a visual feedback alone remains true even for long term training, which had not been tested before. Also, the order of presentation of the different modalities of feedback might have an influence. Using an unimodal visual feedback only seems to be better suited for untrained participants. We hypothesis that integrating information arising from two modalities of feedback while performing the task could be particularly challenging for a novice learner. Interestingly, we also found a differential evolution of motor execution performances depending on the initial visual imagery abilities of the participants and the modality of feedback.

These results tend to confirm that the traits and state of the learners should not only be taken into account to adapt the content of the feedback but also to adapt the modality of presentation of the feedback. More specifically, the somatosensory abilities of post-stroke patients and the initial visual imagery abilities of neurotypical people should be assessed in future experiments. Once again, we argue that if these traits are not carefully assessed and taken into account in the design of the protocol, they might bias the results of the experiment, and the user training may be suboptimal.

In Part IV, we considered how the timing of the feedback could be adaptive to the state of the users. Our review of the literature informed us that the frequency of the feedback could be related to the attentional state of the users (see Section 2.3). Furthermore, the attentional traits and states of the learners were shown to influence MI-BCI performances (see Section 3.2). Therefore, in Chapter 8, we made a first contribution toward the assessment of attentional states using EEG signals during MI-BCI training. We found that each of the attentional states that is described in the model of van Zomeren and Brouwer, i.e., Alertness, Sustained, Selective and

Divided attention, has specific patterns of activations that can be observed using EEG signals [Zomeren and Brouwer, 1994]. We also tested if the different types of attention could be classified using a Riemannian geometry based classifier based on the EEG data filtered in the alpha or theta frequency band only. The classification provides quite promising results as a little more that two thirds of the trials were correctly classified for a 5-class problem. Future studies should be led in order to test if adapting the timing of the feedback depending on the attention state of the participants has a beneficial impact on the performances.

Throughout this thesis, we assessed the three characteristics of feedback independently. Even if the current literature does not provide much insights regarding the matter, we can hypothesis that the different characteristics of feedback might influence one another. Changes to one characteristic of the feedback might therefore imply different recommendations for the other characteristics. For instance, the recommendations that are currently made regarding the modality of presentation and the timing of the feedback might not be relevant if a feedback of performance is used instead of the current feedback of results. Also, the research on the modalities of feedback are most often comparing a feedback to an equivalent visual one. To our knowledge, no studies compared non-visual feedback, such as auditory or somatosensory feedback, together for MI-BCI user training.

Overall, the results from this thesis indicate that the feedback can have a beneficial or negative impact on the BCI user training which partly depends on the traits of the learner. Therefore, the profile of the learner should be taken into account when designing and assessing a feedback for BCI user training. Assessing the traits and states of the users might also provide information regarding potential inter-participant and inter-study BCI performance and user-experience variability.

9.2 Limitations

Despite the promising results that we have reported in the previous section, our different studies have different limitations. First of all, the contributions that we made focus only on MI-BCI. Other conclusions would probably be drawn for BCIs based on other neurophysiological markers, such as P300 BCIs, which rely on the appearance of a characteristic positive electrical peak in EEG 300ms after the appearance of an infrequent and relevant visual stimulus.

Also, the trade-off between the number of participants included in our studies and the number of sessions of training might limit the generalisability of our results. The experimental results from Chapters 4, 5 and 7 are respectively based on the comparison of 28, 59 and 16 participants over 3, 1 and 10 sessions. These numbers are in accordance with the number of participants reported in previous studies and relatively high compared to most previous MI-BCI studies. However, further studies with a larger number of participants and sessions would provide more generalisable results and be more informative regarding the long term influence of the different effects that we found on MI-BCI performances and user-experience.

Also, it might be worth using new metrics to evaluate the efficiency of different feedback. For instance, the literature on motor skill learning indicates that the dependency toward the feedback should be evaluated, particularly to compare different modalities of presentation [Sigrist et al., 2013]. Few studies have evaluated the impact of the modality of feedback on the information transfer rate, which could be more informative that the classification as it also takes into account the time required to produce the specific pattern of brain activity associated with the task [Darvishi et al., 2015, Krausz et al., 2003]. Finally, it would be more relevant to test different feedback in ecological settings, which would be more representative of the future contexts of use of the BCI technologies.

9.3 Prospects

The following sections present opportunities, challenges and possible solutions that we considered and are related to each of the three main characteristics of feedback addressed in this thesis. First, we will focus on the content of the feedback, which currently only provides users with information regarding their performances but should also provide indications on how to improve the performances. We argue that educational agents offer great opportunities to improve the feedback other than by providing social presence and emotional feedback. Then, we assess how somatosensory sensations could be leveraged to improve the modality of presentation of the feedback. Finally, we discuss the potential benefits that could arise from the assessment of the users' states throughout the training.

9.3.1 Toward a supportive feedback oriented toward a knowledge of performances

9.3.1.1 Recommendation - Knowledge of performances

From our review of the literature that we have reported in Section 2.1.1 Feedback of results, we established that the feedback is currently oriented toward a "Knowledge of results", i.e., an output measure regarding the achieved value or the deviation from the desired value. Though, the literature on feedback recommends the use of a feedback oriented toward what [Baca, 2008] calls a "Knowledge of performances", i.e., specific information on how to improve the results. The feedback must provide information regarding the modification that should be done while performing the task to improve the skill [Wallace and Hagler, 1979]. In other words, not only should the feedback provide some information about how well the learner *does* perform the task, but it should provide information about how they *should* perform it. Despite the controversial influence of instructions on MI-BCI performances on the long term [Kober et al., 2013], feedback might benefit from providing an explanation to the users about how they should change their strategies, e.g., imagining a right hand waving or playing the piano, for the system to recognize them as well as possible. In order to do so, users would have to explain the different strategies they used to control the BCI. Models providing information regarding the strategies that benefit the training could then be developed and might be useful to provide feedback.

9.3.1.2 Challenge - Lack of cognitive model

To provide more relevant cognitive feedback to BCI learners, we should first deepen our theoretical knowledge about the MI-BCI skills and about their underlying processes. As stated above, there are no model providing an explanation on why a given mental-imagery task performed by a user is correctly recognized or not. This represents a challenge, in particular because of the variety of strategies users can use which would then have to be analysed, but also because the verbalization of motor-related strategies is subjective. Neither do we know which information should be conveyed by a feedback of performances. Informative models regarding the traits (e.g., computer anxiety) and states (e.g., motivation) of MI-BCI users which influence their performances, and how these characteristics interact, exit [Jeunet et al., 2017, Kleih and Kübler, 2015]. As this thesis demonstrates, these models can already be informative regarding the improvement that could be made regarding the feedback. However, new models should be developed to provide information on how to adapt not only the feedback but all the training, e.g., task, to the different profiles of learners. Therefore, the main challenges to address are the following:

1. Define and implement a computational cognitive model of which skills are acquired throughout MI-BCI training and how the traits and states of the users, feedback and signal processing influence the acquisition of these skills [Jeunet et al., 2017]

2. Based on these skills, define relevant measures of performance

3. Based on these measures of performance, design adapted and adaptive feedback to help each BCI learner achieve a high performance, i.e., to acquire the target skills

9.3.1.3 Potential solution - Educational agents

Beside emotional feedback and social presence, learning companions can also be designed to provide a cognitive support to the learner. In this perspective, there are many solutions in the field of Intelligent Tutoring Systems (ITS), which use computational tools to tutor the learner. For instance, the companion strategy can be based on the current student learning path and compared to an explicit cognitive model which highlights the different solution paths and skills involved [Aleven et al., 2010]. A learning path gathers the actions taken by the learner (providing an answer, asking for help, taking notes, etc), and the context of these actions (e.g., did the learner attempt an answer before asking for help?). Recognizing learners' learning path and skills can also be done using a constraint-based model of the task [Mitrovic, 2010] or a model of the task learnt using relevant machine learning or data mining techniques. Whatever approach is used, the goal is to create a model where a learning companion can act and track learners' actions or behaviour to determine how they learn and provide them with an effective cognitive accompaniment or assistance. On the sidelines of these cognitive tutors, *example tracing tutors* have been developed [Koedinger et al., 2009]. They elaborate their feedback by comparing the actual strategy of the user with some previous correct and incorrect strategies, which means that they do not require any pre-existing cognitive model of the task. This type of tutoring is based on imitating the successful behaviour of others. Two types of imitations are possible, one by studying worked examples, the other by directly observing someone else performing the task [Van Gog and Rummel, 2010].

The latter second type of imitation based training has already proven useful in motor imagery based BCIs by Kondo et al. [Kondo et al., 2015]. They showed that BCI training could be enhanced by having users watch someone performing the motor task they imagined. Though providing the users with worked examples has never been tried and might be worth exploring by using a learning companion to provide those worked examples. In order to do so, the users would have to explicit the different strategies they used to control the BCI. One way to do so could be by teaching the companion. Methods developed for clarifying interview and user experience assessment could be adapted in order to clarify these verbalizations [Wilson, 2013]. Such research could be linked to the semiotic training suggested for BCI, which consists in training participants to improve their capacity to associate their mental imagery strategies with their BCI performances [Timofeeva, 2016]. The benefit of these methods is that they do not require a cognitive model of the task. Though, they could help determine learning paths and prove useful to develop such a cognitive model.

Additionally, an interesting research direction could be to use several learning companions, including Teegi (see Section 2.2.1 Abstract to realistic and embodied visual feedback Figure 2.2) or another tangible system which could display the brain activity of the user. Each companion could have a different role and one of them could be a tutor which would provide insights about how to interpret the information related to brain activity displayed.

9.3.2 Leveraging somatosensory abilities to improve the feedback

9.3.2.1 Recommendation - Assessing somatosensory abilities and providing kinaesthetic instructions

Interestingly enough, the review we have reported in Chapter 6 Theoretical contribution 3 – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke? indicates that BCI-based rehabilitation might improve somatosensory capacities, along with motor ones. Sun et al. [Sun et al., 2011] mentioned the improvement of somatosensory abilities post BCI therapy in a non randomized clinical trial. This improvement could be related to the instruction given to the patients to perform kinaesthetic motor imagery, i.e., focus on somatosensory sensations associated with the imagined movement. Asking the participants to perform kinaesthetic motor imagery might contribute to somatosensory rehabilitation. Most motor imagery BCI-based RCT, i.e., 73%, report providing such instructions (see Table 6.1). Motor attempt based BCI RCT do not report asking their participant to focus on their sensations while trying to perform the movement. Mihara et al. reported the activation of the somatosensory associative cortex and the somatosensory primary cortex that could underlie such somatosensory improvement [Mihara et al., 2013]. Based on these results, BCIs might also be used to foster somatosensory abilities. Just as providing a feedback while people are imagining performing a movement, using a BCI to provide feedback when patients are imagining a somatosensory feeling might lead to improvements of somatosensory abilities. The results of Yao et al. indicate that sensory imagination tasks can be recognized using EEG [Yao et al., 2018]. Imagining a tactile sensation of the right or left hand could be discriminated from one another with 75.7% of online classification accuracy, i.e., the percentage of mental tasks accurately recognized by the BCI, which is comparable to the accuracy associated with motor imagery tasks.

Use BCI therapy for somatosensory rehabilitation would be interesting for several reasons. First, because it has been shown that somatosensory therapies have a long term influence on the use of the impacted arm during daily life activities [Smania et al., 2003]. Second, because the neural mechanisms of somatosensory deficits remain insufficiently understood and the findings could participate to advances in sensorimotor neuroscience [Schroeder and Chestek, 2016]. More research are needed to investigate the time course of somatosensory recovery and how recovery of motor and somatosensory functions interact [Kessner et al., 2016].

In Chapter 6 Theoretical contribution 3 – Which influence does somatosensory feedback have on BCI-based motor rehabilitation after stroke?, we argued that the assessment of somatosensory abilities would benefit BCI training. We hypothesized that the modality of feedback should be adapted to the somatosensory abilities of the patients. Two solutions are possible to do so. The first one would be to prioritize the motor rehabilitation and use a somatosensory feedback that patients will be able to feel reliably despite their somatosensory deficits to ensure the co-activation of motor efferences and sensory afferences. However, as presented in Section 6.3.2 the rehabilitation of motor abilities is highly related to the somatosensory abilities. Therefore, the second solution, which consists of the opposite choice, to use a somatosensory feedback that stimulates the impacted somatosensory abilities with the expectation that it would promote both motor and somatosensory rehabilitation, might be better suited.

9.3.2.2 Challenge - Assessing somatosensory abilities

Further studies using reliable tools to assess motor and somatosensory abilities and taking into account the spontaneous rehabilitation process are required. Existing methods of somatosensory assessment are not always in accordance with one another. The impact of somatosensory stimulation have proven efficient, e.g., transcutaneous electrical stimulation or neuromuscular stimulation. We hypothesize that the co-activation of afferent and efferent processes could be beneficial for both motor and somatosensory improvements. However, a variety of instructions based on motor imagery and/or somatosensory imagination, e.g., imagining pressure, vibrations or proprioceptive stimulation, could be provided. Different instructions could have differential impact on the rehabilitation. Several new types of feedback could be provided based on somatosensory stimulation, e.g., pressure or vibrations. The combination of different types of stimulations might improve the rehabilitation. Models regarding the different instructions and modality to use depending on the somatosensory abilities of the patients would probably be needed. Therefore, the main challenges to address are the following:

1. Improve the reliability of the somatosensory assessment

2. Based on these somatosensory assessment, the influence of different types of instructions should be tested

3. Together with the influence of instructions, the different types of modalities of feedback should be tested to help each patient improve both motor and somatosensory abilities

9.3.2.3 Potential solution - Combining methods

Combining different methods of assessment of somatosensory abilities such as, analysis of brain lesion location, dedicated protocols of assessments, e.g., "Rivermead Assessment of Somatosensory Performance" [Winward et al., 2002], and the specific biomarkers, e.g., somatosensory evoked potentials, could improve the reliability of the somatosensory assessment. Several mechanic receptors enable the transduction of solicitations to the skin, joints and muscles into neuronal signals available to humans. Depending on the receptors the spatial and temporal resolution of these accessible information differs. The somesthetic information arising from the skeletal muscles benefits from the fastest conducting somatosensory afferents. The differences in spatial and temporal resolution of the different receptors might provide first indications on the type of somatosensory stimulations to favour.

9.3.3 Addressing the state of the learner

9.3.3.1 Recommendation - Modelling the users' learning

Cognitive, affective and motivational states have a great impact on learning outcome and machine learning plays a key role in monitoring them. Monitoring the state of the learners might even provides us with information regarding the learning phase that learners are in. In part IV When should the feedback be provided? we argued that assessing the attentional state of the learners could be possible using EEG data and might be beneficial to adapt the timing of the feedback. It would be relevant to assess other states, such as motivation, to have a more comprehensive assessment of the learners' state and potential learning phase. Motivation is at the center of several models of instructional design [Keller, 2010] and seems to have an influence of BCI performances [Hammer et al., 2012, Neumann and Birbaumer, 2003, Nijboer et al., 2008]. Biasing the feedback was found to influence BCI performances depending on the level of skill of the learner [Barbero and Grosse-Wentrup, 2010]. It was hypothesized that the bias impacts the motivation of the learners differently depending on their level of skills [Barbero and Grosse-Wentrup, 2010]. Therefore, we hypothesize that the user training might benefit from the adaptation of the feedback to the level of motivation of the learner. Attention and motivational states are just two examples. In chapter 3.2 we describe all the different states that were shown to impact the BCI training.

9.3.3.2 Challenge - EEG classification of users' states

Modelling the learners to assess their skills and need might require the assessment on several states. Assessing states using EEG presents some challenges that remain to be overcome, such as detecting and removing artefacts in real time. For example, facial expressions often occur due to change in mental states and may create artefacts polluting EEG data and for which real time removal still represents an issue. Limitations also arise from the number of different users' states we are able to differentiate. The quantity of data to train the classifier increases with the number of classes to differentiate. Future studies should also focus on the reliability and stability of the classification within and across individuals [Christensen et al., 2012]. Indeed, the classification accuracy, particularly the online accuracy, still needs to be improved. Furthermore, calibration of classifiers is often needed for each new participant or session, which is time consuming and might impede the use of such technology on a larger scale. Finally, while several states can be recognized from user's behaviour, there is usually very limited overt behaviour, e.g., movements or speech, during BCI use. Therefore, the main challenges to address are the following:

1. Developing reliable protocols to elicit the different states
2. Assessing if these different states have been elicited as intended
3. Finding specific EEG patterns for each attentional states

9.3.3.3 Potential solutions - Relying on bio-physiological signals and ITS research

During the last decade, many new classification algorithms were developed to improve the reliability of BCIs, some of them, i.e., Riemannian based classifiers for instance, are less sensitive to noise [Lotte et al., 2018]. Furthermore, as presented in the section 3.2 Influence of learners' states, several other bio-physiological markers are correlated with the different users' states. For instance, the galvanic skin response is correlated with workload [Verwey and Veltman, 1996]. These markers could be used to improve the classification accuracy of the different states.

Also, the field of Intelligent Tutoring System could provide some insights on how to leverage informations regarding the state of the learner. Indeed, ITS must adapt their behaviour to each learner. For instance, a companion that adapts its behaviour to learners' profile increases the development of positive attitude [Gordon et al., 2016]. The experiment of Gordon et al. is an example of adaptation of a training to the emotional state of the learner [Gordon et al., 2016]. They developed a social companion robot, named Tega, which interprets students' emotional response (measured from facial expressions) in a game aiming at learning Spanish vocabulary [Gordon et al., 2016]. Tega approximates the emotions of the learner and over time, determines the impact of these emotions on the learner to finally create a personalized motivational strategy adapted to the later. To ensure adaptation, machine learning techniques are often deployed. With the advancement of artificial intelligence, more efficient techniques are now used to help the companion to better learn from the learner's behaviour. In case of the social companion NICO (a Neuro-Inspired COmpanion robot), the model used for the learning of the emotions and the adaptation to the user is a combination of a Convolutional Neural Network and a Self-organization Map to recognize an emotion from the user's facial expression, and learn to express the same [Churamani et al., 2017]. The model allows the robot to adapt to a different user by associating the perceived emotion with an appropriate expression which makes the companion more socially acceptable in the environment in which it operates.

Conclusion

An improvement of the robustness of BCIs in necessary before the technology can be massively developed outside research laboratories. Along with signal acquisition and processing, BCI user-training should be improved to reach this goal. The user-training rely on the use of feedback. The operant conditioning theory is mostly used to explain the learning occurring during BCI user training and thereby explain the role of the feedback. Though, behavioural theories do not account for the neutral and even detrimental effect of feedback found in the literature. Distancing ourself from the behavioural theory would enable to take into account the plurality of impact that feedback was shown to have in the literature. Studying the role of feedback in the user-learning could provide relevant insight on the underlying mechanisms of BCI user-training. For instance, the presence of an intrinsic feedback enabling learners to know if the mental imagery task they performed produces reliable and distinct patterns of activation could be investigated. The use of standard definitions and classification of the different feedback, such as the ones proposed in this thesis, could enable a better understanding of the current state of the literature and the challenges that remain to be overcome. Beyond that, assessing how feedback impacts differently people might enable to better understand the between-studies and between-participants differences. This thesis contributed to the answer of these challenges. In the future, models should be designed to know how to select a feedback depending on the task and participant profile. Also, once we will have enough knowledge regarding each type of feedback independently, adopting a more systematic view of the different characteristics of the feedback will be necessary.

Appendix

Appendix A

Participants' confusion matrices for attentional state classification in Theta and Alpha

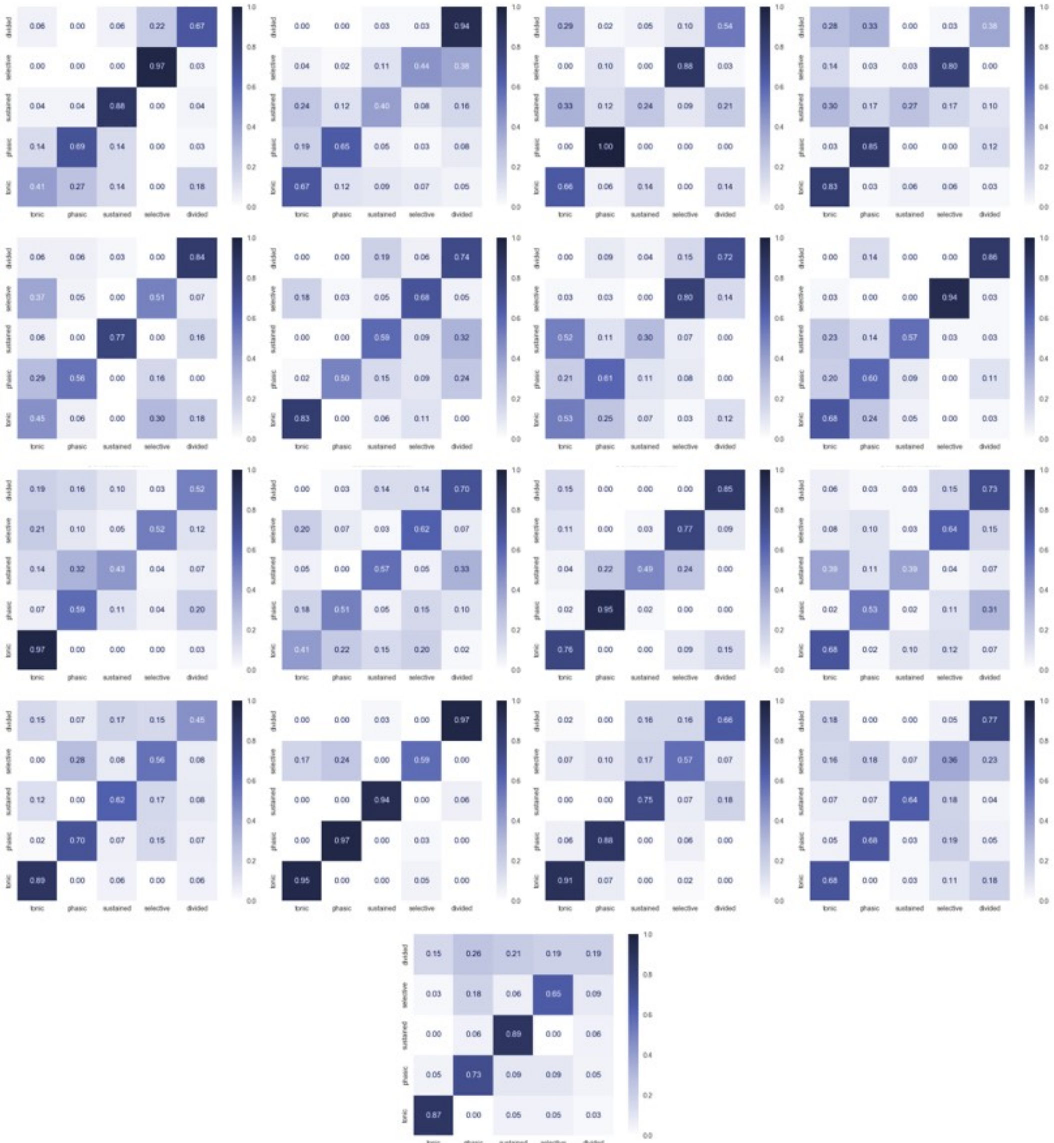

Figure A.1: Confusion matrix for each participant for the classification performed with the data filtered in the Theta band.

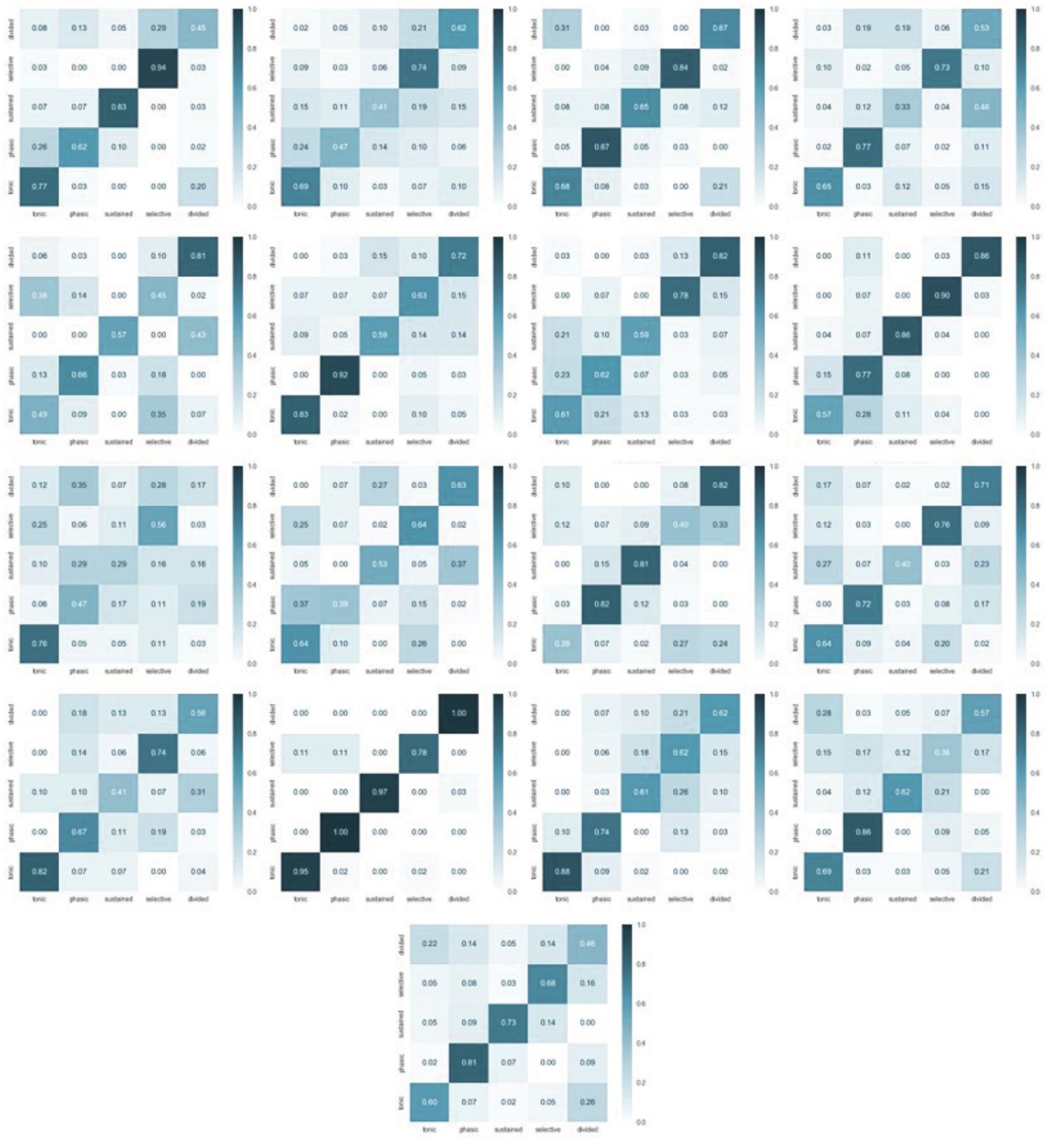

Figure A.2: Confusion matrix for each participant for the classification performed with the data filtered in the Alpha band.

Appendix B

User-experience questionnaire from Jaumard-Hakoun et al.

B.1 Pre and post training questionnaires

Pour chacune des propositions suivantes, indiquez la réponse qui correspond le plus à ce que vous éprouvez en ce moment entre les deux options proposées. Il n'y a pas de bonne ou de mauvaise réponse.

En ce moment :

Je me sens	Calme	□	□	□	□	□	Nerveux(se)
Je me sens	Endormi(e)	□	□	□	□	□	Réveillé(e)
Mon esprit a tendance spontanément à	S'évader	□	□	□	□	□	Rester dans le moment présent
A l'idée de faire cette tâche je me sens	Motivé	□	□	□	□	□	Ennuyé
Je me sens	Heureux(se)	□	□	□	□	□	Triste
Je me sens	Tendu(e)	□	□	□	□	□	Relaxé(e)
Lorsque mon esprit s'égare, j'arrive à me reconcentrer	Facilement	□	□	□	□	□	Difficilement
Je me sens	Satisfait(e)	□	□	□	□	□	Contrarié(e)

Figure B.1: Questionnaire pre-training assessing the mood, mindfulness and motivation of participants.

Pour chacune des propositions suivantes, indiquez la réponse qui correspond le plus à ce que vous éprouviez pendant cette session entre les deux options proposées. Il n'y a pas de bonne ou de mauvaise réponse.

Pendant cette session :

Le temps me semblait s'écouler	Rapidement	□	□	□	□	□	Lentement
Je me sentais	Calme	□	□	□	□	□	Nerveux(se)
Mon esprit avait tendance spontanément à	S'évader	□	□	□	□	□	Rester dans la tâche
Mon implication dans la tâche était	Légère	□	□	□	□	□	Résolue
Le signal de feedback me semblait	Déroutant	□	□	□	□	□	Prévisible
Mon niveau de confort pendant la tâche était	Elevé	□	□	□	□	□	Bas
Je me sentais	Endormi(e)	□	□	□	□	□	Réveillée
La tâche m'a paru	Ennuyeuse	□	□	□	□	□	Motivante
L'effort mental que j'ai fourni m'a paru	Élevé	□	□	□	□	□	Bas
De mon point de vue le feedback était un signal	Que j'observais	□	□	□	□	□	Qui venait de moi
Je me sentais	Heureux(se)	□	□	□	□	□	Triste
Lorsque mon esprit s'égarait, j'arrivais à me reconcentrer	Facilement	□	□	□	□	□	Difficilement
Je me sentais	Tendu(e)	□	□	□	□	□	Relaxé(e)
J'étais volontairement engagé dans la tâche	Assidument	□	□	□	□	□	Négligemment
Pendant la tâche, je me sentais	Accompagné	□	□	□	□	□	Seul
Le signal de feedback me semblait	Pertinent	□	□	□	□	□	Inadapté
Pendant la tâche les conditions (température, bruit, etc.) me semblaient	Défavorables	□	□	□	□	□	Favorables
Je me sentais	Satisfait(e)	□	□	□	□	□	Contrarié(e)
L'exigence mentale demandée par la tâche me semblait	Basse	□	□	□	□	□	Élevée
Le signal de feedback me semblait	Incontrôlable	□	□	□	□	□	Contrôlable
Je sentais que mes expérience et mes actions	Venaient de moi	□	□	□	□	□	Étaient contraintes

Figure B.2: Questionnaire post-training assessing the mood, mindfulness, motivation, workload and agentivity of participants.

B.2 Quotation of the questionnaire

Les scores sont notés de 1 à 5, de droite à gauche pour les questions notées « R », de gauche à droite pour les autres questions. On peut de cette manière étudier chaque item indépendamment :

Pré-session : 1R, 2, 3, 4, 5R, 6, 7R, 8R,

Post-session : 1R, 2R, 3, 4, 5, 6R, 7, 8, 9R, 10, 11R, 14R, 15R, 16R, 17, 18R, 19, 20, 21R

On peut aussi les regrouper par facteurs (attention néanmoins, ces facteurs n'ont pas encore été confirmés, car nous sommes en train d'agréger des sujets pour l'étude factorielle). Dans ce cas, on cote séparément les dimensions mesurées en faisant le total des scores, avec le questionnaire pré-session puis séparément avec le questionnaire post-session (on obtient deux scores par facteur, sauf pour la charge cognitive et l'agentivité qui ne sont mesurés qu'en post-session).

Humeur

- Pre-session (/25) : 1R, 2, 5R, 6, 8R
- Post-session (/25) : 2R, 7, 11R, 13, 18R

Mindfulness

- Pre-session (/10) : 3, 7R.
- Post-session (/10) : 3, 12R

Motivation

- Pre-session (/5) : 4R
- Post-session (/30) : 1R, 4, 8, 6R, 14R, 15R, 17

Charge cognitive

- Pre-session (X) : NA
- Post-session (/10) : 1R, 9R, 19

Agentivité

- Pre-session (X) : NA
- Post-session (/25) : 5, 10, 16R, 20, 21R

Figure B.3: Quotation of the questionnaire.

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