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Mise en oeuvre d'un système de localisation indoor s'appuyant sur une analyse du mouvement d'un terminal embarqué

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Abstract

Ubiquitous computing refers to providing a global computing service where the user access seamlessly resources. User tracking is one of the most important location-aware applications for maintaining the service even with the users' mobility. Unlike outdoor localization technologies like GPS, indoor localization systems have to encounter many problems such as interferences from external sources, low cost and low latency infrastructure requirements, and high accuracy in a limited space.

Our localization approaches associate with technologies that are currently equipped in mobile devices, including NFC technology and inertial sensors and Wireless LAN. The aim of this thesis is to design a simple and effective architecture ensuring two requirements: a high accuracy and an adaptation to the multiple scenarios. Therefore, our proposed system does not address to the fingerprint technique and learning machine algorithms. In this thesis, we propose three approaches as follows:

- The NFC-tagging approach is an instant on-the-spot localization with almost zero-latency

- A combination of accelerometer and magnetometer in the sensors-based approach permits to characterize the user's movement

- The signal-strength-based approach using the similarity of radio conditions between the neighbors can update in real time the radio map for long period localization.

We analyze the performance of the proposed approaches based on rigorous simulation and experimentation tests. We then implement the proposed approaches in a wireless testbed with Android smartphone. Although the implementation is not a final product, the current application can be used to evaluate the feasibility and the performance of the proposed approaches.

Chapter 1

Introduction

Ubiquitous computing was first introduced by Weiser in order to demonstrate a large number of embedded devices which are deployed in the networking environment [99, 100]. One definition that the authors in [28] is that Ubiquitous Computing is an attempt to break away from the current paradigm of desktop computing to provide computational services to wherever the users are in needed. Instead of imposing the searching process in each user, Ubiquitous computing supports an interface which can be able to take charge of serving the users in searching data throughout a wide area. Thus, Ubiquitous computing is one of the emerging technologies that we should be concerned, and it could be applied to my applications in wireless sensor networks, and embedded systems, etc. Typically, Ubiquitous Computing means that the information is available and can be easily accessible from fixed/mobile devices such as handsets, smartphones, tablets, etc. For example, Ubi-bus and Ubi-board provide context-based services to diffuse the required information to the users [66, 74]. These systems are capable of addressing automatically the specific data to particular devices, which are known in prior, with the users' properties, e.g., the spoken language, or visually impaired person. The user and the application can be interacted to each other through the context entities. Note that these entities can be defined as any context information in order for characterizing the situation of a person, place or thing [29]. In addition, context sensing is classified to two types of operation: (1) getting on the context attribute that is a reading process/operation on the context-derived data; (2) triggering an operation when a context-specific condition is satisfied. There has been introduced many prototypes of context awareness systems as in [83], [25] and [50].

Through the discussion as above, we can figure out that human interaction by using mobile devices is one of the promising aspects in our real life. There are some reasons for this promising aspect. First, the functionalities of the mobile devices are smarter and more diverse through the time, and therefore, they can provide context-awareness applications to the users. Moreover, localization has been recently studied in Ubiquitous computing as a potentially perspective. The user location information becomes very important to the context-awareness services to keep maintaining the operation of the users' mobility. Thus, it is clear that a localization system is referred to providing location-based services in which the location is a crucial component of context. In terms of technology, accuracy varies from one to the other as mentioned in Figure 1.1.

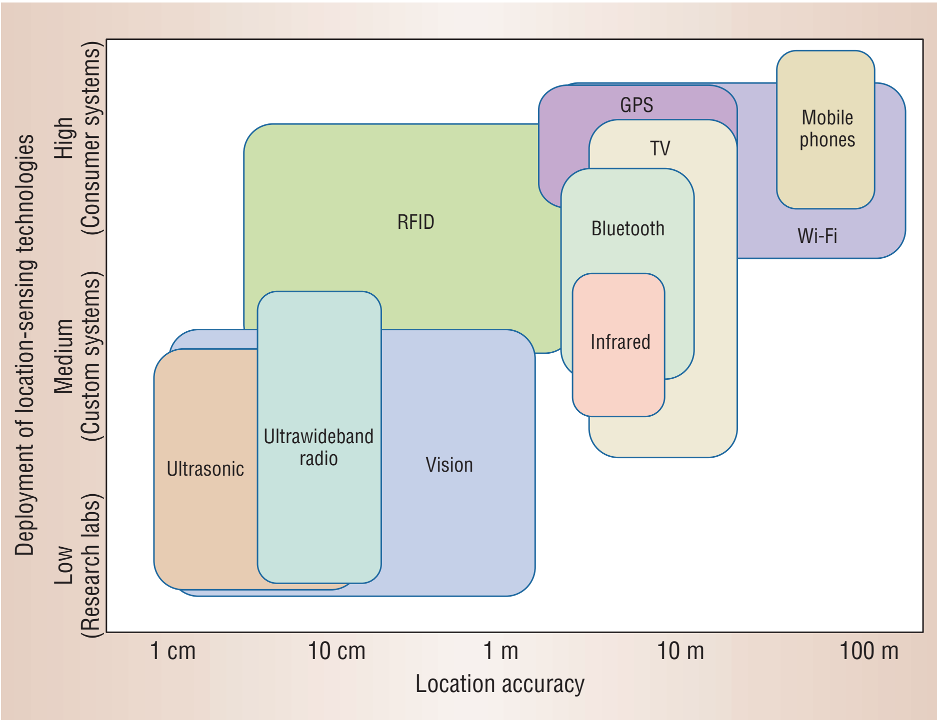


Figure 1.1: Location-sensing technologies [47]

Indoor possitioning applications

In addition to specialized applications for military purposes, a below list of applications is omnipresent as location-aware applications for everyday scenarios:

- Location-based services at home include turning on/off household appliances by detecting the presence of human, the detection of lost items, as well as helping the disabled and aged in performing daily tasks

- In hospitals, it is necessary to implement a tracking system for monitoring patients or for finding the medical personnel in case of emergency

- For the supply chain management, location-based systems provide a tracking service to parcels inside the warehouses as well as on the way to the destination

- There are several location-aware applications in museums, such as guiding visitors and tracking for surveillance the visitors' behavior
- The navigation systems facilitate disabled and aged people using public services such as bus, train, or road guide in parking garages and conferences.

1.1 Motivations

As we can figure out that the users/nodes are usually present in the outdoor environments where the GPS devices can be used effectively. Through the development of location-based application, the vehicles' position can be determined by using handheld GPS units. The accurate tolerance of the GPS unit is in the vicinity of tens of meters. However, its signal is blocked by the structural buildings. Thus, this degradation causes why GPS units cannot be utilized in the indoor environment. In order to locate objects or people inside a building, an indoor localization system based on the context of the mobile device should be deployed. However, locating people/ objects in the indoor environment remains substantial challenges. Several following reasons explain why the positioning performance differs greatly between indoor systems and outdoor systems:

- Multipath/fading from signal reflection from wall and furniture
- Non-Line-of-Sight (NLoS) signal and high attenuation due to obstacles
- Environment changes due to weather conditions, object's displacement, or people movement
- High requirement of installation and accuracy.

As can be seen in Figure 1.1, several alternative solutions (RFID, Infrared, Ultra-Sound, UWB, WiFi or even computer vision) can be replaced to overcome the weakness of GPS and they can be active to locate the users, who are inside the building, within tens of meters. On the other hand, all of them also have their advantages and limitations. Performance and limitations of each of each technology are investigated in Chapter 2.

Most of the current indoor localization systems are based on the approaches of measuring the signal strength information. The signal strength information, which is also called fingerprint, is concerned about the distance between the transceivers with fading over the distance. However, there is no mathematical formula for calculating the distance/location accurately because a radio propagation model cannot flexibly conform to environmental changes. Among RF-signal-based technologies for implementing an indoor localization system, WiFi is a good alternative because of its wide deployment for high speed networks. The WiFi signal has ability to overcome the obstacles such as walls, furniture, etc., hence the fingerprint can be characterized as the context at the measurement places. Thereby, the fingerprinting technique is represented to build a radio map that illustrates a set of fingerprints gathered in each place of the map. Unfortunately, this technique is not a good candidate since it costs too much time for fingerprint collection in the entire network scenario. Moreover, this also encounters some privacy issues, and a high volume of database, and environmental influences.

For short communication networks, the NFC technology has emerged as a standard for local connectivity between "smart" objects [33]. This standard is adopted by NFC forum [5] and has been developed by Nokia and Philips. Similar to the RFID technology that is an automatic identification process using the passive or active tags, the NFC technology also supports to exchange data between two NFC devices. As the low cost equipment, the NFC technology has recently been integrated to the smartphones, mobile devices such as Nokia, Samsung Nexus, etc. Producers have also begun to bring the NFC technology into the emerging smart ticketing and electronic payment infrastructures. It is apparent that the NFC technology could probably be a potential alternative to replace the RFID technology and QR code through creating new localization systems in the short communication. Thus, reading NFC tags can provide location-aware applications. For example, whenever tagging at an object' place in the museum, an interpretation via the NFC tag is active to show in which room the user is.

With the emergence of new data communication technologies, semiconductor technologies has recently been developed by meeting the size, the power supply, and cost requirements for mobile devices. Such recent advances allow modern mobile devices having more capability and mobility. As regarding the Micro-Electro-Mechanical Systems (MEMS), inertial sensors consist of accelerometers and gyroscopes, and those are embedded to the smartphones to measure the physical properties in the situation of UI auto-rotate as well as in motion sensing games. Hence, the inertial navigation systems become attractive navigators for users by combining the inertial sensors and digital compass. Nevertheless, it is hardly to deploy the inertial-sensors-based localization techniques because the precision of sensors' measurements is limited. Little error estimations could possibly be higher depending on the drift rates throughout the time. In fact, most of the proposed approaches for the user localization require many inertial sensors that are generally fixed to the user's body.

The three previous types of technologies will be used throughout this work. In the next sub-section, we present the contributions in developing the proposed approaches in the indoor localization system.

1.2 Thesis contributions

In the indoor localization systems, there is a big challenge to design a low cost and effective architecture that assures a high accuracy. Due to the limitations of the battery, the processing and storage capacity of mobile devices/smartphones, the localization systems can be endured by strict requirements through the computational time, memory consumption, data communication, etc. Most of existing systems have been implemented by high cost infrastructures and complex designs. Moreover, it is not guaranteed to the location accuracy in large buildings where interference from external sources is present. Hence, the dissertation contributes to the studies for the indoor localization systems by combining of the NFC-technology-based, sensors-based and signal-strength-based approaches. The interaction of various solutions results in transforming this combination into a mutual self-correction system that can minimize the location faulty in each approach. The properties of the proposed indoor localization system can be listed as follows:

- Simplicity and low cost: installation, data collection and implementation
- Dynamicity: the ability to maintain operation when the environment changes
- Availability: the localization service is always available due to the locating time reduced
- Accuracy: at the room-level
- Extensibility: coverage with a large number of mobile devices supported

Our proposed system does not address to the fingerprint technique and learning machine algorithms; instead, we design a simple and effective architecture ensuring two requirements: a high accuracy and an adaptation to the multiple scenarios. The proposed system is a combination of the three approaches without any additional infrastructures.

- Firstly, we propose an instant on-the-spot localization approach with almost zero-latency based on NFC technology.
- Secondly, we track the user's position in short period after NFC tagging by using a combination of an accelerometer and a magnetometer. This solution also expresses its simplicity with a low-latency response.
- Finally, a signal-strength-based localization approach is used to locate users in either short or long time period. This approach is based on the similarity of radio conditions between the neighbors. The combination of the WLAN with the NFC technology helps to easily construct a signal strength map in order to determine the user's location.

Our work for designing the location service is an extension of the architecture [14] studied within the FP7 SmartMuseum European project [7]. The project aims to address the efficient on-site cultural heritage content access by monitoring the user's activities. The mobile device is one of the two main subsystems in the SmartMuseum architecture, another one is the profile matching / recommendation server. The latter is able to assist the user to find the contents that are likely of interest for the user [96]. It reduces the interaction required on devices. This is particularly important in ubiquitous scenarios, where the accessibility of the mobile devices often limits the user's willingness to perform the complicated search queries.

1.3 Thesis outline

The rest of the thesis is organized as follows:

Chapter 2 presents the background of this work. We review the related literatures that concern about the common components of indoor localization systems including sensing technologies and communication technologies. We also discuss the existing measurement techniques and locating algorithms for indoor localization systems. By analyzing the fundamental knowledge and challenges of existing indoor localization systems, we make the scope of our research work in the field of the indoor localization.

Chapter 3 presents the NFC-technology-based approach that allows locating the user whenever reading a NFC tag. However, this is a simple localization approach that location reliability is decreased over time. The limitations of the NFC-technology-based approach will be improved by a sensors-based approach. The later approach is responsible for detecting whether the user is still staying at the last defined location. We describe step-by-step the process of forming this proposed approach and its limitations.

Chapter 4 presents the signal-strength-based approach using the similarity of radio conditions related to the neighbors. Using the NFC technology, the proposed approach highlights a method of constructing a radio map without using fingerprinting technique. Through the results, the proposed approach shows its performance and capability of implementing them into location-based applications. Empirical results obtained show the significant advantages when compared to the RADAR system, which is known as a fingerprinting-based system.

Chapter 5 summarizes the contributions of our research work and proposes directions for future works.

Chapter 2

State of the art

This chapter serves as a review of issues related to the recent technologies for localization systems. The localization is an important aspect in the ubiquitous computing environment. Beside new kinds of networking technologies, the usage of sensors embedded into mobile devices allows the ubiquitous computing environment to provide a number of location-based services. The mobile device makes uses of sensors to measure the physical properties of the environment around such as images, movements, vibrations, etc. and then performs algorithms to estimate the user's location. Therefore, the aim of this chapter is to review the networking and sensing technologies, measurement techniques as well as positioning algorithms that have been used in indoor localization systems. In addition to general fundamental knowledge, the state of the art also mentions the advantages and limitations of current indoor localization systems.

2.1 Introduction of indoor localization systems

Indoor localization systems can be classified by different criteria. Using and combining technologies, methods and positioning algorithms allow modeling the characteristics of an indoor localization system. For example, with a requirement of localization accuracy, there are many ways to design a system based on different technologies and methods. Each method can be applied by different algorithms to locate users in different kinds of scenario. In the taxonomy of indoor localization technologies of Torres Solis Jorge [92, 93], the indoor localization technologies are divided into six categories based on the physical quantity measured: (1) radio frequency, (2) photonic energy, (3) sonic waves, (4) mechanical energy, (5) magnetic fields, and (6) atmospheric pressure. Within the scope of my research, we present a modified version of this taxonomy, which is depicted in Figure 2.1, related to our indoor localization systems.

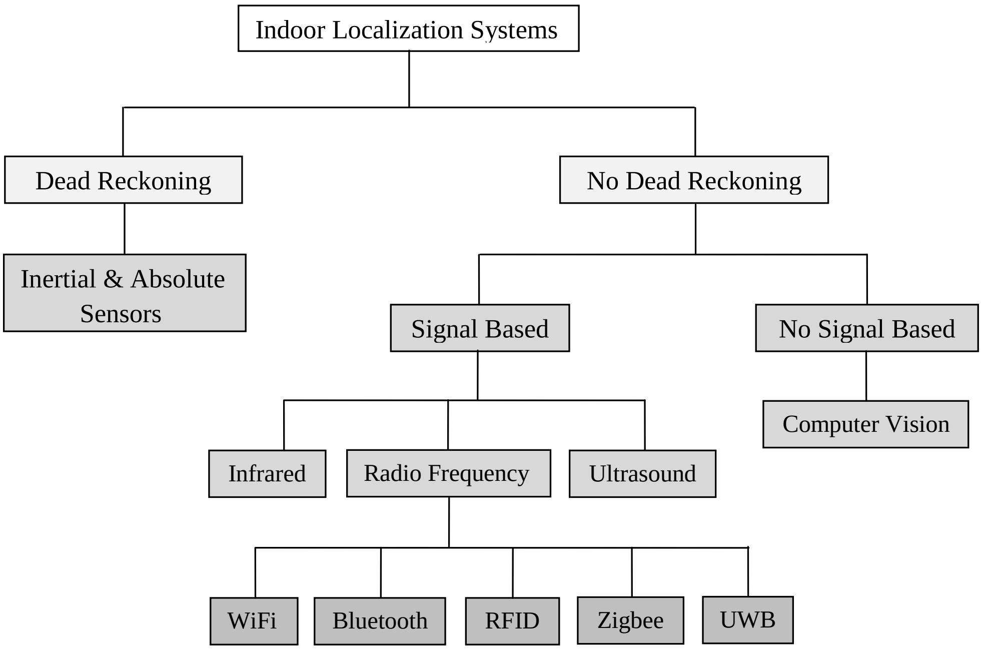


Figure 2.1: Indoor localization system classification

The indoor localization systems are classified into 2 groups: Dead reckoning (DR) and No Dead Reckoning approach. DR systems employ inertial sensors (accelerometer and gyroscope) or both inertial sensors and absolute sensors (compass). No DR systems do not use these sensors but they can be classified based on the usage of radio signal. A signal-based system usually employs Ultrasound, Infrared, Radio Frequency technologies; in contrast, the computer vision system is referred to as a localization system, which does not use radio signal.

In the next Section 2.2, we describes the common components of indoor localization systems. Section2.3 presents the components of mobile terminal used for indoor localization systems including sensing technologies and communication technologies. The two following Sections 2.4 and 2.5 discuss the existing measurement techniques and the positioning algorithms for indoor localization systems respectively. Fundamental knowledge as well as challenges is briefly discussed in these sections. Specific existing indoor localization systems are then presented in Section 2.6 and finally Section 2.7 concludes the literature of indoor localization systems.

2.2 Common components of indoor localization systems

Figure 2.2 illustrates the functional block diagram of the wireless location system suggested by Kaveh Pahlavan and al [59]. This system has three major components: a number of location sensing devices, a positioning algorithm, and a display system. The location sensing devices are a mobile terminal (PDA, smartphone, portable) or sensors that allow users to exchange information and measure metrics related to the relative location of the mobile terminal with respect to a known reference point. These devices use the communication network to transfer data between the user and the location-based service. Communication technologies such as radio frequency (RF), infrared, and ultrasound allow terminal devices to communicate through the wireless environment. The sensed signal, such as time, angle, pulses, and signal strength, is converted into such location metrics as Time-Of-Arrival (TOA), Angle Of Arrival (AOA), Time Difference Of Arrival (TDOA) and Received Signal Strength (RSS). The positioning algorithm then processes these metrics and estimates the location of an object using such approaches as signal processing, learning machine, probability, fingerprinting approach, etc. The positioning algorithms will normally be processed by a system's server where the object's data is stored and updated. The accuracy of the estimated location depends on the accuracy of the location metrics and the effectiveness of the positioning algorithm. After determining the object's location, the display system exhibits the coordinate information to the user.

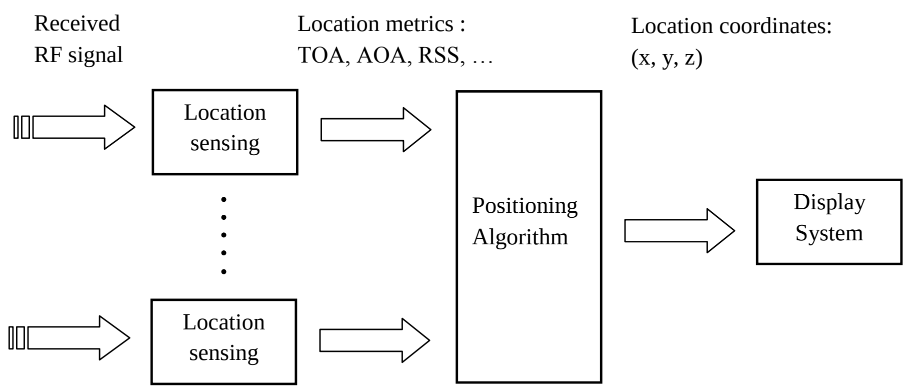


Figure 2.2: A functional block diagram of location system

In order to model a location system, layered software engineering models have been proposed. The University of Washington [56] came up with the Location Stack framework that has seven layers similar to those of the Open System Interconnection (OSI) model for networking. This model permits to divide a positioning system into smaller research questions and provides a layered approach that are flexible enough to be implemented with multiple location systems.

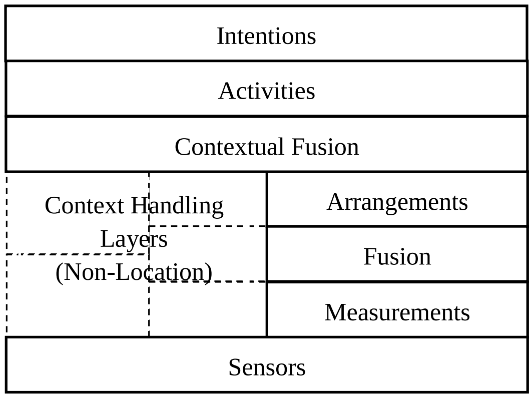


Figure 2.3: The seven-layer Location Stack, a design abstraction for location-aware ubiquitous computing systems

The Location Stack is based on five properties of a location-aware system extracted from a survey of different location systems [57]. They are fundamental measurement types, measurement methods, object relationship queries, and applications related to activities, etc. Although this abstract model has not specified any interfaces between layers, their properties facilitate a common approach to develop future ubiquitous computing systems using location information. The Location Stack framework consists of seven layers as follows:

- Sensor Layer: Sensor hardware and software drivers (such as GPS navigation device, WLAN card, RFID reader, inertial sensor, wireless sensor system, etc.) to detect a variety of physical and logical phenomena. The output of this layer is raw data values.

- Measurement Layer: provides data pre-processing capabilities to transform raw data into such canonical types as distance, angle, proximity, or fingerprint information.

- Fusion Layer: the Fusion layer provides the methods that are responsible for fusing streams of measurement data into a representation of object's locations. After streams of measurement data are fused, the uncertainty of pre-processing data is reduced by the exploitation of different capabilities, redundancies, and contradictions.

- Arrangement Layer: this layer provides information on the relationships between two or more objects. Because each object is related to a corresponding environment description (map, floor plan), this layer presents the ability to test for multi-object proximity given a specified distance and to test for object containment with a predefined map region.

- Context Layer: is responsible for emerging location information with other non-location contextual information such as personal data (calendar, email, and contacts list), temperature, light level, color, and others.

- Activity Layer: consists of a machine-learning-based system that categorizes all contextual information including location into different activities. The activities are described by semantic states to define an application's interpretation of the environment. For example, the semantic states that describe user movement activities are: running, walking, standing, going up, going down, etc.

- Intention Layer: provides the users' needs in relation to the recognized activities.

The Location Stack framework aims to build a robust standardized software abstraction that allows multiple sensing technologies to be connected by aggregating properties of individual locating systems. Based on this kind of location stack, my dissertation focuses on the first four layers.

2.3 Components of a mobile terminal for indoor localization systems

A mobile terminal is network equipment usually worn by users and is capable of maintaining service when the user moves. It could be a laptop, a mobile phone, a Personal Digital Assistant (PDA) or a smartphone. The mobile terminal must have computing capacity, memory and wireless network connectivity. The modern mobile terminal is also integrated with advanced technologies to provide users with more services. One of the mobile terminals known by new services supported is a smartphone. The fundamental components of the mobile terminal are illustrated in figure 2.4:

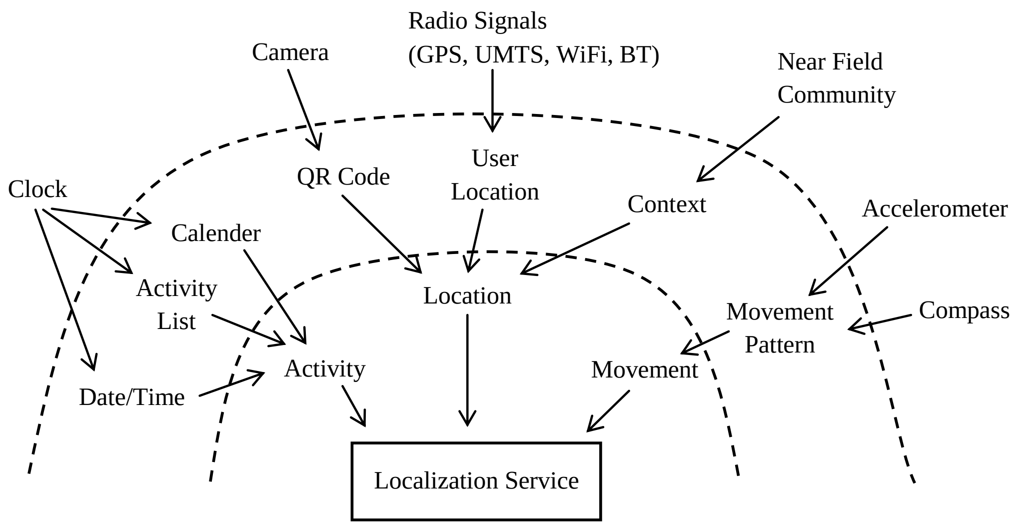


Figure 2.4: Components inside a mobile terminal

Among the emerged services is an outdoor location service called Global Navigation Satellite System (GNSS) that uses mobile terminal as personal navigation assistants. GPS sensors are integrated in the mobile terminal to receive signals from GPS satellites to process positioning users. Although this system works well for navigation in outdoor environment, it presents the problem of inaccuracy for indoor location because GPS signals are blocked by structural buildings. Therefore, an indoor localization system is required to provide services depending on the context of a mobile terminal to locate objects or people inside a building. Indoor localization systems can be categorized based on their sensing technologies and measurement techniques. Sensing technologies refer to the types of signals captured by sensors integrated in the device, while measurement techniques refer to the approaches measuring signals from other devices to predict the user's location. The components of a mobile terminal for indoor localization systems are summarized below:

2.3.1 Sensing technologies

2.3.1.1 Inertial sensors

Inertial sensors, which are the micro electro mechanical systems (MEMS), consist of accelerometers and gyroscopes without external reference. An accelerometer is used to measure the rate of the acceleration force. These forces could either be static like the constant force of gravity or dynamic because of the moving or vibrating of the accelerometer. In addition, by measuring the amount of static acceleration due to gravity on the three acceleration axes, we could find out the angle the device is tilted at with respect to the earth. By sensing the amount of dynamic acceleration, we could analyze the way the device move. Gyroscopes are proprioceptive sensors that measure the angular rate and orientation of a mobile object. There are several types of gyroscopes: vibrating structures, capacitive, etc. Mechanical and optical are the most popular.

The inertial sensors have already been integrated into the iPhone and Android smartphones with an accelerometer, a gyroscope, a proximity sensor, and an ambient light sensor. The most common use of MEMS technology in new smartphones is the 3-axis accelerometer sensor for UI auto-rotate and also in motion sensitive games. In modern smartphones, 3-axis gyroscope consists of tiny vibrating elements like miniature tuning forks and sensors that detect small changes in vibration forces when the phone is moving. When a gyroscope and an accelerometer work together, we would get much more accurate motion sensing and more fluid responses in applications.

Using this kind of technology for a localization system, we need to carefully analyze the signal from inertial sensors; meaning that we have to make some algorithms to reduce interferences from user's activities before using measurements for the locating process.

2.3.1.2 Camera

The current camera embedded mobile phones not only implement various kinds of applications such as taking photos or shooting movies, but they also support symbol recognition, such as QR-code (2D barcode) that contains URLs, or other types of data (contact information, text, geo location, etc.). Once a user uses a phone camera to scan a QR Code, the basic information encoded in this barcode will be explored and displayed on the phone's screen. The user can easily have access to a network service by clicking a ULR address or acquire location information.

Figure 2.5: Reading QR code by phone camera

By scanning the QR code using a phone camera, the user can easily obtain his or her actual location. This application, however, indicates only a temporary location for a short period of time. Another limitation of this approach is that the user has to carefully scan the QR code to expect accurate results.

2.3.2 Communication technologies

2.3.2.1 Near Field Communication

Near Field Communication (NFC) [5] is a new standard based on short range wireless technology of mobile terminals that operate at 13.56 MHz to provide a cost-effective and easy-to-use access. It has been accredited as the second generation standard for radio frequency identification (Smart Card/RFID tag) by the International Organization for Standardization. Based on this technology, NFC devices are able to read from and write information on RFID/NFC tags and are also used for safe two-way interaction among NFC devices. The first NFC devices are already available and it is predicted that several hundred million NFC equipped mobile phones will be used in 2013 [9].

NFC has four features: three basic functions and a connectivity standard with other devices.

- Card emulation:

An NFC device behaves like an existing non-contact Smart card / tag of compatible ISO/IEC 14443 both Type A and Type B, FeliCa and ISO 15693. This function has been built for applications in transportation, access control, and attendance control.

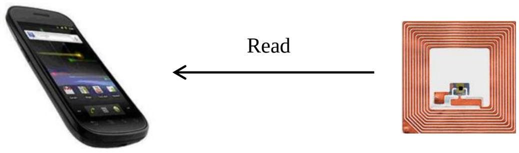


Figure 2.6: Reading card with NFC

- Reader/Writer Emulation:

NFC phones are able to read from and write information on Smart cards that support the standards listed above. For example, whenever an NFC phone is held near or made to touch a Smart card, which is embedded in a poster, sticker, or advertisement, it can receive all poster information (e.g. URL) contained in the Smart card.

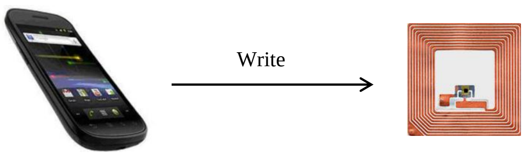


Figure 2.7: Writing card with NFC

-Terminal-to-Terminal Communication:

An NFC device may also have a safe two-way interaction with other NFC devices at a speed of 212 kbps or 424 kbps. This kind of communication assures the receiving and transmitting of data such as text data between NFC devices. By simply bringing two NFC phones close to each other or an NFC phone close to a NFC-enabled PC, smooth authentication will be enabled before exchanging data.

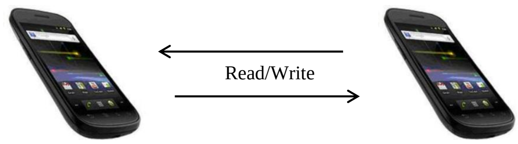


Figure 2.8: Two-way interaction with NFC

- NFC Terminal-to-Terminal Pairing

When NFC-enabled terminals need to exchange large volumes of data in a quick response, pairing could be done with the NFC and the high-speed network such as Bluetooth and WiFi. The process of pairing/authentication is done before transferring data by faster standards is called as Connection Handover.

By simply placing an NFC device close to a Bluetooth-enabled device, Bluetooth connection handover would happen automatically with no need to enter numeric codes. When handover is complete, both devices can use Bluetooth communication for the transmission of data even after the device is moved out of the NFC range. Similarly, connection handover enables connection to wireless LAN at hotspots without having to go through complicated authentication procedures. The authentication and connection to hotspots, therefore, is fast, simple and more secure.

Currently, NFC capabilities are integrated in some smartphones such as Google Nexus S, Samsung Galaxy II, Nokia C7, and Samsung Wave 578. Besides, development designers begin to bring NFC into the emerging smart ticketing and electronic payment infrastructures. NFC technology might also replace RFID and QR code for localization systems.

2.3.2.2 Bluetooth

Bluetooth is a wireless technology standard for exchanging data over a low-cost short distances (10 meters) between fixed or mobile devices to create personal area networks (PANs). Created by The Bluetooth Special Interest Group, it was originally conceived as a wireless alternative to RS-232 data cables. Frequencies are in short wavelength radio of the ISM band from 2400-2483.5 MHz. The frequency spectrum is divided into 79 channels of 1 MHz. Data is transmitted from 108/108 kbps for symmetric channel to 723/57 kbps for asymmetric channel.

Several communication schemes were defined by normalizations. The first one corresponds to a single network (piconet) that can support up to eight terminals: one master and seven slaves. The master manages the communication with the slaves. The communication between two slaves is necessarily passed by the master. For security benefits and noise reduction, Bluetooth employs a frequency hopping technique that switches channels up to 1600 times a second. At the same piconet, all terminals use the same frequency hopping sequence.

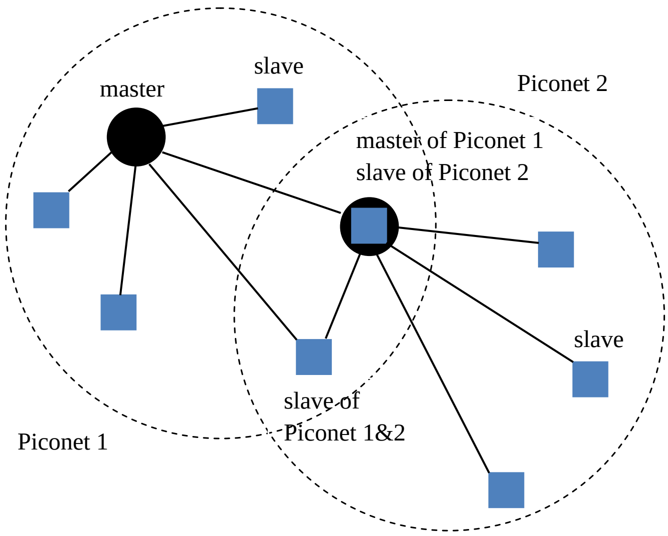


Figure 2.9: Connectivity infrastructure of Bluetooth

Another communication schema is to interconnect piconets to form a scatternet. In a scattenet, one master in one piconet can participate as a slave in another piconet because the communication is always in the form of master-slave. Similarly, a slave might have many masters; it can be temporarily detached from one master to connect to another piconet and then comes back to the previous master when finishing its communication with the latter.

Figure 2.9 illustrates the connections among Bluetooth terminals in a scattenet of two piconets where there is one slave of the two piconets and one terminal that is the slave in piconet 2 but master in piconet 1.

With such advantages as low cost, low power query, and communication in a short range up to ten meters, Bluetooth is a good choice for an indoor localization system. However, a significant drawback of the Bluetooth protocol is the large delay incurred in the discovery phase used for detecting visible beacons. This phase should last, by specification, approximately 20 seconds in order to run the Bluetooth inquiry protocol [46]. The delay can block the usability of Bluetooth-based localization methods because the set of visible beacons is likely to change every few seconds with user movement within a short communication range.

2.3.2.3 WiFi

WiFi[3] is a standard for wireless devices that utilizes radio frequencies to transfer data at a high data rate. The standard IEEE 802.11 has resulted in two generations of wireless networks: IEEE 802.11b works at the speed of 11 Mb/s and IEEE 802.11a/g at the speed of 54 Mb/s. The third generation has reached the speed of 320 Mb/s with IEEE 802.11n. The base frequency of WiFi technology is on 2.4 GHz band.

WiFi device generally works in infrastructure networks such as Basic Service Set (BSS) and Extended Service Set (ESS). In both types of networks, the access point is shared with all stations that are in the same cell and these stations have to associate with an access point to obtain network services. BSS does coverage in small houses or offices. In order to provide coverage in larger areas, some BSSs are linked to form an ESS, which is not very different from a radio system in a mobile network. Another less popular type of network is independent BSS (IBSS) where stations communicate directly with each other within a direct communication range.

WiFi technology has the advantage of reaching long distances (up to 100m) and being independent upon line of sight between the transmitter and the receiver. The access point, therefore, can be placed at a single location in a building and still provide signal coverage to other rooms.

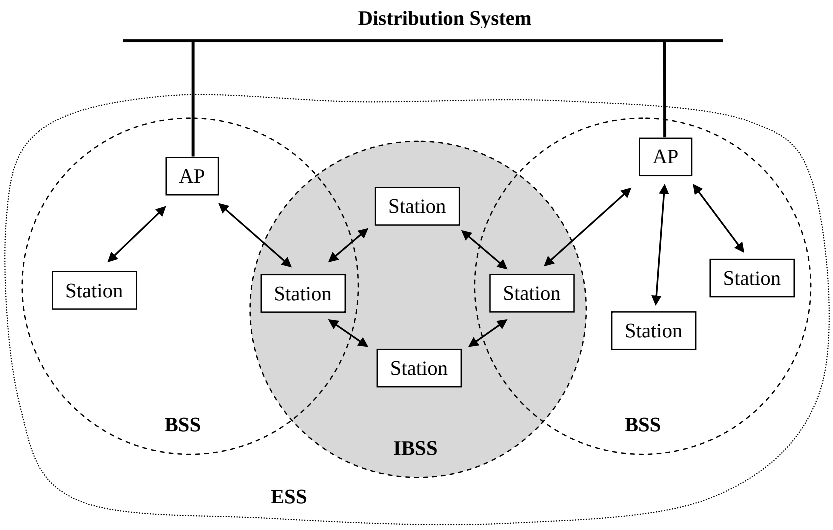


Figure 2.10: Connectivity infrastructure of WiFi

Compared to non RF-based localization system such as camera or laser rangefinder systems, WiFi system has great advantages. First, the devices are less expensive and more available to users because the system is built on an existing WiFi infrastructure for data transmissions. Second, WiFi can cover multiple rooms and floors in a building and the user's portable device then can easily capture the non-LOS signal from the transmitter, and vice versa. The WLAN localization system, therefore, is suitable for indoor environments. However, transmission quality is affected by interference environment wherein the signal from access points is attenuated by walls or obstacles. In order to deploy the WiFi network for a localization system, we need to concern measurement techniques that will be presented in the next section.

2.4 Measurement techniques

Similar to the sensing technologies, localization systems are also categorized by measurement techniques for predicting the location of mobile devices. An important requirement is that the mentioned techniques must express metrics correspondent to location features of the relevant indoor map. The measurement techniques are mainly classified by geometric, statistical, scene analysis and proximity. Figure 2.11 shows a taxonomy of the measurement techniques.

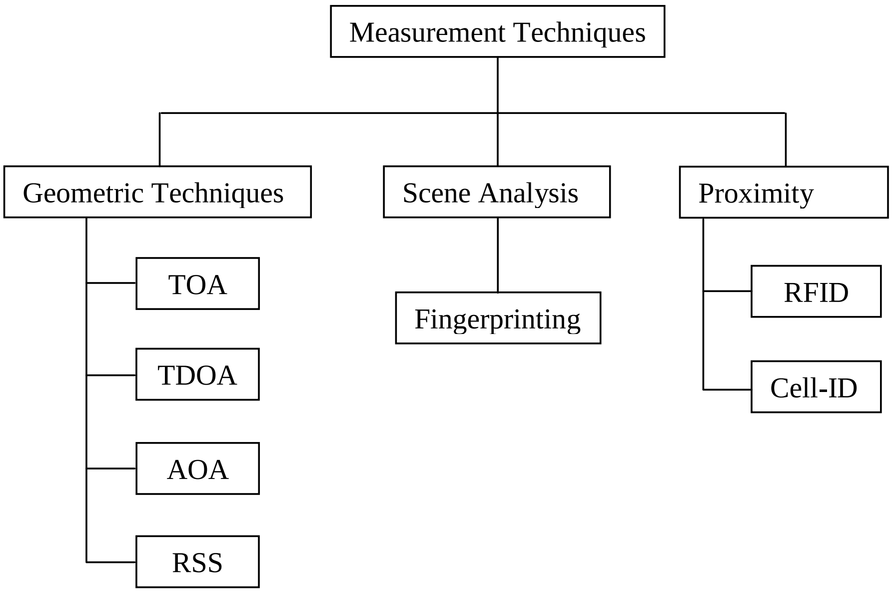


Figure 2.11: Measurement techniques for indoor localization systems

2.4.1 Geometric technique

The geometric based technique uses triangulation [48] that divides into subcategories of lateration and angulation, both of which utilize triangle geometry in determining a location. Lateration is based on distance measurements from multiple reference positions to compute location. For example, an object's position in two dimensions is computed by measuring distance from 3 non-collinear reference points as in Figure 2.12, and in three dimensions from four non-coplanar reference points. Different localization systems that use lateration have different ways to estimate the required distances. In the lateration technique, the three general approaches are direct, time-of-flight, and attenuation:

- Direct is an approach usually used in robotics where the robot moves, probes and measures distance. This approach is simple to understand but difficult to accurately obtain because of the complexities of the autonomous movements of the robots.

- Time-of-flight is a more useful approach that uses the travel time from a well-known reference point to a particular location with a known velocity. Two popular methods of time-of-flight are: TOA and TDOA. Time-Of-Flight, however, is limited by timing and clock synchronization between BTS and MS. For example, distance measurements in UWB are calculated by arrival pulses, which are assigned in a defined slot of time.

- Attenuation: Intensity of a transmitted signal decreases by the distance from a source to a destination. The decrease of the signal strength relative to its original intensity is called attenuation. A given function describing the correlation between the decrease in signal strength and the distance can be used to estimate location relative to the source of the signal. For example, a radio signal transmitted in a free space environment would be attenuated by a factor proportional of $1/r^2$ where r is the distance from the source to the destination point. In the multipath environment by obstructions such as offices, the poor correlation between the attenuation and the distance in a period of time leads to inaccurate distance estimates. A popular technique of attenuation is called Received Signal Strength (RSS) that uses a path loss model of a specific indoor environment to estimate the distance between the transmitter and the receiver. This technique is described in Section 2.4.2.1.

2.4.1.1 Time-Of-Arrival

The Time-Of-Arrival (TOA) method measures the time at which an RF LOS signal takes to travel from the source to the receiver on a forward or backward link. Because the signal propagation time is directly proportional to the physical distance between the source and the receiver, the distance is estimated by the intersection point of three estimated ranges as shown in Figure 2.12.

The geometric method computes the intersection points of the circles of TOA. The position of the target is estimated by minimizing the sum of squares of a nonlinear function. The Least-Squares algorithm is a conventional approach to minimize the value of this function f(X) formulated as:

$$f(X) = \sum_{i=1}^{N} (\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i)^2$$

where X = (x,y) is the target location to be determined, N is number of base station points that are located at (x_i, y_i) with i = 1,2,...,N. If the estimated location of the user is true, function f(X) would be identically zero, meaning that f(x) = 0. However, in practice, the distance measurement is generally inaccurate due to the presence of non-LOS signal. The source of measurement errors principally comes from the delay of received stronger non-LOS signals that distort the distance measurement. Consequently, the sum of function f(X) will never be identically zero. In such case, the optimal position (x,y) can be found by minimizing the value of f(X) by a least squares algorithm.

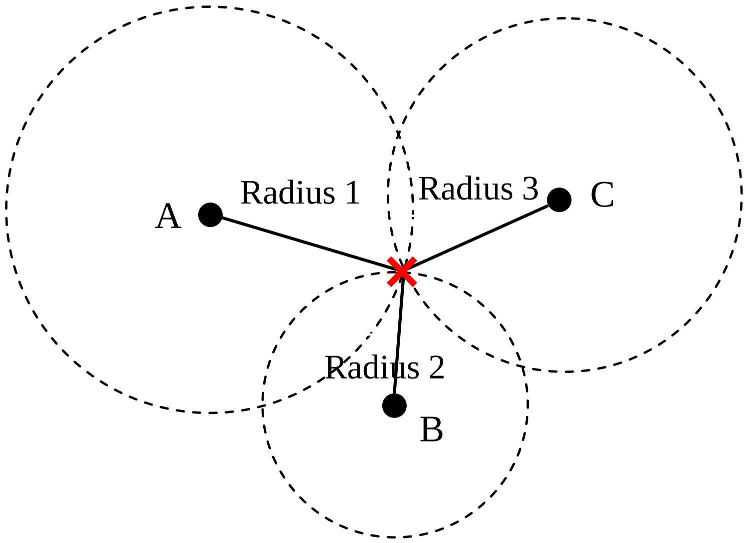


Figure 2.12: Localization based on TOA measurements with circle intersection

Because of severe multipath effects, the LOS path cannot always be accurately detected [58, 59]. The multipath signals probably arrive after the LOS signal a short period of time. When the LOS signal is severely attenuated compared to multipath signals, measurement error would be substantial. In addition, the heterogeneity of the radio receivers/transmitters from different manufacturers leads to the response delay within the receivers/transmitters might be difficult to determine accurately. Consequently, the measured TOA also consists of measurement errors that corresponding to the precise time synchronization of involved transmitter and receiver units. The time synchronization error must be minimized when arrival RF signal has to be correctly captured at the receiver unit. Solving this problem requires a complicated and expensive architecture on the receiver side. In recent research, Ultra-Wideband technology offers a high potential for range measurement using ToA method because the large bandwidth ($>$ 500 MHz) and pulse signal provide a high ranging accuracy [81]. The new WSN standard IEEE 802.15.4a [35] specifies two optional signaling formats based on UWB and Chirp Spread Spectrum (CSS) with a precision ranging capability [82].

2.4.1.2 Time-Difference-Of-Arrival

Similar to the TOA technique, TDOA measures at least three signal transmission times at three reference points to estimate the source's location. These times are then converted to range differences. Consequently, the TDOA technique estimates the difference in the arrival times of the signal from the source at multiple receivers.

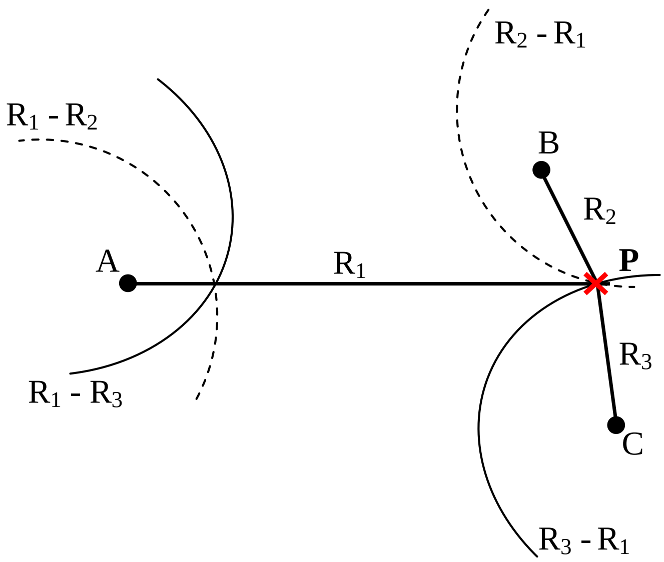


Figure 2.13: Localization based on TDOA measurements with 2D hyperbolic intersection

At each receiver, the arrival time is measured by taking a snapshot of the signal in a synchronized time period. The cross correlation between the arrival times received at each pair of receivers is then formulated. At the peak of this cross correlation, the time difference of the arrival signal at those two receivers is discovered. This value of the time difference estimate draws a hyperbola between the two receivers. Similarly, a new pair of receivers, which combines another receiver with the previously used receiver, generates another hyperbola. Finally, the intersection of the two hyperbolas results in the location estimate of the source.

Suppose that a signal s(t) is transmitted from a source through a channel with interference and noise, received signals at two receiver units are $x_i(t)$ and $x_j(t)$ as formulated below:

$$x_i(t) = s(t - d_i) + n_i(t)$$
$$x_j(t) = s(t - d_j) + n_j(t)$$

where $n_i(t)$ and $n_j(t)$ consist of noise and interfering signals and d_i and d_j are the signal delay times. A cross-correlation function in the observation interval T is given by

$$\hat{R}_{x_i,x_j}(\tau) = \frac{1}{T}\int_0^T x_i(t)x_j(t-\tau)\,\mathrm{d}t$$

The TDOA estimate is defined at a value t such that R_{x_i,x_j} is maximal. The conventional cross correlation technique that is used to estimate TDOA is Generalized Cross-Correlation (GCC) [24] as summarized in Figure 2.14:

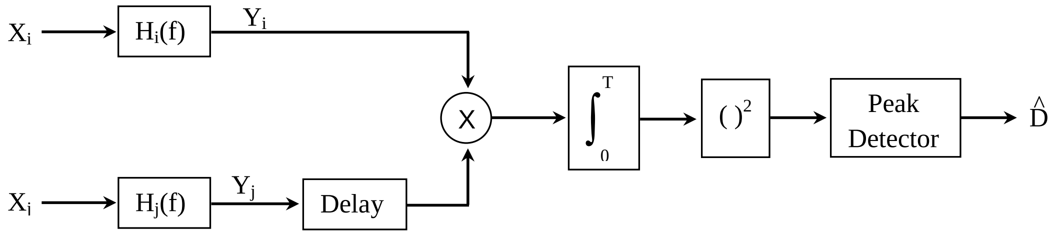


Figure 2.14: Generalized Cross-Correlation method for TDOA estimate

Both signals $x_i(t)$ and $x_j(t)$ are respectively filtered through $H_i(f)$ and $H_j(f)$ to choose frequencies at which Signal-to-Noise Ratio is the highest before these signals are correlated, integrated and squared. After detecting a peak correlation, the time delay corresponding to the cross-correlation peak is the TDOA estimate.

Next, TDOA estimates are converted into range difference measurements that are inserted into non-linear hyperbolic equations. As these hyperbolic equations are non-linear, several algorithms are proposed to resolve them, each of which, however, has different levels of complexities and accuracies.

In Figure 2.13, the 2D target location P is estimated from two hyperbolas which are formed from TDOA estimate at three fixed measuring point. These two hyperbolas are described from a mathematical model of hyperbolic equations. Suppose that (X,Y) is the target location that transmits signal to i^{th} measuring point with known location (X_i, Y_i). The squared range distance between the source and the i^{th} receiver is given as

$$R_i = \sqrt{(X_i - X)^2 + (Y_i - Y)^2}$$

The range difference between the i^{th} receiver point and the j^{th} receiver point is

$$\begin{aligned} R_{i,j} &= c\,d_{i,j} = R_i - R_j \\ &= \sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_j - X)^2 + (Y_j - Y)^2} \end{aligned}$$

where c is the signal propagation speed, and $d_{i,j}$ the TDOA estimate between the ith receiver point and the jth receiver point. The set of range differences forms nonlinear hyperbolic equations whose solution produces a 2D source location. However, solving the nonlinear equations of (2.30) is a complex computation, the Taylor-series expansion [40, 94] is then referred to linearize these equations.

The TDOA method is better than the TOA method in that it can work accurately in some cases of non-LOS signal. Moreover, the time synchronization is only required among BSs and is easily established by connecting all BSs to a wired backbone. The TDOA localization system, however, is more complicated in estimating the position because it has to resolve a set of non-linear hyperbolic equations. In order to optimize the results, a minimum mean square error (MMSE) solution leads to high computational complexity. Nonetheless, this approach is taken by a number of systems [78].

2.4.1.3 Angle-Of-Arrival

The AOA method utilizes multi-array antennas to estimate the direction of arrival signal from the target node to reference nodes. The node's location in two dimensions can be found by the intersection of two LOS bearings. In Figure 2.15, the AOA method use at least two known reference nodes (A, B) to measure angles θ_1, θ_2 derive the 2D location of target node P. The node's location in 3D is estimated by the intersection of a minimum of three LOS bearings. Multiple pairs of angle direction lines are used to improve the accuracy of estimation by rejecting redundant information.

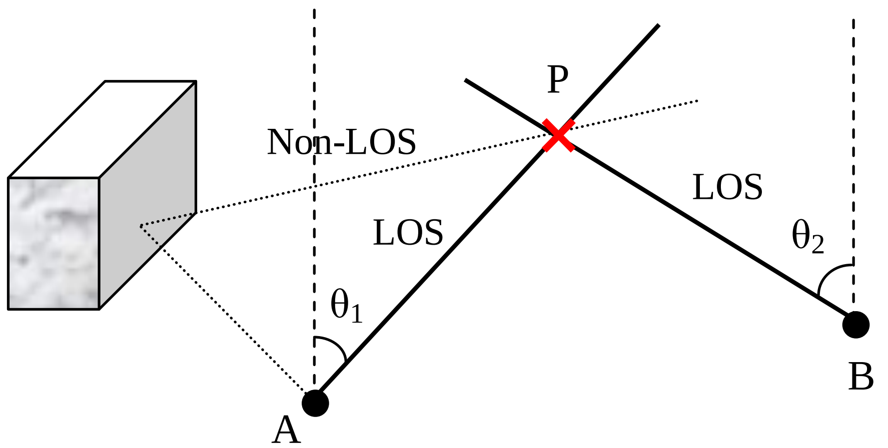


Figure 2.15: Localization based on AOA measurements

The AOA method is advantageous because it does not require time synchronization between nodes and only uses two reference nodes to estimate the target location in 2D. The accuracy of AOA measurements depends on the distances between relative geometry of the target node and the antenna arrays at reference nodes and also on the AOA itself. The dependency of relative geometry is shown in Figure 2.16.

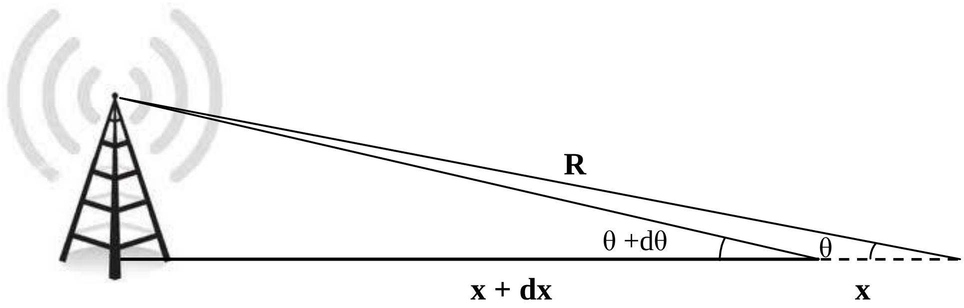


Figure 2.16: typical measurement error in AOA method

the node's location is expressed as follows:

$$x = R\cos(\theta)$$

If there is a measurement error $d\theta$, an estimate error in x is:

$$dx = -R\sin(\theta)d\theta$$

The AOA method is usually measured with directional antennas or antenna arrays that work well with LOS signal. Thus, it is not preferable in an indoor environment where the harsh multipath would reduce the measurement accuracy of the AOA. In addition, the required antenna arrays at reference nodes increase the cost and complexity of the existing system.

2.4.1.4 Received Signal Strength

The three methods above have a common drawback: the LOS signal between the transmitter and the receiver would be difficult to get in an indoor environment. The presence of multipath effect in an indoor environment results in the inaccuracy of location estimation. Signal attenuation-based methods, therefore, would be more suitable because they measure the distance in a more accurate manner as we could apply path loss models [73] in radio propagation. Modeling the radio propagation allows determining the distance between the mobile terminal and reference points whose coordinates are known. The terminal's location can then be solved analytically using triangulation. Similar to the case in TOA, it is necessary to have at least three reference nodes to determine the two-dimension location of a given terminal. The attenuation of the carrier wave signal is dependent on the medium traversed and the distance traveled by the signal. Even in an environment without obstacles, the wave weakens and it is also affected by environmental factors such as humidity, temperature, etc. The power loss is related to the distance traveled and the transmitter frequency. Friis's formula [41] is widely used in calculating the loss of the signal strength:

$$\frac{P_R}{P_T} = G_R G_T (\frac{\lambda}{4\pi d})^2$$

where P_R is the power received by receiver, P_T is the power input to the transmitter, G_T is transmitter antenna gain, G_R is receiver antenna gain, λ is wavelength, and d is the distance between the transmitter and the receiver. This formula, however, is only used in the case of free space; it does not take into account the obstacles existing between the transmitter and the receiver in the case of indoor environment.

The RSS method is favorable because a simple device is used to measure the energy of the receiving signal even in a harsh environment with path loss factors. In an indoor environment, the path loss factor depends on a number of such factors as multi-path fading, temperature, humidity, the presence of obstacles and the mobility of human beings. These indoor environment's factors will cause certain errors in measurement. One important aspect of ranging with the RSS method is that a good channel propagation model is necessary to accurately sense the characteristics of the channel. This would obviously reduce the errors of the RSS measurement in the case of channel variations or terminal mobility.

2.4.2 Scene Analysis

The scene analysis technique analyzes typical features of an observed scene from a particular vantage point to infer the location of an object in the scene. An observed scene usually contains features that are easy to be represented as well as be compared to other scenes. Scene analysis approaches have two separated phases. In the first phase, the features within the observed scene are collected to construct a predefined database. The object's location is then estimated by matching online measurements with a set of scene features in the database. The actual object's location will correspond to the possible locations found in the second phase. Generally, the RSS-based fingerprinting technique, which will be discussed in the next sub section, uses scene analysis for wireless indoor localization.

In the scene analysis method, the object location can be inferred using passive observation whose features do not correspond to geometric angles or distances. As we have discussed in the previous sections, measurements in geometric methods usually require signal emission, passive observation then assures better privacy and lower power requirement. A significant drawback of the scene analysis, however, is that when environmental features change, the database has to be reconstructed because the perceived features from the environment are compared to its observed scenes in an existing predefined database.

2.4.2.1 Fingerprinting

Fingerprinting generally takes place in two phases: an offline phase and an online one. The offline phase includes measuring the signal strength vectors of a certain number of locations in a building to create a signal strength map that is saved in a database. At each chosen location, the signal strength from every visible Access Point (AP) is captured. Due to the fact that received signal strength is affected by many factors, the expected reliability of measurements is improved by taking a mean value of a number of sequential measurements. After a period of measurement, the mean value of the received signal strength at each location will be calculated and stored in the database. Obviously, every position in the signal strength map consists of a list of visible APs with different measurement values that is used to locate users in the online phase.

The online phase is a phase when the user realizes a localization process. The user's mobile device captures the signal strength from visible APs. This measurement value is compared against the values obtained from the offline phase, which then helps to calculate the device's location. The calculation is executed by positioning algorithms such as deterministic and probabilistic methods. The most common algorithm computes the Euclidean distance between the captured signal strength vector and the vectors predefined in the database to find the closest set of locations.

Suppose that V $= (RSS_1, RSS2, \ldots, RSS_N)$ is the observed RSS vector of N APs at the unknown position $P = (x, y)$, and $P_i = (x_i, y_i)$ is the reference position whose fingerprint vector recorded in the database. The Euclidian distance is calculated as following:

$$d(P, P_i) = \sqrt{(RSS_j(x, y) - RSS_j(x_i, y_i))^2}$$

where $RSS_j(x_i, y_i)$ is the mean signal strength value recorded in the database for the $AP_j(j = 1, \ldots, N)$ at the position $P_i(x_i, y_i)$.

Recent research in indoor localization system focuses on the combination of fingerprinting technique and Wireless LAN infrastructure. This combination is popular because of the widespread usage of WiFi network in most buildings and the simplicity of the fingerprinting technique. An advantage of the fingerprinting technique is that, instead of exploiting signal timing or signal strength, the user's location is detected using passive observations and features that are independent of geometry or distances. Whenever a signal strength database is built, localization process depends only on this database. The accuracy, however, is positively associated with the density of the reference points in the database. Compared to the triangulation technique, the fingerprinting technique consumes more time and efforts during the collection of the received signal strength data. Also, a huge volume of data is needed in the database. In addition, because signal strength data depends on a number of reference points, the offline phase could require several hours for a large floor [17]. Concerning adaptability, the triangulation technique performs better than fingerprinting technique. When a new AP is installed in the network, the triangulation technique only needs to delete the existing record and update the information of the new AP to the database during operation process. On the other hand, for the fingerprinting technique, signal strength data has to be recollected at each location in the operation range of that new AP. The solutions to these drawbacks of the fingerprinting technique will be detailed in the proposed system.

2.4.3 Proximity

The Proximity technique is referred to as a location sensing technique that senses an object when it is near a known reference point and within a specific limited range. There are three main approaches to the proximity technique [48]: detecting physical contact, monitoring wireless cellular access points and observing automatic identification systems. Technologies to detect physical contact are pressure sensors and capacitance field detector. Smart floor system [71] uses this technique of physical contact to identify and locate a user living in an equipped space. Another approach is monitoring a mobile device in wireless cellular when it is in range proximity, such as the Active Badge Location System [80]. Finally, observing automatic identification systems will identify or track an object in their coverage area [87].

2.4.3.1 Radio frequency Identification

Radio Frequency Identification (RFID) is a technology primarily used to identify or track objects. Retrieving information is done through an electromagnetic transmission to an RF compatible integrated circuit. An RFID system consists of several basic components: at least one RFID reader and several RFID tags. An RFID tag is attached to an object and is read by the RFID reader from several centimeters to meters. There are two main types of tags [98]: active tags and passive tags. Active tags are small transceivers that have their own power source in the form of batteries. The advantages of active RFID tags are to offer longer operation ranges and smaller antennae. In contrast, passive tags rely on the power transferred wirelessly from the readers. Due to their capability to identity and track tagged objects without physical contact, RFID technology is recently used to replace the traditional barcode technology in commercial settings such as retailing, supply chain, transportation and logistics [75, 55].

Figure 2.17 illustrates an example of using mobile RFID reader with small coverage areas to detect an object's location by reading a tag attached to the object.

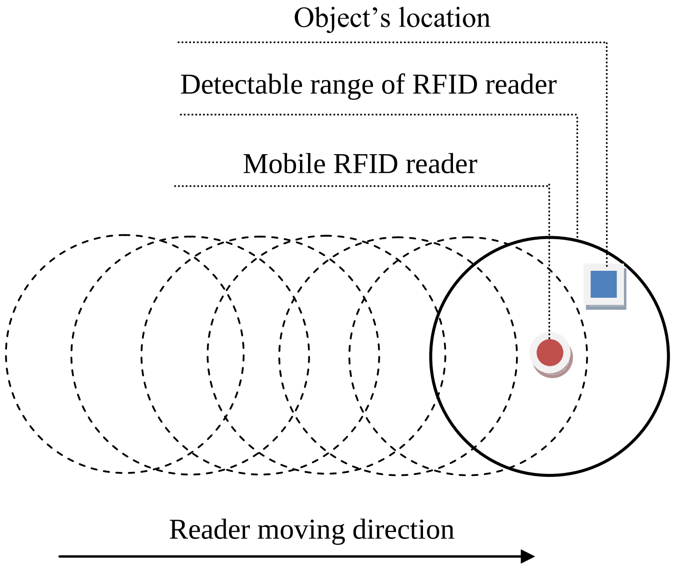


Figure 2.17: Proximity localization using RFID technology

Suppose that an RFID proximity reader has a radial read range with radius r. The RFID reader at the unknown position (x_1, y_1) is called proximity of an RFID tag at position (x_2, y_2) when the RF communications connectivity exists between the reader and the tag, meaning that: $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \leq r$. Proximity information is then used to estimate the RFID reader location.

2.4.3.2 Infrared

Similar to RFID technology, an infrared (IR) based localization system determines the location of an object based on the proximity of an object or people. The IR based localization system has two components: IR transmitter and receiver. IR transmitter is generally installed in the ceiling or wall of every room and IR receiver is integrated into mobile devices. Each transmitter periodically broadcasts its unique ID to IR receivers located across the room. The IR based localization system locates the user by determining the presence of the user in its operation range. The IR signal cannot pass through walls or obstructions; it, therefore, has a rather limited range in a room. The presence of the user in a room is detected by the mobile device whenever it receives the IR beacon from the IR transmitter. The advantages of the IR based localization system are the signal inside the room and the absence of radio electromagnetic interference. However, because the IR signal has the same properties as visible light, indoor lighting can present problems in accurate sensing.

2.5 Positioning algorithms

2.5.1 K-Nearest-Neighbors

The K Nearest Neighbor algorithm (K-NN) is a deterministic algorithm that finds the location of the mobile device according to the similarity of measurements between the device and the K nearest neighbors. The metric used to determine the degree of similarity is the Euclidean distance that is formularized as in section 2.4.2.1:

$$d(V, V_i) = \frac{1}{N}\sqrt{\sum_{j=1}^{N}(RSS_j(x,y) - RSS_j(x_i, y_i))^2}$$

where V = $(RSS_1, RSS2, \ldots, RSS_N)$ is the observed RSS vector of N APs at the unknown position P = (x,y), and V_i is the RSS vector at the reference position $P_i = (x_i, y_i)$ recorded in the database.

It is necessary to find in the database a set of the k nearest neighbors as:

$$S_k = \left\{ \underset{\boldsymbol{V_i}}{\operatorname{argmin}}\, [d(V, V_i)] \ \ \backslash V_i \notin S_{k-1} \right\}$$

Finally, the location of the mobile device is the closest match to k detected locations:

$$P = \frac{\sum_{j=1}^{k}(1/d(V, V_i)) \times P_j}{\sum_{j=1}^{k}(1/d(V, V_i))} \qquad with P_j \in S_k$$

The K-NN algorithm was first used for indoor localization in RADAR [17] and has achieved some significant results. Although this algorithm is simple to implement, its accuracy depends on the density of the reference points. An accurate result can be achieved with a small grid of reference points. However, a great number of reference points results in a large database that takes more computational time.

2.5.2 Probabilistic approaches

The probabilistic approach is utilized to determine the location of a mobile device by modeling location with conditional probability and using Bayesian estimation problem [22]. Similar to the K-NN algorithm, this approach is always employed in the fingerprint technique. However, it uses signal strength data from various known locations to draw a model that can predict the unknown location associated with a set of new signal strength data. This model is built by a probability function from a histogram of training data to estimate the probability of a particular measurement corresponding to a particular position. The probabilistic technique has previously been proposed in different papers [95, 90].

Given a set of known locations L in the database and a set of observations o, it is necessary to infer the most likely location $\hat{l}$ of the mobile device. The observation o consists of a set of signal strengths for each AP_i detected $s_i \in o$. Applying the Bayes rules, the posterior probability of location l from an observation o is as follows:

$$P(l|o) = \frac{P(o|l)P(l)}{P(o)}$$

According to this formula, it can be seen that the estimated location $\hat{l}$ corresponds to the maximum posterior probability $P(o|l)$. Because $P(o)$ is a normalizing constant that does not depend on location l, estimated location $\hat{l}$ becomes:

$$\hat{l} = \underset{l}{\operatorname{argmax}}\,[P(o|l)P(l)]$$

According to Naïve Bayes model, each signal strength s_i is independent from each other at a given location l, thus the probability distribution $P(o|l)$ assigns a probability for each s_i in the observation o as: $P(o|l) = \prod P(s_i|l)P(l)$

The formula of the estimated location $\hat{l}$ is rewritten as follow:

$$\hat{l} = \underset{l}{\operatorname{argmax}} \left[\prod_i P(s_i|l)P(l) \right]$$

where the conditional distribution $P(s_i|l)$ models signal strength of AP_i for a given location l; $P(s_i|l)$ is estimated from the labeled observation. The prior probability of each location l $P(l)$ can be calculated from the labeled data.

The drawback of the probabilistic state estimation is its complexity in two aspects: Representational complexity and Modeling complexity [84]. In order for the probabilistic state estimation to work properly in practice, it is necessary to reduce the complexity of this basic scheme.

2.6 Taxonomy of indoor localization systems

2.6.1 Dead Reckoning based localization system

Semiconductor technologies have been rapidly developed in recent years by meeting the size, power, and cost requirements for mobile devices. Such recent advances allow modern mobile devices more capability and mobility. Particularly, inertial sensors, which belong to Micro-electromechanical systems (MEMS), are embedded into mobile devices. Inertial sensors consist of accelerometers and gyroscopes. Combining inertial sensors and compass sensor, the inertial navigation system has recently become more attractive thanks to the fact that no external motion information is needed for positioning. This technique is self-contained because gyroscopes and accelerometers are integrated into mobile devices to measure the rate of rotation and acceleration. Location estimates are acquired from the obtained information from these sensors. Although inertial navigation systems are independent of external information sources, the errors in location estimates increase over the time because measurements are made by integration in mobile devices.

In the application of activity-based navigation, Greenfield [13], a mobile device interface uses an inertial measurement unit (IMU) to help people find their cars in parking lots. However, this application cannot produce user's precise movement directions. In most solutions, the mobile device or inertial sensors are fixed to the body to only get the vertical acceleration measurement; they do not address the issue of movement direction. The most related work, which is Redpin system [72], to our solution uses a set of fingerprints to indicate the user's activity calendar by labeling the user's location at each stationary time. This solution demands the user to move long distances before labeling a stationary location and labels are contributed by users, so the user sometimes has to remember their location. The Redpin system uses the "Interval Labeling" technic in which the user has to know his actual place and distribute it to a fingerprint. This process is supported by an accelerometer, which is used to detect whether the user is moving or stationary. The drawback of this solution is that it forces the user to manually assign a fingerprint to a location. This activity would be restricted in public services where users do not know geographical patterns. Moreover, the system accuracy is moderate and one third of survey participants reported that the accuracy is likely to decline over time.

The inertial navigation system has recently been based on Dead Reckoning, which is a relative navigation technique. Dead Reckoning uses speed and heading measurements: from a known position, a successive movement position is updated by an estimated speed and direction. The speed and heading measurements are resolved by velocity and north-south-east-west components in that order. The movement estimates can be represented by the form of changes in Cartesian coordinates such as coordinates (x, y). For indoor environment, the Pedestrian Dead Reckoning (PDR) technique is usually used by simply estimating walking speed (or a step length) and the direction of the walk on the ground. This technique has appeared in a great number of research [54, 63, 79, 42].

The PDR technique, however, is only effective if inertial sensors are hardly mounted on the pedestrian and they must be worn by the same pedestrian since the step model is accurately trained with a particular individual's walking pattern. The problem of PDR system is the fact that the absolute positioning error grows proportionally with the traveled distance due to the unbounded accumulation of errors. Figure 2.18 shows an example of a pedestrian movement where S is the speed and H is the heading. The red line is the path estimated from the pedestrian's mobile device, the estimated location (red cross) is far from the original expected location (black cross).

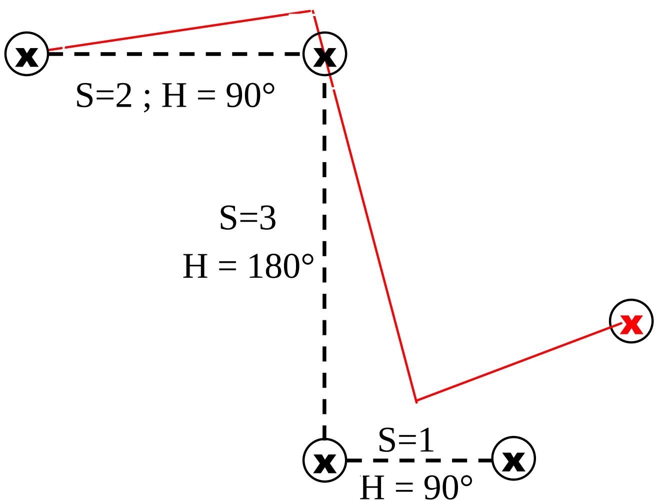


Figure 2.18: Drift errors of the PDR technique

Applying the Kalman filter technique as a smoother, PDR systems [19, 85] could substantially improve the precision. Kalman filter [86] is used as a recursive algorithm to estimate states in linear systems from a set of discrete measurements. Kalman Filter does not need much computational power however it has to construct a state vector and observation models that require a lot of complicated matrix and vector math. Besides, Kalman filter presents poor estimates in highly non-linear systems. Therefore, in order to avoid the drift errors in a long traveled distance of the Dead Reckoning technique, we have some first idea for using the map matching technique. This technique can assign geographical objects to locations on a digital map [65].

Most of map matching algorithms are recently used in satellite positioning systems GPS with a digital map to determine the location of a vehicle on the road. According to a research [76], map matching algorithms can be categorized into three groups: geometric, topological and advanced. There are two general types of existing map matching [65]: online and offline map matching. In online map matching, the object's current location needs to be updated in real time on the map. The GPS system is a well-known example of this kind of map matching. In offline map matching, a set of known positions is given, meaning that they are available for map matching a future position.

For indoor localization systems, we have to integrate the map matching technique into a mobile device. The device has to create a map of its local environment. This local map is then compared to a global map previously stored in memory. If a match is found, the mobile device can compute its actual location in the environment. Possessing these properties, the offline map matching and geometric/topological algorithm promise feasible solutions for indoor localization system. This, however, is challenging because the mobile device has to use measurements integrated sensors.

2.6.2 No Dead Reckoning based localization system

2.6.2.1 Radio frequency localization system

Radio frequency emission is a radiation of the energy of the electromagnetic wave through space. The properties of electromagnetic wave typically depend on the location of the mobile device relative to the transmitter and the characteristics of the surrounding environment. The location estimation of the mobile target is, therefore, obtained by measuring the properties of an electromagnetic wave radiated by the transmitter. In indoor localization systems, technologies in personal and local area networks popularly deployed are: IEEE 802.11, Ultra-Wideband (UWB), ZigBee, or Bluetooth, RFID.

The RADAR system [17] is proposed as an indoor location and tracking system that uses signal propagation modeling and deterministic location algorithm K Nearest Neighbors. RADAR captures and processes signal strength information from multiple base WiFi stations. This process is divided into two phases: offline and online. During an offline phase, the system builds a radio map of location fingerprints by empirically measuring the RF signal strength from base stations. During an online phase, using the information from the user's measured RF signal strength, the central controller uses the approach of deterministic K-Nearest-Neighbors algorithm to determine the position of the user on the radio map.

The RADAR system has median error from 3.6 m to 4.3 m [91]. It is reported that the accuracy of the location estimation could be affected by the user's directions, the number of nearest neighbors, the number of location fingerprints, the number of samples in real-time phase, and the signal propagation model. In some work [16], the authors improved RADAR by a Viterbi-like algorithm. The median error distance and the 90th percentile of the error distance are around 2.37-2.65 m and 5.93-5.97 m respectively.

RADAR is advantageous because it is built on an existing wireless network that requires only a few base stations. However, the empirical construction of the radio map in RADAR requires a lot of time and efforts and encounters some privacy issues. Besides, a technician has to visit every location for at least a few minutes to collect fingerprints; he must also be given access to every location. In addition, the process of expert surveying might be inflexible and expensive in large environments. ARIADNE [102] proposes a clustering algorithm that constructs the signal strength map from the signal measurements of a mobile devices. Although this approach constructs a two-dimensional floor plan with minimal manual intervention comparable to those to traditional systems, its result is better with localization error of 2.69m - 4.22 m.

The LANDMARC positioning system [62] uses fixed active RFID tags and readers as reference points. This approach requires the signal strength measurements from each tag to readers in a detectable range. Each reader scans the mobile tag through eight different power levels in the vicinity. The received signal strength information from a mobile tag is compared to signal strength information from the fixed tags; the KNN algorithm is used to calculate the location mobile tag via triangulation method. LANDMARC's advantage is that 50% error distance is around 1 m while the maximum error distances are less than 2 m. The accuracy of the system depends on the number of these reference tags and readers and their placements. This approach, however, faces the problems, such as the important interference of a large number of tags and readers, the movement of people within the operation range and the infrastructure cost.

2.6.2.2 Infrared localization systems

The infrared (IR) based localization system is referred to a system that determines the location of an object based on the proximity of an object or people. A specific infrared based localizations system is Active Badge [80] which is developed in the early nineties. This is a cellular proximity system that uses infrared (IR) technology and provides locating accuracy in a room level. An IR badge worn by the user periodically emits a unique IR signal. The IR sensors are fixed as reference point to pick up the signal and send it to a central server. The central server is responsible for locating the IR badge by data captured from fixed IR sensors around the building. As an IR system, Active Badge, however, incurs high installation costs and is sensitive to interference in the presence of direct sunlight.

2.6.2.3 Ultrasound localization systems

Ultrasound is acoustic (sound) energy in the form of waves that have frequency above human hearing range (20,000 Hz) [4]. Ultrasound can be used to locate objects by means similar to those by which radar works. High-frequency acoustic waves are reflected from objects, even relatively small ones, because of the short wavelength. The distance to an object can be determined by measuring the delay between the transmission of an ultrasound pulse and the return of the echo.

The Active Bat system [12, 67] and Cricket [68] both use a combination of RF control signal and ultrasound technologies to provide location service. The ultrasonic pulse time-of-flight is used to estimate the location in an indoor environment. Active Bat is based on multiple ultrasonic receivers embedded in the ceiling to measure the time-of-flight to them. Although Active Bat is much more precise than Cricket, its usages is limited due to its scalability. In contrast, the Cricket system does not require a grid of ceiling receivers with fixed locations. Each mobile device can locally perform the computation of their location without any outside communication and no central unit to register and synchronize elements. Cricket, therefore, is advantageous in user privacy and decentralized scalability. It is, however, less preferable for lack of centralized management or monitoring, computational burden and consequently power burden on mobile devices.

In summary, both RF-based and ultrasonic-based systems have to be manually installed and require a number of additional devices to send and receive ultrasonic pulse. Thus, the setup, management and hardware costs would be undesirable when applying them in a large-scale environment. Different from the Active Bat or the Cricket system, the DOLPHIN system [101] requires only a few pre-configured reference nodes to provide coordinate based positioning service. Being a peer-to-peer system, each node has both ultrasound and RF receivers and transmitters in order to execute hop-by-hop locating mechanism. The accuracy of this system is around 15 cm.

2.6.2.4 Vision based localization systems

Although not based on communication signal, vision based localization systems largely exist in person/objet tracking research. For example, in the vision-based robot localization, robots determine their position based on the landmarks that are visible. Localization solutions in this category are mainly based on the images of walls and objects in the room. According to a survey [31, 37], the vision based navigation and localization systems are within one of the following three groups:

- Map-based navigation systems: These systems provide navigation devices the geometric models or topological maps of the environment. The typical model of the map based localization system can be divided into four stages [53]: acquiring sensory information, detecting landmarks, establishing matches between observation and expectation, and calculating the position.

- Map-building-based navigation systems: These systems use sensors to explore the environment, build geometric or topological models of the environment by themselves and use these models for navigation.

- Mapless navigation systems: These systems have no explicit representation of the environment in which the navigation takes place. The navigation devices have to observe and extract the characteristics of the recognized objects (doorways, desks, etc.) in the environment to locate themselves.

A review of the state-of-the-art tracking methods is proposed in [104] to classify them into different categories, and identify new trends. Microsoft's EasyLiving [36] uses real time stereo cameras to provide stereo-vision positioning capability and tracking people in a home environment. Stereo images are used to locate people and color histograms to maintain their identities when they move around the room. The system reported that the localization accuracy is around 10 cm on a ground plan. The system's drawback is that multiple cameras are required to cover all corners. The authors in [30] present an approach to real-time person tracking in crowded and/or unknown environments using multi-modal integration (silhouette, color, and face pattern) to improve accuracy. Another vision based localization system by two independent cameras has also been proposed [43]. The authors presented a new method for new feature initialization and feature matching with two cameras to locate people. The computational complexity was reduced by quickly converging the covariance of the camera and the feature location. Experimental results have shown that the location estimation of the objects in this system is more accurate than in cases of single camera. Using computer-vision technique, this system presents some drawbacks in the captured frame analysis and its complex computation. Besides, the cost of camera deployment in allrooms and the user privacy poses major concerns.

Bruns et al. developed a museum guidance system called PhoneGuide [21] that uses widespread camera-equipped mobile phones for on-device object recognition in combination with pervasive tracking. Using pervasive tracking allows recognizing a small subset of objects at a time. In addition, the object recognition is directly computed on the mobile phones to ensure less network traffic during runtime. Compared to traditional vision-based methods, this approach improves the scale of operation by using pervasive tracking via Bluetooth. This approach, however, needs to reconfigure and re-train the neural network during operation for each object in the user's proximity.

2.7 Conclusion

The research area of indoor localization systems has been quickly approached with various methods, each of which has its own advantages and disadvantages. Some studies have yielded better results than the others; choosing an appropriate approach, therefore, depends on the situation of the application and the user's requirement. Most indoor localization systems have limitations in the installation cost and the complexity of the localization algorithms. The Table 2 (in Annexes) resumes the comparison between indoor localization systems.

A number of costly systems deploy sensors all around buildings or use expensive hardware to get good estimations. Time-of-flight information is widely used to identify the user's presence in a room. For example, Active Bat and Cricket systems use ultrasonic signal to determine the user's location while others such as Active Badge [80] use active RFID and Infrared. The accuracy of such systems depends on the number of sensors / reference tags and readers and their placements. In addition, related to the cost limitation, these systems are vulnerable to indoor multipath and reflection effects from walls, other obstacles, or people displacement. Moreover, interferences from other systems or the environment significantly affect indoor localization results. For instance, IR system is sensitive to the presence of direct sunlight. UWB technology, which uses time modulation to estimate the distance from the sender to receiver, also has its own limitations. Because the localization method of this system is based on very short transmitting pulses (nanoseconds), it requires very high technical specifications such as antenna quality, power emission, and little interference from other systems. Several systems require the implementation of complicated localization algorithms to obtain an accurate estimation. For example, some approaches use cameras to visually detect the user's motions [64] and estimate his location. These solutions face the problems of specific environmental conditions, such as light, distance, and the user's displacement in the room. In order to increase the quality of the localization service, vision based localization systems need to implement complicated algorithms in image signal processing. With a large number of cameras deployed, these systems have to process a huge amount of data from each camera. Therefore, this solution does not seem feasible in indoor localization.

For inertial-sensors-based localization approaches, the precision of sensors' measurement is limited, and little error estimations could possibly be higher depending on the drift rates throughout the time. Thus, most of the proposed approaches for the user localization require many inertial sensors that are generally fixed to the user's body [60, 34, 18]. When using this kind of technology for a localization system, it is necessary to carefully analyze the signal from inertial sensors. Besides, specific methods are considered to reduce interferences from user's activity before using the measurement for the localization process.

Compared to non RF-based localization systems such as cameras or laser rangefinder systems, WiFi localization system (WLAN) has greater advantages even though the surrounding environment affects the transmission quality of WLAN. Despite the interfering from multiple access points and the signals distorted by walls and obstacles, the WLAN system is more suitable for the indoor environment because the WiFi signal can cover multiple rooms and floors in the building. The advantage of a localization WLAN system using signal strength information is that the WLAN card can capture signal strength information at a packet level and from a number of APs simultaneously. The position estimation is obtained by correlating the signal strength measurements at different access points. For example, fingerprint based localization systems, which have been studied extensively in recent years, are affected by environmental factors. RADAR system [17] is fingerprint based indoor localization system that uses the RF signal strength to estimate the distance between receivers and transmitters. During the first phase (offline stage) RSS vectors corresponding to each location (fingerprint) are measured and stored in a database server as a RSS map. During the second phase (online stage), thanks to the information from the user's signal strength RSS, the server uses the K Nearest Neighbors method to determine the position of the user on the map of RSS. The empirical construction of the signal strength map in RADAR requires a lot of time and efforts and encounters some privacy issues. In addition, the technologies that utilize fingerprints stored in advance in a database encounter problems in real scenario because the electromagnetic environment varies over time with the changes in the number of users, the user's movement, and the environment.

Another fingerprint-based system called Redpin [20, 72] can determine the device's location with room-level accuracy. The authors propose the conception of "Interval Labeling" that allows multiple measurements taken consecutively to be added to the same fingerprint. Redpin uses a K-NN for fingerprints that consist of only a few measurements while SVM is used for big fingerprints. Interval scanning periodically performs a scan of WiFi networks and creates fingerprints by attaching the current location to the new WiFi measurements. The measuring stops whenever the system detects the user's movement. However, a long process of measuring will consume a significant amount of device power. Moreover, the user is more likely to remember his location and contributes labels to these measurements. This system will also be limited to public services when users do not know their locations on the map to accurately contribute a label. The system accuracy is about 50% and 1/3 of participants reported that the accuracy level seemed to decline over time.

In summary, major limitations of existing indoor localization systems are the high cost of infrastructure deployment and the complexity of the system design. Moreover, an accurate estimation of the user's location in large buildings is not assured. The purpose of our proposed system is to meet requirements of efficiency and low cost installation for buildings with large number of rooms. Moreover, our approaches still ensure enhanced accuracy at room-level in multiple-user environments. That is a combination of a NFC-tagging approach, a sensors-based approach and a signal-strength-based approach using the similarity of radio conditions between close neighbors.

The reminder of this thesis is organized as follows. In Chapter 3, we firstly propose two approaches: a NFC-tagging localization approach that allows the user to locate himself whenever tagging an NFC tag and a sensors-based approach that uses a combination of a accelerometer and a magnetometer to appreciate the quantity of the user's movement. Secondly, Chapter 4 presents an improvement of the previous approaches by using the similarity of radio conditions between close neighbors. The proposed approach does not address to the fingerprinting technique. Instead, the combination of the simple and effective technology of WLAN with the short-range communication (NFC technology) helps to easily construct and implement a signal strength map to determine users' location. Finally, Chapter 5 presents some conclusions about the proposed approaches and perspectives.

Chapter 3

Indoor localization system using a combination of the NFC-tagging and sensor-based technique

3.1 Introduction

The location of users/objects relative to the indoor environment is an important part for developing services in ubiquitous computing. The localization is able to provide many applications such as tracking shipping box or helping users to find their way inside buildings (e.g. showroom or museum). Besides, localization systems can be deployed in hospitals where it is necessary to monitor patients or to find the nearest doctor in case of emergency. The existing outdoor localization systems using satellite signal, such as The Global Positioning System (GPS), cannot ensure such a localization service. Although GPS can provide positional accuracy of approximately 10-15m for suburban areas [105], consumer-grade GPS units are usually used as road navigation device. In fact, GPS suffers one fundamental problem in the indoor environment: the signals sent from satellites cannot penetrate the structure of most buildings. Therefore, an indoor localization system was developed to overcome this inconvenience.

The identification of the user's location in an indoor environment has always been a big challenge. The indoor environment contains obstacles, such as walls, furniture, doors, and people that can cause signal interference and attenuation. Due to these effects, an indoor localization system requires particular solutions. For example, ultrasound sensors and active RFID tags have been used in many systems but they become quite expensive when sensors are disseminated all around the building [80, 12, 67, 68, 62]. Similarly, other systems [36, 30, 43] implemented cameras with complicated algorithms to visually detect the user's face and motions for localization. The major limitations of existing indoor localization systems are the high cost of infrastructure deployment and the complexity of the system design. In addition, these systems do not ensure an accurate positioning calculation in large buildings. Nevertheless, there are some other simple solutions such as indoor localization system using the short communication of NFC technology to locate users with moderate room-level accuracy [70]. A user can determine his current location by touching his NFC-enabled device to NFC tags. Tags can be easily deployed at many places in building like hall/room entries, check-in table, special objects, etc. Each NFC tag can contain information about the place (description and location in the building). Whenever tagging, the NFC-enabled device updates the user's actual location from a predefined map. However, such a system cannot work well with the user's mobility.

The purpose of our proposed system is to satisfy the requirements of an efficient and low-cost architecture that could adapt to the multiple scenarios. We develop localization solutions integrated into the public mobile devices like PDAs or smartphones. After considering the advantages and drawbacks of each of supported technologies for smartphones, we firstly present a combination of the NFC-tagging and sensors-based technique. The NFC tagging uses NFC technology and the sensors-based technique characterizes the user's movement using accelerometer and magnetometer sensors.

The rest of the chapter is organized as follows: Section 3.2 describes our first approach based on the NFC-tagging. This approach allows the system to locate the user whenever reading a NFC tag. Next, Section 3.3 presents the sensors-based approach using accelerometer and magnetometer to improve the accuracy of the NFC-tagging approach by characterizing the user's movement. Section 3.4 describes the implementation for testing these two proposed approaches. In the last Section, the conclusion discusses about their results and limitations.

3.2 The indoor localization approach based on the NFC-tagging

3.2.1 The tagging technique

The tagging technique uses a short-range communication to easily interact with objects in the environment by reading information from the object's tag. The user only needs to take his device close to a tag to read the information. Nowadays, the short-range communication such as RFID/NFC technology is quite mature and there is a trend to develop indoor sensing applications. This technology provides a quick response thanks to its small computation after tagging. The interesting point of the tagging technique is to allow users to be located at the place of tags. Moreover, compared with other positioning technologies, the tagging technique is a more cost effective solution. The next subsection will present an experiment using the tagging technique in the museum.

3.2.2 An experiment of the SMARTMUSEUM project [7]

The SMARTMUSEUM project develops a platform for innovative services enhancing on-site personalized access to digital cultural heritage through adaptive and privacy preserving user profile. In the SMARTMUSEUM scenario, the user is equipped with a PDA or a smartphone as the main mobile device for presenting textual and multimedia information. Each RFID tag, which is attached to an object inside the museum, contains a unique URI, a URL, and text. Whenever touching a RFID tag, users can acquire contents describing recommended object by clicking on ULRs captured. According to the user's profile preferences, the relevant contents (multimedia, text, or text-to-speech) are automatically released when they are available. Detail of this process is shown as follows:

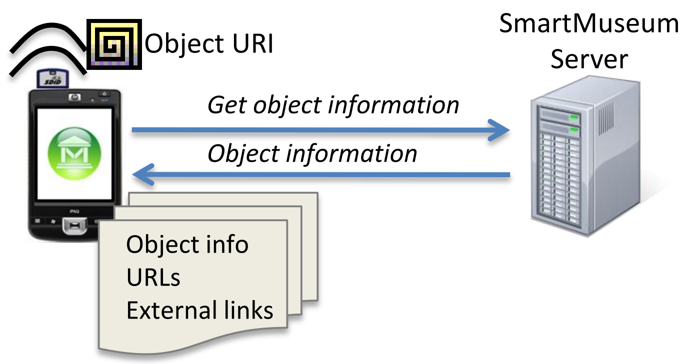


Figure 3.1: The user's device retrieves the object information in the SMARTMUSEUM scenario

Visitors do not need to download full information about every object in the museum; they get information on the spot about objects as needed via tagging. This allows a small-size application on smartphone.

Besides, an administrator application allows writing and updating information to RFID tags near doors and objects by an RFID writer build in the PDA/smartphone. This device is connected to an IP network through WLAN. Whenever updating information on an RFID tag, the administrator can select parts of the information to be written. In case of implementing a new object with an RFID tag, the PDA/smartphone connects to the museum server to register the new RFID tag. The information, which is related to the museum object, is written on the RFID tag via the PDA/smartphone.

One of prominent functionalities of this project is to recognize the user's location. Interestingly, the system allows users to locate themself at the same place of

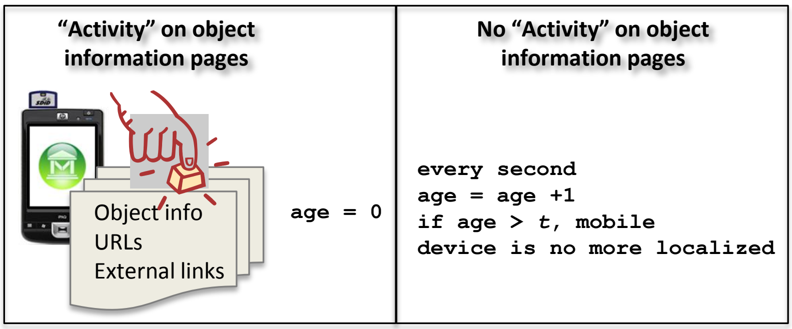


Figure 3.2: Location accuracy depends on the regularity of tagging

the tag. A RFID tag not only provides to users object's relevant contents but also the object's location information. As the objects' location in museum is known via a map downloaded into application, a visitor can get location information by tagging an object's tag. A RFID reader is built in the PDA/smartphone.

3.2.3 The NFC-tagging approach

Using the tagging technique, we propose a NFC-tagging approach as a part of our proposed positioning system. The NFC technology is utilized for touching a tag to gather its location information. With a low latency response, this approach demonstrates a practical solution in real scenarios because of its simplicity and effectiveness. However, it has its own localization limitations.

The first limitation is that the NFC-tagging approach requires users to tag regularly; otherwise the location information becomes obsolete. It means that the user's location is no longer reliable if the user stops tagging for a long time. In fact, the reliability of location information is reduced over time. In order to characterize the validity of location information, we define a counter "age" which is initialized to 0 when reading a tag and is incremented every second if no tag reading. The system considers the user's location as "non-localized" when "age" is superior to a predefined parameter of time t. The parameter t represents a threshold value of time when the user's location is still valid. This principle is presented in Figure 3.2.

The value of the parameter of time t depends on which scenarios are implemented. For example, at the entry, a user can do a tagging and immediately goes to another place but the user seems to stay longer in the coffee/souvenir shop. Thus, in order to well predict how long the user still staying in the same place after tagging, the administrator has to examine the scenario before choosing the value t.

The second limitation of the NFC-tagging approach is that it is necessary to deploy a tagging infrastructure. This approach performs well in scenarios with the appearance of a large number of tags. In fact, the locating accuracy depends not only on the regular tagging, but also on the density of tags. Thus, the NFC-tagging approach limits its operation in several specific scenarios, which deploys tags.

3.2.4 Summary

Recently, the tagging technique is widely used with the RFID/NFC technology for capturing information from tags and its applications have been deployed for public services. Development designers begin to bring NFC technology into the emerging smart ticketing and electronic payment infrastructures. Because of its popularity for services in the indoor environment in recent years, we choose NFC technology for implementing the NFC-tagging approach. Moreover, this approach is feasible to be implemented in mobile devices equipped the NFC technology.

With the purpose of designing an effective architecture that takes advantage of current technologies integrated into smartphones, the NFC-tagging approach is presented to satisfy the following properties: simplicity and effectiveness. The NFC-tagging approach is considered as a process of tag reading. This approach can easily be deployed at many kinds of indoor environment to provide a localization service with a room-level accuracy without additional infrastructure or extra sensors. In the indoor environment, each room has several tags that contain the room's identity corresponding to the room's location. Whenever the user's device reads a tag, it will acquire the user's actual location or in which room the user is.

However, the NFC-tagging approach permits users to be located at a predefined place in a short period of time due to the user's mobility. Location information can then become obsolete if no new tag is read. Thus, the localization reliability decreases and the system needs an additional solution to enhance the locating accuracy. Besides, this approach is only suitable for some scenarios with the appearance of a large number of tags. Therefore, the main proposal for improving the NFC-tagging approach is to enhance the accuracy even in cases when scenarios have fewer tags disseminated.

In order to enhance the localization accuracy of the NFC-tagging approach when its scenario has a few tags disseminated and the location information becomes unreliable, we propose the sensors-based approach. The sensors-based approach uses the accelerometer and the magnetometer to characterize the user's movement from the last NFC tagging. Additional information captured from the accelerometer and the magnetometer, which is uncorrelated to the NFC-tagging approach, will allow having a seamless estimation of the user's trajectory.

Details of the sensors-based approach will be presented as in the following Section

3.3 The sensors-based approach using accelerometer and magnetometer

As previously explained, constraints related to the NFC-tagging approach could be resolved by the sensors-based approach using an accelerometer and a magnetometer. The purpose of our work is to provide a combination of the accelerometer and magnetometer sensors to remedy drawbacks of the NFC-tagging approach.

In general, the inertial-sensors-based systems do not need external references because the inertial sensors are self-contained. In spite of this, **why is not the inertial-sensors-based approach popular for a user localization service ?**

The response is the fact that determining the user's location encounters some reasons: (1) the noisy sensors, (2) the user moves a long trajectory so that the sensor data collected is no longer reliable and (3) the user does many arbitrary activities. These reasons normally result in cumulative locating errors during operation.

Working context

An indoor localization system based on the inertial sensors and the magnetometer needs a specific technique that is capable to appreciate the user's actions as well as to handle sensor noises. Doing this on the smartphone with sensor readings reveals significant challenges:

- People with different physical profiles such as age, sex, active, and less active have different actions

- Device's positions, such as in the user's hand or the device's pocket, can affect the sensor readings

- Structural elements or electronic equipment in the indoor environment may have a significant effect on magnetic field. Measurement errors are then presented by a variance of time and temperature

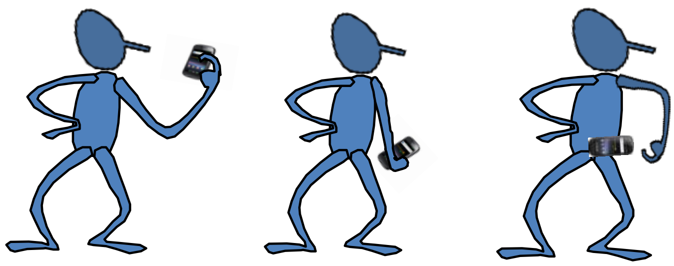
In order to adjust for these cumulated errors, many approaches propose additional infrastructures or complex algorithms. Besides, almost previous works have used highly accurate sensor, a large number of sensors or the sensors are usually fixed on the user's body [60, 77, 34, 18]. However, for a localization service using mobile devices, it is necessary to consider an issue of device's positions. The device's position has an important effect on the sensor measurements. Thus, the current inertial-sensors-based systems have also encountered this common challenge.

Contributions

The sensors-based approach permits users to feel comfortable when using the localization service on the mobile device. The main idea of the proposed approach involves a characterization of the user's movement by combining an accelerometer and a magnetometer. The proposed approach needs to accurately detect the user's activities, from that it could quantify the degree of the user's movement. To do this, the approach needs to refine movement activities by filtering noise actions. From the movement activities obtained, the approach estimates the user's movement distance relatively.

By analyzing acceleration data captured from the accelerometer for the device's proposed positions, a mobile device can predict which motion level the user is performing, like static, walking, running, or arbitrary actions. A combination of the accelerometer and magnetometer sensors provides a measure that can be used to estimate relatively the user's movement in the short-term. The advantage of this fusion is that it can provide a bounded-error solution that does not require any additional infrastructure and is robust to signal noise. Additional information captured from the accelerometer and the magnetometer, which is uncorrelated to the NFC-tagging approach, will allow the localization system to have a seamless estimation of the user's trajectory.

During operation, the user can handle his smartphone in multi-positions even when standing, sitting, or walking. That is a highlight compared to inertial-sensors-based systems that depend on a large number of sensors fixed at a part of the user's body. We aim to adopt the three device's positions that are popular to the users: the mobile device can be held in the user's hand or placed in the device's pocket at the user's waist. These positions will be used throughout experiments to build our proposed approach. In Figure 3.3a, the user holds the mobile device in his hand and he can look at the screen while standing or walking. The mobile device is held in the user's hand in a natural way (Figure 3.3b) and placed in the device's pocket at the user's waist (Figure 3.3c).



a) b) c)

Figure 3.3: The device's positions

The remainder of this Section 3.3 is divided into sub-sections as follows: Sub-section 3.5 will present features and limitations of accelerometers and magnetometers. The next Sub-section 3.3.2 shows how we characterize the degree of the user's activities. After that, experimentations for extracting activity features will be presented in the next Sub-section 3.3.3 the two final Sub-sections 3.3.5 and 3.3.6 show experimentation results and a summary of the proposed approach, respectively.

3.3.1 Features and limitations of accelerometers and magnetometers

Like any other sensors, the accelerometer and the magnetometer have their own disadvantages. We will explore why these sensors must be treated before using their measurements for characterizing the user's movement. The next sub-section will present features and limitations of the accelerometer and the magnetometer to explain why we cannot use raw data for characterizing the user's activities.

The accelerometer

The MEMS accelerometer is a sensor whose acceleration measurements are provided by inertial state changes of the sensor itself. The three-axis accelerometer has been recently integrated in smartphones for a number of games, power management and other context-aware applications. The three-axis accelerometer is able to measure the acceleration of device in three axes (x, y, and z-axis). The three-axis acceleration values are represented by A_x, A_y, and A_z. The accelerometer can expose two main kinds of accelerations on the mobile device: gravity and motion acceleration. There are two kinds of mobile device's activities: static and dynamic activities.

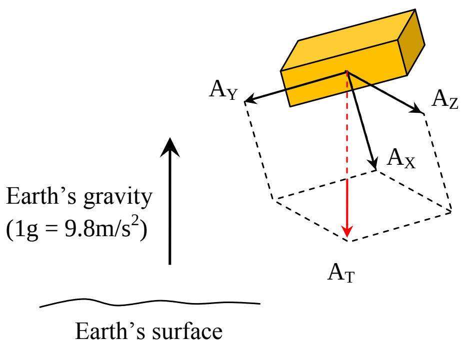


Figure 3.4: Gravity

- When the mobile device is in the static status, its accelerometer is only

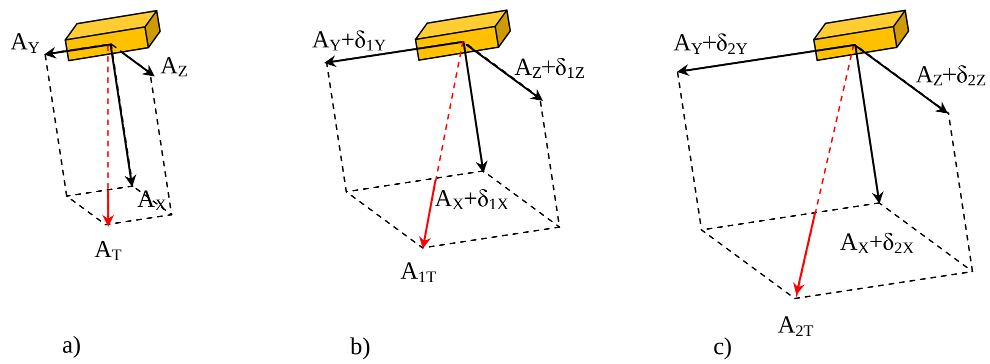


Figure 3.5: The total acceleration in the three activities: Static, Movement, and Unknown; Fig. a: the total acceleration in the Static activity; Fig. b: the total acceleration (with the variance of the acceleration δ_1) in the Movement activity; Fig. c: the total acceleration (with the variance of the acceleration δ_2) in the Unknown activity

affected by the Earth's gravity. The magnitude of the total acceleration value A_T, $A_T = \sqrt{A_X^2 + A_Y^2 + A_Z^2} = 1\text{g}$ (Earth's gravity), is depicted in Figure 3.4

- In the dynamic activity, acceleration values in the three axes (x, y, z) of the accelerometer are changed because the accelerometer is affected by external forces (e.g. the user moves while holding the mobile device in hand). Although the gravity acceleration is always present, its value in three-axis direction is not constant but changes with the three-axis direction of the mobile device. When the user is walking, the three axes of the mobile device are not only affected by the Earth's gravity, but also by the motion acceleration. The acceleration vector of any motions changes dynamically due to the movement phases (Figure 3.5 b, c). The greater the device's motion is, the larger the acceleration vector varies.

Among other existing sensors in the inertial sensors, our work will only deal with the MEMS accelerometer since it provides enough acceleration information to describe the movement. Nevertheless, with the raw acceleration data captured, **is it good enough to accurately measure the quantity of movement ?**

The acceleration information, which is supplied by the accelerometer, is represented as a vector of three elements indicating the acceleration directions. This vector, however, is not the true acceleration on the mobile device because it contains the gravity force. The limitation of the accelerometer is then an ambiguity between the gravity and the motion acceleration [26, 61]. In real movements, the gravity value on the three acceleration axes is not precisely known because the two components (gravity and acceleration) are linearly combined and overlapped both in time and frequency. When we do not know the gravity vector precisely, these two components then cannot be easily separated. If the value of the gravity vector is known, we are able to eliminate the gravity component since it will be a constant on the three axes of the accelerometer. However, determining the gravity component is really difficult in usual movements. Hence, many research works propose a combination of numerous accelerometers and other sensors to remove the contribution of the Earth's gravity. In addition, the acceleration measure is not always favorable since the performance of the accelerometer in smartphones is limited.

The magnetometer

With regard to features of the magnetometer, the magnetic Heading information of mobile devices can be determined (in degrees) from the magnetometer's axes. The Heading information measured in the mobile device is considered as rotational value around the yaw (Z) axis $[0^o, 360^o)$ from the North Pole. The principle of magnetic sensing is to measure the Earth's magnetic field that has a component parallel to the ground surface and points towards the magnetic north.

Although the magnetometer is attractive because of its popularity in modern mobile devices, it has certain drawbacks. In fact, the accuracy of Heading measurements in the magnetometer depends on the device's position (tilted or parallel to the ground surface)[88]. In many handheld applications, the mobile device is usually held in the user's hand or placed in the device pocket. Hence, the tilted positions of the mobile device are changed frequently by the user's activities. That can result in errors of Heading measurements. In addition, the magnetometer is subject to interference factors such as RF signal (caused by RF transmitters, car engines, etc.). The magnetic measurement is thus distorted when the mobile device is close to TVs, cell phones, metal furniture or is inside buildings. Due to the influence of magnetic disturbances or large noises, a number of calibration methods [97, 27, 44] have recently been proposed but they are limited by the inaccurate error estimation.

From the significant challenges of the accelerometer and the magnetometer integrated into mobile device, we propose a method for characterizing the degree of the user's activities in the following Sub-section.

3.3.2 Characterization of the degree of the movement

As using the raw data would be inefficient, so we need to extract features from the raw data. There are many methods of extracting meaningful motion features like mean, standard deviation, signal peak point, and correlation between signals captured. Nonetheless, almost methods work well in constrained situations as the sensors are fixed on objects. The raw data should be processed in order to convey relevant information.

In order to represent the quantity of movement, we use the standard deviation conception, like in [52], to distinguish the user's static status from the dynamic status. In the context of our work where we accept an ambiguity between the gravity and the motion acceleration, signal variations all three axes of the accelerometer have attracted considerable attention. In order to formulate the variance of the acceleration on three axes of the accelerometer, we utilize the signal magnitude vector (SVM) metric, which was used by [60] to detect a fall using data set from a single tri-axial accelerometer unit worn at the hip. In this work, falls occur if the system detects at least two consecutive peaks in SVM above a defined threshold. SVM essentially provides a measure of the degree of movement intensity and is calculated using the following formula:

$$SVM = \sqrt{x_i^2 + y_i^2 + z_i^2} \tag{3.1}$$

where x_i, y_i, and z_i is the i^{th} samples of the x-axis, y-axis, z-axis signal, respectively. By combining with the standard deviation conception, we measure the variance of the acceleration on three axes of the accelerometer. Particularly, the standard deviation value on each axis is calculated and the total value then can describe a quantity of the acceleration variance. The total standard deviation value of the acceleration σ_A is measured as followed:

$$\sigma_A = \sqrt{\sigma_{a_X}^2 + \sigma_{a_Y}^2 + \sigma_{a_Z}^2} \tag{3.2}$$

$$with \;\; \sigma_{a_i} = \sqrt{\frac{1}{N} \cdot \sum_{p=1}^{N} (a_{i,p} - m_{a_i})^2}$$

where σ_{a_i} is the standard deviation value of the acceleration on the i-axis (i = (X, Y, Z)) while m_{a_i} is the mean value of the acceleration on the i-axis. N is a number of samples

Because the mobile device is subjected to an acceleration with varying degrees, the absolute standard deviation value of the acceleration will be greater than 0 (fig. 3.6 b, c). Moreover, when the mobile device is affected by unknown actions such as the mobile device shaken (fig. 3.6 c), the magnitude of the standard deviation value of the acceleration is extremely greater than that in the case of user's normal movement (fig. 3.6 b).

The next sub-section will present the first experimentation for quantifying the degree of movement.

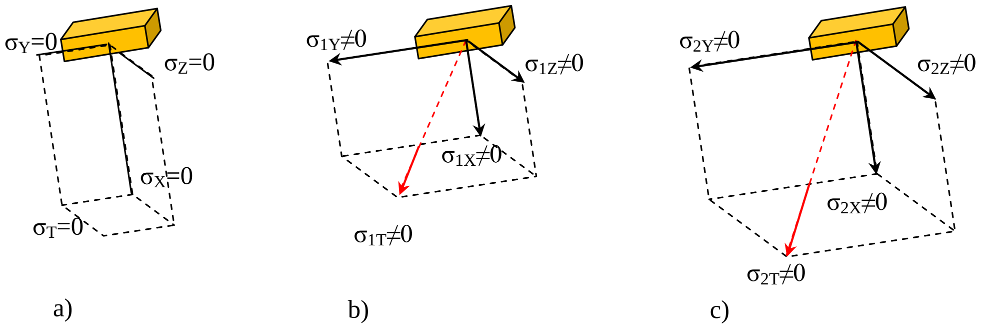


Figure 3.6: The standard deviation of the acceleration in the three cases: Static, Movement, and Unknown; Fig. a, b, c: the standard deviation of the acceleration in the case of Static, Movement, Unknown respectively.

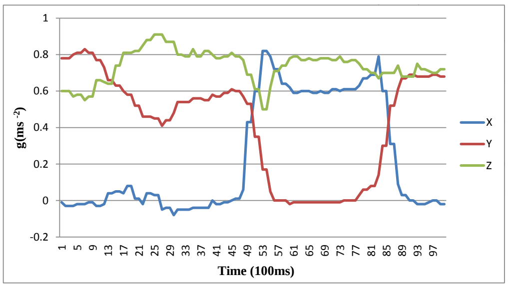
3.3.3 Experimentation for extracting activity features

Collecting data for the experimentation

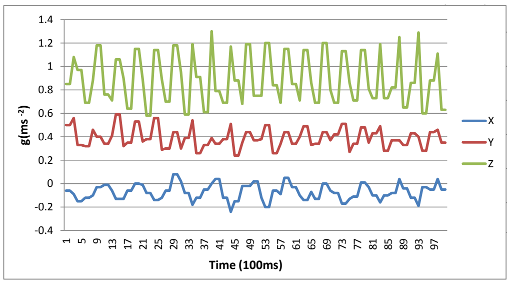
Based on the combination of the accelerometer and the magnetometer, the system measures Forward, Lateral, and Vertical accelerations in the three axes and calculates Heading (H), Pitch (P), Roll (R) values. Pitch describes the rotational angle around the x-axis in $[-180^o$ to $180^o)$ and Roll represents the rotational angle around the y-axis in $[-90^o$ to $90^o)$ of the mobile device. The Heading information is determined by the magnetometer using the Earth's magnetic that considers the North Pole as a reference point. The Heading information measured in the mobile device is considered as rotational value around the yaw (Z) axis $[0^o$, $360^o)$ from the North Pole.

Since most human movements occur between 0.3 and 3.5 Hz [61], the sampling rate of 10 Hz is high enough to capture the user's movement. This sampling rate is in the frequency range from 5 to 20 Hz of the study in [15], which analyzes a trade-off between battery lifetime and classification accuracy for varying sampling rate. Moreover, it is also comfortably within the capability of the smartphone's accelerometer.

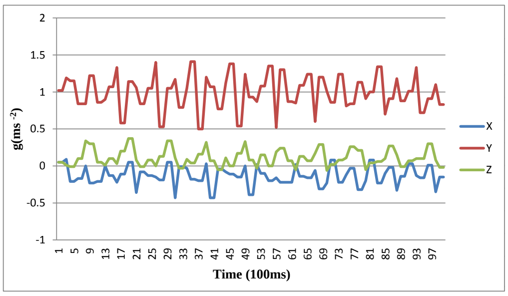
We realize the four tests corresponding to the user's activities (standing, moving, doing arbitrary actions) for capturing raw data. In Figure 3.7a and Figure 3.7b, the user holds his mobile device in hand and looks at the screen while standing and walking, respectively. In the first test, the mobile device stays static and its UI screen is changed twice. The mobile device is placed in the user's device pocket while walking (Figure 3.7c). Finally, Figure 3.7d shows acceleration measurements from the user's arbitrary actions while the device is held in his hand. Raw data is captured at the sampling rate of 10 Hz. The curves of acceleration measurement in each test will be shown as in Figure 3.7:



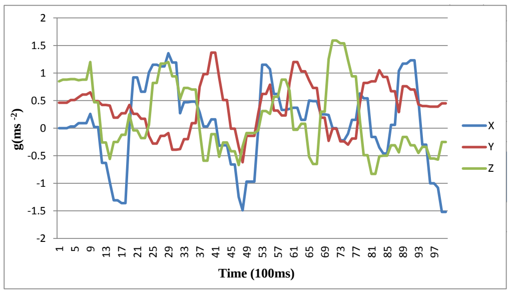
(a) The mobile device stays static in the user's hand



(b) The mobile device is placed in the user's hand when moving



(c) The mobile device is placed in the device's pocket when moving



(d) The mobile device is shaken by the user's arbitrary motions

Figure 3.7: Raw acceleration data in the three axes X, Y and Z of the mobile device in the four tests. Horizontal axis describes the test time by sampling cycles of 100 milliseconds, and vertical axis describes the acceleration data in m/s^2

.

Extracting features of the user's activities

The user's activities will be represented as a sequence of features extracted from the raw acceleration data. Each feature contains continuous samples of the accelerometer and the magnetometer and represents data for during half of a second (500 ms) with a window size of 5 samples. The total standard deviation value of the acceleration for each window is calculated as follows:

$$\sigma_A = \sqrt{\sigma_{a_X}^2 + \sigma_{a_Y}^2 + \sigma_{a_Z}^2} \qquad (3.3)$$

$$\text{with } \sigma_{a_X} = \sqrt{\tfrac{1}{5} \cdot \textstyle\sum_{p=1}^{5} (a_{X,p} - m_{a_X})^2}$$

$$\sigma_{a_Y} = \sqrt{\tfrac{1}{5} \cdot \textstyle\sum_{p=1}^{5} (a_{Y,p} - m_{a_Y})^2}$$

$$\sigma_{a_Z} = \sqrt{\tfrac{1}{5} \cdot \textstyle\sum_{p=1}^{5} (a_{Z,p} - m_{a_Z})^2}$$

where $\sigma_{a_X}, \sigma_{a_Y}, \sigma_{a_Y}$ are the standard deviation values of the acceleration in the three axes X, Y, and Z, respectively; $m_{a_X}, m_{a_Y}, m_{a_Z}$ are the mean acceleration values in the three axes X, Y, and Z, respectively; $a_{X,p}, a_{Y,p}, a_{Z,p}$ are the acceleration values measured at the p^{th} sample in the three axes X, Y, and Z, respectively .

As previously mentioned, raw data captured from sensors is not capable of representing for the user's activities. From the previous experimentation, raw data is transformed into features representing for the standard deviation values of the acceleration. The data set of the four previous tests is shown as the standard deviation values of the acceleration as in Figure 3.8. From these experimentations, there are three kinds of user's activities: *Satic*, *Movement*, *Unknown*.

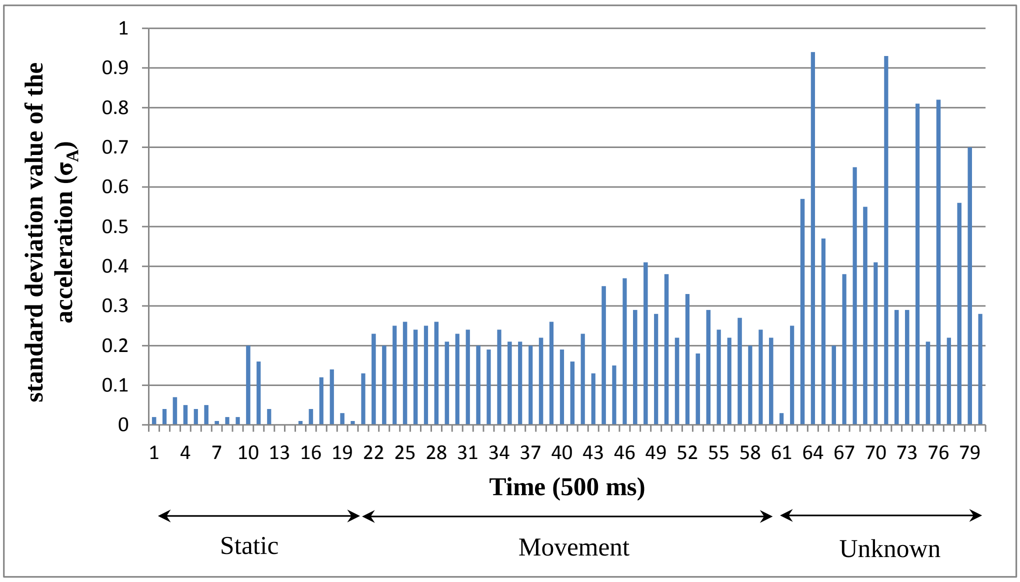


Figure 3.8: The user's activities in experimentations of standing, moving, and arbitrary actions

A glance at the previous figure reveals that the degree of the standard deviation values of the acceleration i different from different tests. We see that when the user is standing still (without any motions), moving, or doing arbitrary actions, the total standard deviation values of the acceleration are around 0, 0.2, or much greater, respectively. However, some noise actions appear in the experimentations of *Static* and *Unknown*. The reason is that the device's UI screen is changed twice in the *Static* experimentation (10^{th}, 11^{th}, 17^{th} and 18^{th} windows). And in the *Unknown* experimentation, some activities make us confused as movement activities (62^{th}, 66^{th}, 67^{th}, 72^{th}, 73^{th}, 75^{th} and 77^{th} windows, etc.). Therefore, in order to estimate the user's movement distance, the system needs to refine movement activities accurately. Before doing this, a solution for classifying the user's activities needs to be applied. The next sub-section will present the proposed phase for classifying the user's activities.

3.3.4 Classification of the user's activities

We categorize all user's behaviors into three different activities (*Static*, *Movement*, *Unknown*). *Static* means that the mobile device stays static; there is no action on the device. *Movement* means that the device is held in the user's hand or the device's pocket when the user is walking. *Unknown* means the user does arbitrary actions (i.e. waving the hand or moving the arms) so that there is a strong impact to the device. Each specific activity (*Static*, *Movement*, *Unknown*) will be appreciated by a total standard deviation value of the acceleration captured from the mobile device. Effectively, the system has to be able to distinguish and recognize each activity among others. That why we need to use Machine Leaning algorithms for processing the data captured by classifying and assigning them to certain classes. Each class describes a specific activity. In theory, a commonly used method is the learning method whose algorithm is to construct a classifier based on a set of training examples. A set of training examples E, which is described as the form (X, y), consists of a set of attribute values $(x_1, x_2, x_3, .., x_n)$ where x_i is the value of the i^{th} attribute of example X and y is the corresponding class label that is considered as a discrete qualitative identifier. The learning algorithm learns to classify class labels from the training data and then this classification result is applied to new observed data.

To classify the collected data, there are actually many existing classifiers: Naïve Bayes, Decision Tree, K Nearest Neighbors, Neural Networks, SVM, etc. **Which data mining algorithm should be suitable for classifying the user's activities in our study ?**

The methods like Neural Networks and SVM are more sophisticated than Naïve Bayes and Decision Tree; whereas Naïve Bayes and Decision Tree do not require a long training process but still achieve a satisfactory result. For small training data with independent assumptions, Naïve Bayes and Decision Tree are very similar in prediction accuracy. For some larger dataset, which many attributes need to be classified, the accuracy of Naïve Bayes does not scale up as Decision Tree. Naïve Bayes has a problem with probabilistic because the probabilistic method is useful to independent assumptions, but the assumptions, in fact, are not really independent due to appearance of some relations. By contrast, Decision Tree can be made even with data containing errors. It firstly examines the most important attribute in the tree construction. Analyzing the base-level classifiers (such as algorithms of KNN, Naïve Bayes, J4.8, etc.), authors in [32] appreciate the decision tree C4.5 performed the best. Besides, the work in [89] compares the performance between the classifiers (Naïve Bayes, Decision Tree, K Nearest Neighbors) and its experimental results show that Decision Tree classifier gets the best accuracy within test samples of static/standing, walking, running, etc. Therefore, the Decision Tree is chosen since it uses a simple set of rules if-then that can be easily interpreted by users. The Decision Tree classifier describes a direct acyclic graph with the form of a tree [11] that represents the classification of data attributes.

After having chosen a classification algorithm, the phase of classification will play the role of identifying the movement activity. A sequence of phases is described in the following Figure 3.9:

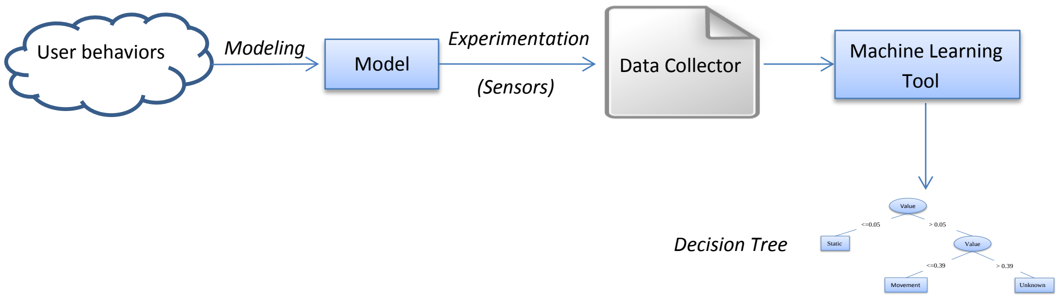


Figure 3.9: Schema of the user activity classification

Classification with the Decision Tree

Similar to the experimentation, we did other eight tests (one when the user is standing still, one when the user does arbitrary motions, three when the user moves with three kinds of speeds: slow, normal, and fast while the device is in the user's hand and the last three tests when the user moves with three kinds of speeds while the device is in the waist pocket). The training data is represented as a form (Activity, Value) and stored in a collected file.

As shown in Figure 3.9, the collected data file is considered as an input data of the machine learning tool for a classification process using the Decision Tree. The Weka tool is chosen as a machine learning tool responsible for classifying the user's activities. The tool WeKa, which is an open-source Java application, is used to bundle features into an interface through which many of the machine learning algorithms can be utilized on preformatted data sets. The Decision Tree J48 classifier, which is based on the algorithm C4.5 [51], is parameterized in the Weka tool. After the training process finished, the resulting decision tree will be shown in below Figure 3.10.

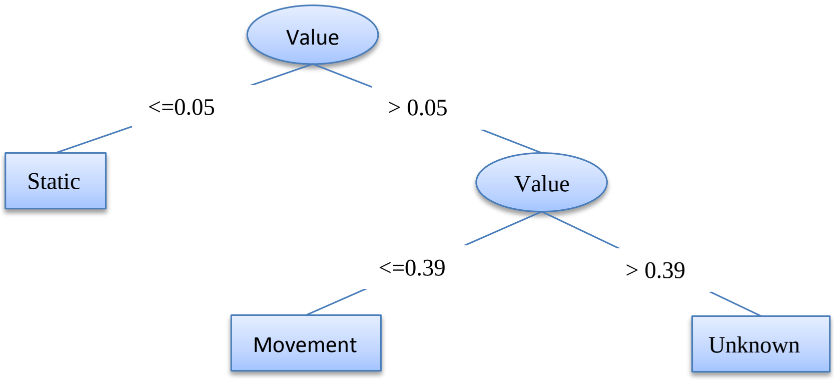


Figure 3.10: The classification of the user's activities is represented as the classification tree

There are three types of nodes in the classification tree obtained from the training data: a root node, internal nodes and leaf nodes. Each leaf node is assigned to one class representing the most appropriate user's activity. Table 3.1 resumes the classification results with 10-fold-cross-validation test mode. The misclassification error is approximately 10%.

Table 3.1: Confusion matrix for 10-folds cross-validation on the J48 algorithm

a	b	c	$\prec$– classified as
66	25	0	a = Static
2	430	18	b = Movement
0	21	56	c = Unknown

After having the classification tree, the threshold values, which are named α and β, are assigned as follows: $\alpha = 0.05$ and $\beta = 0.39$. If the standard deviation value of the acceleration is less or equal to 0.05, the user's activity is considered as *Static*. If the standard deviation value is more than 0.05 and less than or equal to 0.39, the user's activity is *Movement*; finally, if it is more than 0.39, the user's activity is considered as *Unknown*. These threshold values α and β will be used to get experimental results.

3.3.5 Experimental results

Filtering the user's activities

The standard deviation value of the acceleration is used to distinguish between static and dynamic activities. However, dynamic activities are probably not movement activities. As shown in Figure 3.8, there exist some activities making us confused as movement activities in the *Static* and *Unknown* experimentation. In order to assess the activity *Movement* really belongs to the user's movement, it is necessary to utilize additional parameters such as Heading, Pitch, Roll to examine the device's motion. In the smartphone, these parameters, which permit to position the device, are derived from the orientation sensor by processing the raw sensor data from accelerometer and the magnetometer.

Algorithm 1 The noise action filter and the noise action counter

---

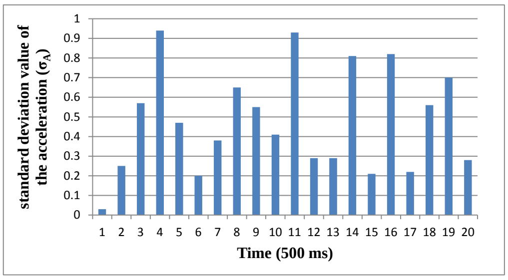
Require: Acceleration, Heading, Pitch, Roll information are measured from the mobile device
  var S_t={True, False}: a Boolean variable that describes the user's activity at the tth window (500ms). S_t= True when $\alpha < \sigma_{At} \leq \beta$, and S_t= False when $\sigma_{At} \leq \alpha$ or $\sigma_{At} > \beta$. True = Movement, False = Static or Unknown
  var σ_{At}: the standard deviation value of the acceleration at the t^{th} window
  var H_t: the Heading information measured from the orientation sensor at the t^{th} window, H_t $[0^o, 360^o)$
  var P_t: the Pitch information measured from the orientation sensor at the t^{th} window, P_t $[-180^o, 180^o)$
  var R_t: the Roll information measured from the orientation sensor at the t^{th} window, R_t $[-90^o, 90^o)$
  var N: the number of noise actions
  while (True) **do**
    if $(\sigma_{At} > \beta)$ **then**
      N ++;
      $S_t == False;$
    end if
    if $((S_t == True)\&((|H_t - H_{t-1}| > 30^o)||(|P_t - P_{t-1}| > 30^o)||(|R_t - R_{t-1}| > 15^o)))$ **then**
      $S_t == False;$
    end if
  end while

From the concept of the user's movement where the user's always walks in the same orientation and keeps the device in the same position most of the time, we accept a deviation of an angle measured to appreciate the device's position.

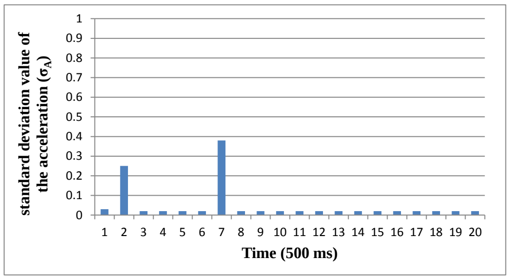
By experiments, the device is considered as staying at the same position if $|H_t - H_{t-1}| \leq 30^o$, $|P_t - P_{t-1}| \leq 30^o$ and $|R_t - R_{t-1}| \leq 15^o$. If the difference of two continuous values of the parameters Heading, Pitch, Roll is beyond these ranges, it is considered that the device's position has been changed. For example, the user swings his hand holding the device can cause confused with the user's movement, but that makes the device's position changed. Hence, of course this activity cannot be considered as a movement one. In summary, the supplementary parameters of Heading, Pitch and Roll allow to eliminate noise actions. The function for filtering noise motions and counting them is represented in the below Algorithm 1:

Experimental results

Experimental results of the previous experimentation (see Sub-section 3.3.5) applied to Algorithm 1 are shown as in Figure 3.11 and 3.12. Horizontal axis describes the test time by sampling windows of 500 milliseconds and vertical axis describes the standard deviation value of the acceleration in m/s^2.



(a) Unknown activities before being filtered



(b) Unknown activities after being filtered

Figure 3.11: Unknown activities before and after being filtered

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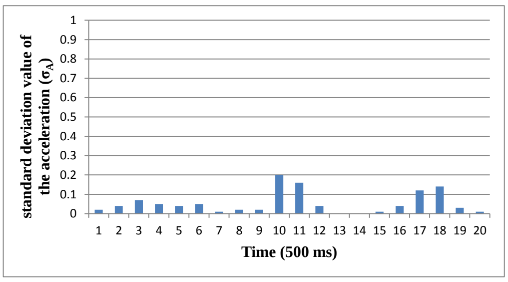
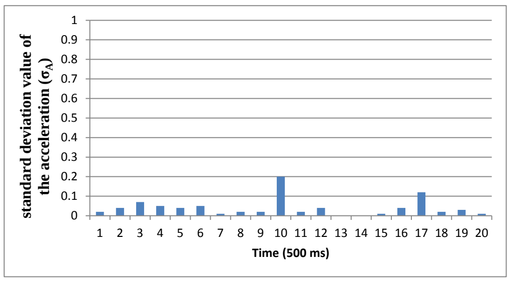


(a) Static activities before being filtered



(b) Static activities after being filtered

Figure 3.12: Static activities before and after being filtered

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One particularly interesting fact highlighted by these figures is that some noise actions are filtered because of the change of the device's positions. Activities of the 11^{th} and 18^{th} windows in Figure 3.12 and activities (66^{th}, 72^{th}, 73^{th}, 75^{th} and 77^{th} windows in Figure 3.11 are filtered.

Measuring the user's movement distance

The user's movement distance is an important parameter for appreciating the feasibility of an inertial approach because errors will be accumulated according to the distance traveled. The proposed approach mainly focuses on determining the user's movement distance. The user is considered as still being in the room if the user's movement distance is negligible. The user's movement distance is only estimated in a relative way to assess the user's actual location. The user's movement distance D is experimentally calculated based on the standard deviation values of the acceleration in the three accelerometer's axes. The time T, which is composed of cycles of half of a second, is the total time of all the user's movement status from the last NFC tagging to the moment of sending positioning request. The user's movement distance D is calculated as the following equation:

$$D = \sum_{t=1}^{T} (\sigma_{At} * K) \qquad (m) \tag{3.4}$$

where σ_{At}: the standard deviation value of the user's movement status on the three acceleration axes at the t^{th} cycle and K: a constant chosen by experiments. The time T is the total time (a set of cycles of half of a second) of all the user's movement status from the last NFC tagging to the moment of sending locating request. The method of measuring the user's movement distance D is resumed as in Algorithm 2:

Algorithm 2 Measure the user's movement distance D

Require: Acceleration data are measured from the mobile device
 var S_t={True, False}: a Boolean variable that describes the user's activity at t^{th} window (500ms). S_t= True when $\alpha < \sigma_{At} \leq \beta$, and S_t= False when $\sigma_{At} \leq \alpha$ or $\sigma_{At} > \beta$. True = Movement, False = Static, Unknown
 var σ_{At}: the standard deviation value of the acceleration at t^{th} window
 var D: the user's movement distance, D is initial 0
 var K: a constant
 while (True) **do**
  if ($S_t == True$) **then**
   $D = D + \sigma_t * K$;
  end if
 end while

It can be seen in Figures 3.13, 3.14, and 3.15, we did three tests to appreciate the feasibility of the previous formula by experimentally measuring the constant K. During the three tests, the mobile device is held in the user's hand and parallel to the ground (Fig. 3.3 a, b) while the user goes straight a distance of 40m with different speeds: slow, normal, and fast, respectively. Noted that when the user walks slowly, the standard deviation values of the acceleration are smaller but the time T is higher than those in the case of fast walking.

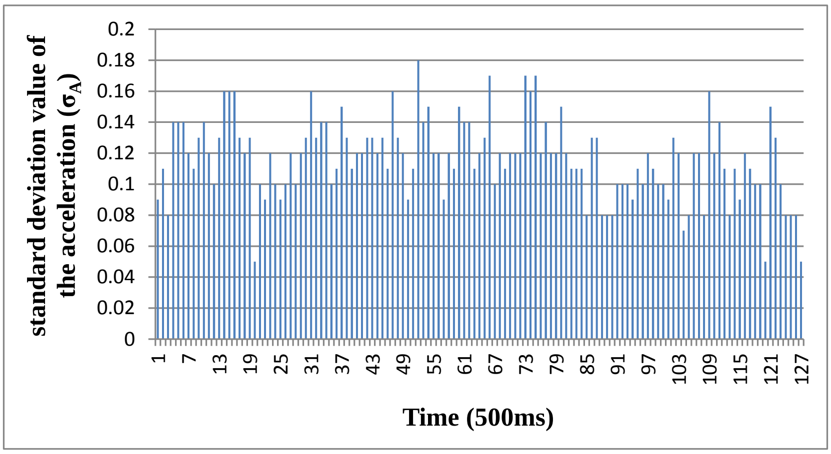

Figure 3.13: Test 1: the user holds the device in his hand and looks at the device's screen when walking with a slow speed

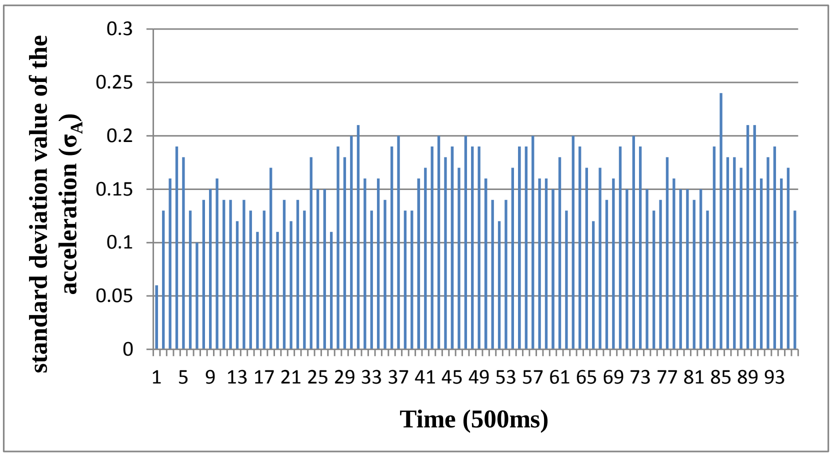

Figure 3.14: Test 2: the user holds the device in his hand and looks at the device's screen when walking with a normal speed

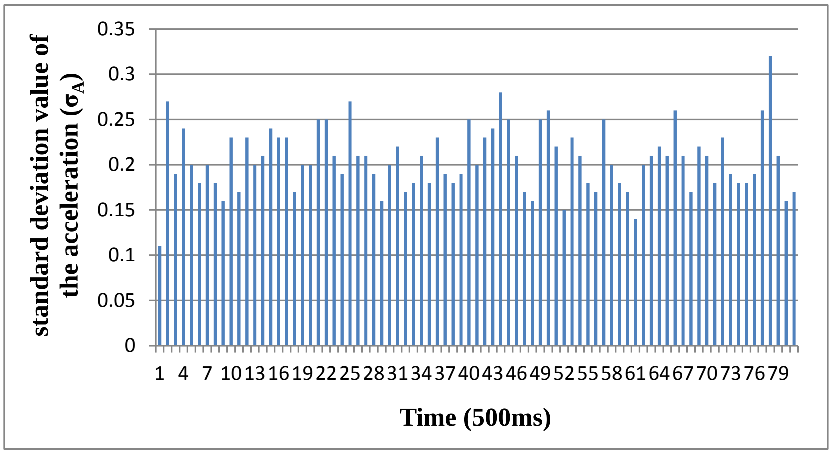

Figure 3.15: Test 3: the user holds the device in his hand and looks at the device's screen when walking with a fast speed

The results of this three test are as follows:
- In the test 1: with $\sum_{t=1}^{T}(\sigma_{At})$ =14.83 , we get $K_3 = 2.7$
- In the test 2: with $\sum_{t=1}^{T}(\sigma_{At})$ =15.39, we get $K_1 = 2.6$
- In the test 3: with $\sum_{t=1}^{T}(\sigma_{At})$ =16.71, we get $K_2 = 2.39$

The object of our study is to calculate relatively the user's movement distance, the constant K is then chosen as an average value, K = 2.5. A small error in determining the constant K is not so important because the movement distance allowed (dozen meters) is much smaller than the test's movement distance (40 meters).

After having the constant K, we can determine the user's movement distance D by the formula 3.4.

Localization decision

As presented in the previous Section 3.2, the short communication NFC technology only ensures to locate the user in a short period of time after tagging an NFC tag. The sensor-based approach estimates relatively the user's movement distance D from the last known location. The last known location is defined by the location of the last tagging NFC tag. Besides, we utilize two parameters for deciding the user's location: the time T and the user's movement distance D. The time T is the period between the last NFC tagging to the present request. The user's movement distance D represents the distance the user has traveled. By combining the time T and the user's movement distance D, the proposed system determines whether the user is still at the same location or has already moved to other location. Particularly, the user is considered still staying at the same place of the last known location if the time T is less than t seconds (see more in Section 3.2) or the user's movement distance D is less than d meters. The threshold values of time t and the movement distance d are predefined according to each application scenario. If the time T and the user's movement distance D are both superior than the threshold values t et d, respectively, the user's last known location is considered invalid. The positioning decision is resumed in Algorithm 3 as follows.

Algorithm 3 Decide the user's location

Require: The threshold values t and d are predefined according to the application scenario
var T: the period of time from the last tagging moment to the moment sending the positioning request
var t: the threshold value of time when the user's location is valid, t is a constant
var D: the user's movement distance from the last tagging moment to the moment sending the positioning request
var d: the threshold value of movement distance that user's location is valid, d is a constant
if $((T <= t)||(D <= d))$ **then**
User stays at the same location
else
User has already moved to other locations
end if

3.3.6 Summary

In summary, raw data is segmented into features with a window size of a half of second. Each window contains 5 samples of acceleration, Heading, Pitch, and Roll. Quantifying the degree of the user's movement at each feature is used for estimating the user's movement distance. Moreover, each feature is assigned to one user's activity like *Static*, *Movement*, or *Unknown*.

The sensors-based approach takes advantages of the existing inertial sensors like accelerometer and magnetometer integrated in the smartphone to measure the movement degree of the users. Because the user holds the smartphone in hand, then the global question of the sensors-based approach is about to characterize the user's activities (*Static*, *Movement*, or *Unknown*) from captured data, and to determine user's movement distance. In this work, we present a solution characterize the user's movement distance. The schema shows the processes of user movement characterization as follows:

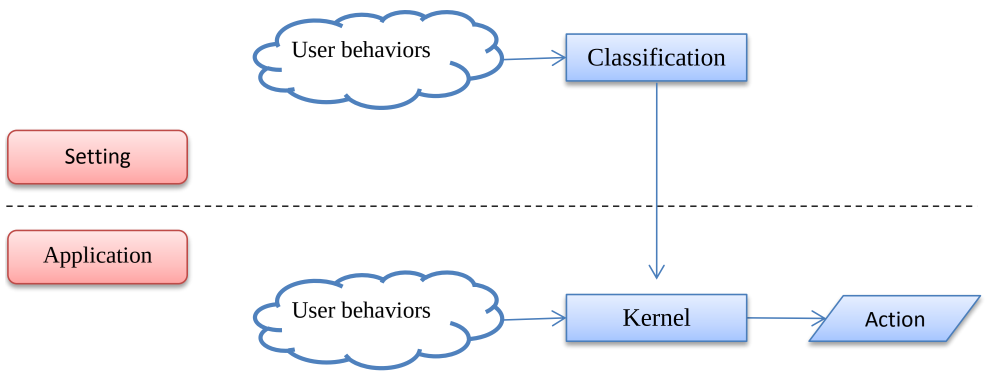

Figure 3.16: Schema of the sensors-based approach

As shown in the previous figure, in the phase *Setting*, raw data is segmented into features with a window size of a half of second. Quantifying the degree of the user's movement at each feature is used to estimate the user's movement distance. Moreover, each feature is assigned to one of user's activities. The Data Mining tool Weka is responsible for classifying the user's observed behaviors into different categories with their threshold values from the Decision Tree. These threshold values will be integrated in the *Kernel* step of the phase *Application*. *Kernel* maps threshold values from Setting phase on tracking data to figure out activity type, then this output will trigger the associated *Action* on the last step to calculate the user traveled distance.

The output data is considered as movement activities that are used in the *Action* step for determining the user's movement distance. From that the proposed approach could decide whether the user has gone out of the latest place.

3.4 Prototype evaluation

The NFC-tagging and sensors-based approaches are implemented on the Android smartphone SamSung Nexus S to run their localization algorithms. For the NFC-tagging approach, the NFC technology supports to get information from a MIFARE classic tag [38]. In order for the tag to be utilized by the NFC technology, this tag is formatted into the NFC standard - NDEF format [39]. Each room in our scenario disseminates several tags, which contains of the room number. Whenever tagging an NFC tag, the accelerometer and the magnetometer are activated for capturing motion data. These data are stored into an external memory for the localization process.

The code source programmed in the smartphone consists of 8 files, which includes 3 Activities, 2 SurfaceViews, 2 Threads and 1 Service. The three Activities are responsible for sending events to the application user interfaces from the

Android program as well as to respond to the possible changes in the device's configuration while the program is running. Each Activity manages one "screen" where the user can navigate from screen to screen. The Intent object provides runtime binding between separate activities. The Service runs in the background and manages long running task such as capturing the data from the accelerometer and the magnetometer. The two SurfaceViews are responsible for calling the onDraw method to show the acceleration graph and scenario map. The two Threads are used to take the data changes from the Service for the onDraw method of the two SurfaceViews to execute. The Thread runs parallel to any other activities. Hence, the data information is regularly updated on the user interface. In order to easily understand the overall scope of the User side program, a visual model is described as a UML diagram (Fig. 2 in the Annexes). The program contains three main components: user interface, monitoring daemon, and data processing. After compiling and building the test project, the programming tool creates an *.apk file in debug mode and it is then installed onto the smartphone by the ADB tool. The size of the application file *.apk is about 588Kb.

After the program starts, the user interface shows an introduction screen (Fig. 3.17(a)). This screen has two buttons: the button "Enter" is to going to the next screen and the button "Exit" is to quit the program. After pressing the button "Enter", the screen contains a graph layout and buttons "Start", "Map", and "Close" (Fig. 3.17(b)). At this moment, there are no data collected. When the button "Start" is pressed, the monitor daemon keeps running in background as a Service in Android. This service is responsible for recording acceleration and Heading measurements from all sensors. The program also graphs the acceleration data and presents in text the acceleration, Heading, Pitch and Roll data. This allows users to see a real-time preview of the sampled data. The actual screen shows the result of the NFC tagging (Fig. 3.17(c)). The *Room_ F* detected from the tag shows that the user is in the Room F of the scenario. At the same time, the accelerometer and the magnetometer start capturing data. The button "Stop" on this screen is to stop the localization system. After pressing the button "Stop", the sensors will stop capturing and stores captured data in memory. At this moment, the screen returns to the previous one (Fig. 3.17(b)). As presented in the previous chapter, when the user likes to known his actual location, he has two solutions from NFC-tagging approach and the sensors-based approach. After pressing the button "Map", the scenario layout will be displayed with the user's valid location (Fig. 3.17(d)). The red circle describes the valid location of the NFC-tagging approach, while the green circle shows the valid location of the sensors-based approach.

(a) The introduction screen (b) The screen of options (c) The data acquisition screen (d) The screen of valid locations

Figure 3.17: The test program of the two proposed system running on the smartphone

Although the program is not a final product, the current application is just a prototype to prove the feasibility and the accuracy of the NFC-tagging approach and sensor-based approach. More works need to be done to consolidate the scalability of these proposed approaches.

3.5 Conclusion

In this chapter, we have presented a localization approach using a combination of the NFC-tagging and sensors-based approach. These proposed approach are feasible because more and more mobile devices are equipped with the NFC technology and inertial sensors. The contribution is to allow aggregating multiple-sensors-based technologies in order to take advantage of each technology.

The approach based on the NFC-tagging can easily be deployed at many kinds of indoor environment and provides a room-level accuracy for locating the user without additional infrastructure or extra sensors. The NFC-tagging, however, could only be used to locate the user in a short period of time. The reason is the fact that location information becomes obsolete if the user stops tagging for a long time. Moreover, the NFC-tagging approach also requires a large number of tags disseminated in scenarios. In short, the localization is decreased on reliability and needs an additional solution to enhance the locating accuracy.

By taking advantage of the existing inertial sensors on mobile device, the sensors-based approach using accelerometer and magnetometer provides a remedy of the drawback of the previous approach. A combination of the accelerometer and magnetometer sensors provides a measure that can be used to estimate the user's movement in the short-term. The advantage of this fusion is that it can provide a bounded-error solution that does not require any additional infrastructure and is robust to signal noise. This approach using a combination of the accelerometer and the magnetometer allows the system to determine the user's movement distance when the user handles the mobile device in the user's hand or in the device's pocket when walking/standing. The contribution of the sensors-based approach is that the standard deviation concept for quantifying the degree of the user's movement. Besides, the approach allows to refine movement activities by filtering noise actions. The user's movement distance is utilized as an importance parameter for deciding the user's actual location. Initial experiments showed that it can determine whether or not the user is still staying at the same place from the last tagging as well as estimate the user's trajectory within a short movement distance. Either if the user's movement distance is longer than a predefined threshold or if the system detects a large number of noise actions, another approach should be applied for improving the actual localization service.

The next chapter will present the signal-strength-based approach using the similarity of radio conditions related to the user's neighbors.

Chapter 4

Indoor localization system using the similarity of radio conditions related to the user's neighbors

4.1 Introduction

The two previous chapters have shown how the proposed indoor localization approaches using NFC technology and sensors (accelerometer and magnetometer). Thanks to the beneficial properties of these technologies integrated in the recent smartphones, it shows simplicity and an effective way in implementing an indoor localization system. Developed from the simple methods without any additional infrastructures, the two proposed approaches could ensure the room-level accuracy. However, the NFC-tagging approach is limited by a period of time via the last reading of an NFC tag. The sensors-based approach has a limitation of the movement distance caused by noises from the user's activities. In order to overcome these restrictions, we propose an approach using the similarity of radio conditions related to the user's neighbors.

Firstly, we explain why the WLAN is popular in the indoor environments. In fact, WLAN is known for its cost and performance. The data speed can reach to 54 Mbps or 300 Mbps for 802.11n. In addition, the WLAN communication range is about tens of meters indoor up to about a hundred meters outdoor. This allows the Access Points (APs) to cover multiple rooms and floors in a building and the user's mobile devices then can easily capture the non-LOS signal from theses APs, and vice versa.

Secondly, the WLAN-based localization systems have some advantages compared with other systems. WLAN devices are less expensive and more available than localization systems such as cameras, Ultrasound, and laser rangefinder systems because WLAN infrastructure has already existed for data transmissions.

Most of existing WLAN-based localization systems use the RF signal strength to estimate the distance between the receiver and the transmitter. The WLAN card can simultaneously capture signal strength information at a packet level from a large number of APs. The position estimation is obtained by correlating the signal strength measurements at different APs. Thus, many existing WLAN-based indoor localization systems implement different ways to capture signal strength information from APs as well as different methods for calibrating signal data and executing localization algorithms.

The closest related work to our proposed approach is the RADAR system. This system is known as using a fingerprint technique to build signal strength vectors. Each signal strength vector, which is called as a fingerprint, corresponds to each location in buildings. A set of fingerprints will build up a signal strength map. The construction of the signal strength map in the RADAR system is executed in the off-line phase by manual measurements. The technicians have to go to all corners in the building for measuring the signal strength information. In fact, the cost for the off-line phase and training time could rapidly increase as the scenario becomes larger. Moreover, storing in advance WLAN-based fingerprints in a database would affect the quality of the localization service in real scenario. The reason is that the electromagnetic environment varies over time with the environmental changes and the user's movement. In short, the fingerprint technique consumes much time and efforts for the empirical construction of the signal strength map and the signal strength map is not updated as often as the environmental changes. Plus, this technique encounters some privacy issues during the off-line phase.

Contributions:

Through our research, we construct a signal strength map for WLAN-based indoor localization without utilizing the constructing manner of the fingerprint technique. In order to construct a signal strength map, we combine the WLAN network with the NFC technology. WLAN network plays the role of capturing the signal strength from APs and NFC is responsible for retrieving the location information at the user's actual place. This combination allows accurately assigning the signal strength information captured to the known location on the map. The goal of this solution is to replace the off-line phase of the fingerprint technique.

In addition, the signal-strength-based approach allows automatically constructing the signal strength map. The interesting thing is that the signal strength map can be updated regularly according to the change of electromagnetic environment during the operation. This permits to improve an estimation error that commonly occurs in the fingerprint technique. This error is caused from a big gap between actual measurements and measurements stored in the database.

The signal-strength-based approach uses the similarity of radio conditions between neighbors to determine the user's location. A user retrieves the location information using the NFC technology. Particularly, the user's mobile device reads a tag to know his actual location. His mobile device evaluates simultaneously radio condition at the user's actual context by capturing all Access Points' signal strength information before sending them to the Server. The locations' information is stored in the device and the Server for the localization process. If every user in the building does this, a signal strength map is then constructed. Therefore, the user's location would be determined by the signal strength information of neighbors.

This chapter is divided into following sections: Section 4.2 presents the indoor localization approach using the similarity of radio conditions between the user's neighbors. Next, Section 4.3 and 4.4 provides steps for simulating and implementing the proposed approach, respectively. Finally, we conclude and compare the localization performance of the proposed approach with the RADAR and Redpin systems in Section 4.5.

4.2 Signal-strength-based indoor localization approach

The signal-strength-based approach uses a signal strength map for locating the user in the indoor environment. Our contribution is to combine the WLAN technology with the short-range communication network to implement an indoor localization system. Among existing short range communication networks such as Infrared, Bluetooth, and RFID/NFC, we choose NFC technology because it has been recently developed and is integrated in many smartphones with large applications and in particular it is already used for the indoor localization approach in Chapter 3.

The main disadvantages of approaches in previous chapters are that the locating reliability is decreased over time or is affected by the user's motions such as the user's unknown actions. Although the NFC-technology-based approach is simple for implementation, the user needs to tag an NFC tag regularly to update the location information. Besides, the sensors-based approach bases on the initial location, which is defined by an NFC tagging, to estimate whether the user still stays at the same location or has already moved to other location. Particularly, the sensors-based approach appreciates the user is not still at the last defined location if (1) the system detects so many noise motions of the user or (2) the user's movement distance is greater than an allowed threshold. In this case, the system needs to change to another approach using the similarity of radio conditions, which are related to the user's neighbors.

The principle of our proposed approach is to allow the user's mobile device to detect a "neighbor terminal" that has recently read an NFC tag. Suppose that the NFC tags are disseminated in rooms of a building. For evaluating the users' proximity, we use the similarity of radio conditions: two terminals are considered as neighbors if (1) both devices are attached to the same WiFi Access Points and (2) the measured radio signal strengths are approximate to each other. The signal-strength-based approach is elaborated as follows:

1. Whenever a user reads an NFC tag, the user can know his actual location and his mobile device evaluates simultaneously radio conditions at the user's actual context by capturing all Access Points' signal strength information before sending them to the Server. The location information is stored in the device and the Server until the user's location becomes invalid.

2. After tagging a tag, the mobile device activates the accelerometer and the magnetometer. The timer is also activated to count the time for evaluating the valid location. The device captures data from them. These data will be utilized to determine either the user is still in the room or out-of-range (see more in Chapter 3).

3. When the user is not available from the last defined location, the mobile device evaluates radio conditions of the user's actual context and sends them to the Server. The Server then executes our proposed algorithm 4 that evaluates these values to other local ones associated with other users. This step results in the user's possible location.

Our signal-strength-based approach does not address to the fingerprint techniques and learning machine algorithms, we instead use NFC technology to identify the user's actual location where the radio conditions are attached. This principle allows constructing a signal strength map without requiring the off-line phase. The NFC tags, which consist of location information, are disseminated to every room in the building. Whenever the user's mobile device tags an NFC tag, the device not only reads information from the NFC tag, but also it captures radio conditions at the user's actual context and sends them to the Server. Thus, the signal strength map on the Server is updated regularly. This procedure is described as Figure 4.1:

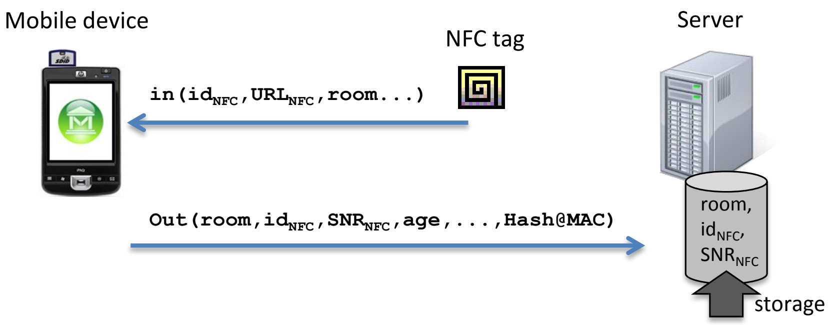

Figure 4.1: The mobile device captures and sends the radio conditions to the Server after tagging

The radio conditions at the user's actual context are represented as the ones at an NFC tag's location: $SNR_{NFC} = \{SNR^1_{NFC}, SNR^2_{NFC}, ..., SNR^P_{NFC}\}$, with P is the number of Access Points in the indoor environment. When an AP$_i$ is out of range, the corresponding $SNR^i_{NFC} = 0$ (see Figure 4.2).

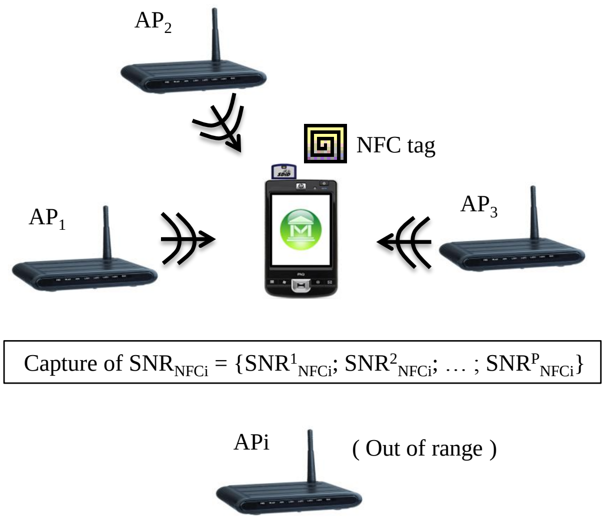

Figure 4.2: Gathering the radio conditions

On the Server's side, the NFC tag's information stored in the database consists of:

- Identification of the user and the NFC tag: ID_U, ID_{NFC}
- Signal strength: $SNR_{NFC} = \{SNR^1_{NFC}, SNR^2_{NFC}, ..., SNR^P_{NFC}\}$
- NFC tag's location: *room*

When the user is no longer localized, the user sends a positioning request with all information (ID, signal radio conditions SNR_U) to the Server. The Server performs the localization algorithm 4 (will be elaborated later), which estimates the best position where the user is likely to be. The algorithm compares the user's radio conditions (SNR_U) and those at the NFC tag's locations, which are stored in the Server's database (a set of SNR_{NFC}). After that, the algorithm generates a list $NFClist$ by collecting all valid locations whose SNR information measured that must be satisfied the SNR condition: the value SNR_{NFCi} at the NFC_i tag are approximately equal to SNR_U with an acceptable error δ_{SNR}. The SNR condition is also represented as follows: $(\forall p, 1 \leq p \leq P, SNR^p_{NFC_i} \in |SNR^p_U \pm \delta_{SNR}|)$. Therefore, we have three steps that can be used to estimate the user's location as below:

1. Among valid positions in $NFClist$, we obtain N positions in the room $Room_N$, M positions in $Room_M$,... that are described as ($NNFC_{Room_N}$, $MNFC_{Room_M}$,..., $KNFC_{Room_K}$). If it only exists one room $Room_N$ whose the number of valid positions N is the maximum value, the Server then can determine that the user is available in $Room_N$.

2. If it also exists another room $Room_M$ that has the M valid positions in $NFClist$ and N, M are the same highest value, the Server will determine which room has the minimum standard deviation (SD). The minimum SD of two rooms $Room_N$ and $Room_M$ is described as σ_N and σ_M, respectively:

$$\sigma_N = \frac{1}{N} \cdot \sum_{i=1}^{N} (\sqrt{\frac{1}{P} \cdot \sum_{p=1}^{P} (SNR^p_{NFC^i_{Room_N}} - SNR^p_U)^2}) \tag{4.1}$$

$$\sigma_M = \frac{1}{M} \cdot \sum_{j=1}^{M} (\sqrt{\frac{1}{P} \cdot \sum_{p=1}^{P} (SNR^p_{NFC^j_{Room_M}} - SNR^p_U)^2}) \tag{4.2}$$

   where P is the number of Access Points; p is one of the APs in range $p = 1, \ldots, P$; i, j is one of the valid NFC tags: $i = 1, \ldots, N$ and $j = 1, \ldots, M$

3. Otherwise, the Server will determine the user's location from the list of valid locations of all rooms. The user is considered to be available in the room $Room_K$ where a valid location has the minimum SD; meaning that $NFC^i_{Room_K} \in NFClist$ and σ_K is min:

$$\sigma_K = \frac{1}{K} \cdot \sum_{i=1}^{K} (\sqrt{\frac{1}{P} \cdot \sum_{p=1}^{P} (SNR^p_{NFC^i_{Room_K}} - SNR^p_U)^2}) \tag{4.3}$$

Note that the user's location is determined as Unknown if the Server could not find any available locations. All above-mentioned steps are presented in the following algorithm 4:

Algorithm 4 Indoor localization using the similarity of radio conditions related to the user's neighbors

Require: Server has received SNR_U
Require: P Access Points are deployed
  var NFClist : set of valid locations
  var K NFC_{Room_k} : set of K NFC tag in the Room_k
  $NFClist \leftarrow \emptyset$
  for all NFC_i such that $SNR_{NFC_i} \in (SNR_U \pm \delta_{SNR})$ **do**
    $NFClist = NFClist \cup \{NFC_i\}$
  end for
  if $card(NFClist > 0)$ **then**
    if $((\exists!\ N :\ N\ NFC_{Room_n} \in NFClist)\ \&\&\ (N\ is\ max))$ **then**
      return $Room_n$
    else if $((\exists\ N\ NFC_{Room_n} \in NFClist)\ \&\&\ (\exists\ M\ NFC_{Room_m} \in NFClist :\ M = N)\ \&\&\ (N,\ M\ is\ max))$ **then**
      for all $N\ NFC_{Room_n},\ M\ NFC_{Room_m} \in NFClist$ **do**

$$\sigma_N = \frac{1}{N} \cdot \sum_{i=1}^{N} \left(\sqrt{\frac{1}{P} \cdot \sum_{p=1}^{P} (SNR^p_{NFC^i_{Room_n}} - SNR^p_U)^2} \right)$$

$$\sigma_M = \frac{1}{M} \cdot \sum_{j=1}^{M} \left(\sqrt{\frac{1}{P} \cdot \sum_{p=1}^{P} (SNR^p_{NFC^j_{Room_m}} - SNR^p_U)^2} \right)$$

      end for

$$\textbf{return} \begin{cases} Room_n & \text{if } \sigma_N\ is\ min \\ Room_m & \text{if } \sigma_M\ is\ min \end{cases}$$

    else
      for all i such that $NFC_i \in NFClist$ **do**

$$\sigma_K = \frac{1}{K} \cdot \sum_{i=1}^{K} \left(\sqrt{\frac{1}{P} \cdot \sum_{p=1}^{P} (SNR^p_{NFC^i_{Room_k}} - SNR^p_U)^2} \right)$$

      end for
      return $Room_k$ if $\sigma_K\ is\ min$
    end if
  else
    return *Unknown Location*
  end if

4.3 Simulation

In this Section, it illustrates the experimental results and simulation performance in terms of signal-strength-based approach through the similarity of the radio conditions. We first construct the framework, configuration, and then simulation results, respectively.

4.3.1 Simulation framework

Assume that the Access Points are guaranteed to the connectivity of the nodes and the server. The NFC tags are distributed for every room in the simulation scenario. The OPNET 14.0 simulation tool [6] is utilized to provide a comprehensive simulation environment to model and analyze the WLAN infrastructure. The description of the simulation framework is presented in Figure 4.3.

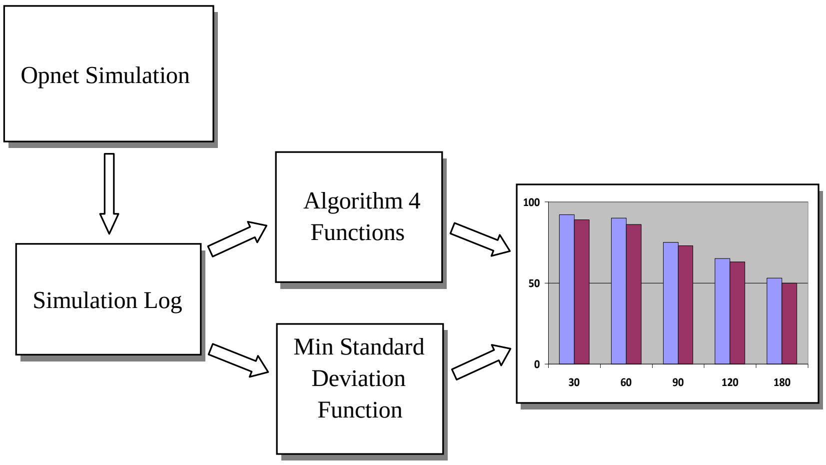

Figure 4.3: Description of the simulation framework

The experimental simulation describes the localization accuracy of the proposed approach in terms of the deviated time. The deviated time at an NFC tag is a fixed value that describes a period of time between the two sequent NFC taggings. In order to evaluate the performance of the proposed approach, we compare the performance of the proposed localization Algorithm 4 and the approach using the minimum standard deviation method. The proposed Algorithm 4 mainly executes the comparison of number of valid locations in each room. If many rooms (more than two rooms) have the same highest number of valid locations, the minimum standard deviation method is applied for determining the valid location that has the minimum SD.

After running the simulation on the OPNET simulator, the simulation log is then used as an input data for localization methods. The two methods are considered: the minimum standard deviation method and the algorithm 4. The performance of two methods is appreciated by a number of possible locations. This number is used as an input of graphs of performance analysis. The two executing methods: the minimum standard deviation method and the algorithm 4 are programmed by C++.

4.3.2 Simulation configurations

The basic features of the topology configuration are described as follows: the simulation area of (100x100) meters, one video conferencing Server, three APs and the simulation time of 30 minutes. The WLAN technology is WiFi IEEE 802.11g [10]. We assume that the simulation area contains of 100 rooms that each room has five predefined positions. The simulation network consists of three APs, one Switch, one video conferencing Server, and mobile nodes. Besides, there are two network topologies with 72 mobile nodes and 102 mobile nodes.

4.3.2.1 Parameters of the Access Points, the mobile nodes and the video conferencing Server

The mobile nodes are evenly distributed on the entire the simulation area and they can access to the resource of the Server via a particular AP. The configuration of three APs and the WLAN nodes in the simulation is described as Tables 4.1 and 4.2, respectively.

Date Rate (Mbps)	54
Physical characteristics	Extended Rate PHY (802.11g)
BSS Identifier	123 ; 456 ; 789
Channel	1 ; 6 ; 11
Transmit Power (W)	0.2
Packet Reception-Power Threshold (dBm)	-95

Table 4.1: Parameters of the WLAN Access Points AP1, AP2, AP3

Date Rate (Mbps)	54
Physical characteristics	Extended Rate PHY (802.11g)
BSS Identifier	123 ; 456 ; 789
Channel	1 ; 6 ; 11
Transmit Power (W)	0.005
Packet Reception-Power Threshold (dBm)	-95

Table 4.2: Parameters of the WLAN mobile nodes

In order to create the applications for the wireless service, a video conferencing service is configured into the simulation. The video conferencing service parameters are set as follows: the type of the service of Best Effort service with the rate of 2 frames/second and every frame of 5000 bytes for the input and output video stream. The video conferencing service will play an important role for providing service to the nodes. The configuration profile of the video conference service is described in Table 4.3.

Attribute	**Value**
Name	Video Conferencing (Light)
Start Time Offset (seconds)	Constant (30)
Duration (seconds)	End of Profile
Inter-repetition Time (seconds)	Constant (500)
Number of Repetitions	Unlimited
Repetition Pattern	Serial

Table 4.3: Profile-configuration attributes of the video conferencing service

4.3.2.2 Mobility of mobile nodes

Mobile nodes are divided into three groups: the first and second groups move on the predefined path for collecting the SNR information, the third group moves on Random Way Point (RWP) as described in [23, 69].

Regarding the first and second groups, the purpose is to take SNR traces from the simulation for the test. The first and second group moves on the predefined trajectory. The predefined trajectory contains stops, which are situated at the predefined positions. Suppose that each room has five stops. For example, in the museum, since each room has several NFC tags deployed for the user to gather information, the NFC tags' locations are corresponding to the objectives' positions such as statues, paintings, etc. Thus, each NFC tag's location corresponds to a stop on the simulation area. The first group moves with velocity v = 0.5 m/s and has a ceasing period around 5 seconds at each stop for capturing SNR values from the APs. This means that whenever the user's device reads an NFC tag, it captures radio conditions in the surrounding area and then sends them to the Server.

The difference between these two groups is that the SNR information captured by the first group is used as the initial data stored in the database, while the one captured by the second group is used as the data of a positioning request. The Server will utilize the two SNR data for the positioning process. Note that the first group starts before the second group a period of time. This period of time is called as the deviated time between groups. Therefore, the deviated time describes the difference of arrival time to a position of two groups. This is one of parameters for evaluating the performance of the proposed approach.

With regard to the third group, mobile nodes are initially uniformly distributed in the pre-defined simulation range. Then, they move in directions and distances randomly with a constant speed v = 0.5 m/s. Upon arrival, mobile nodes cease approximately 60 seconds before turning to the next movements. The second group generates the interference that can intentionally influent to the first group during the testbed.

4.3.2.3 Signal-to-Noise Ratio measurement

The SNR information is the ratio of the average power of the information signal to the accumulated average power of all background and interference noise sources [8]. The SNR information's formula is formulated as follows.

$$SNR = 10log_{10}[P_r/(P_b + P_i)] \tag{4.4}$$

where P_r = Reveiced Power (watts), P_b = Background noise (watts) , P_i = Interference noise (watts)

In OPNET, the P_r is calculated by using the path loss model in the free space propagation as shown in Subsection 2.4.2.1), and it takes all valid and noise packet. P_b is obtained from the sum of the power of noise sources which are measured at the receiver's location and channel's band. P_b is composed of different noise sources, such as thermal noise, emissions from neighboring electronics, etc. The interference noise occurs only when two packets are simultaneously present at the same receiver.

An example of the SNR information captured on the 100 positions is given by Figure 4.4:

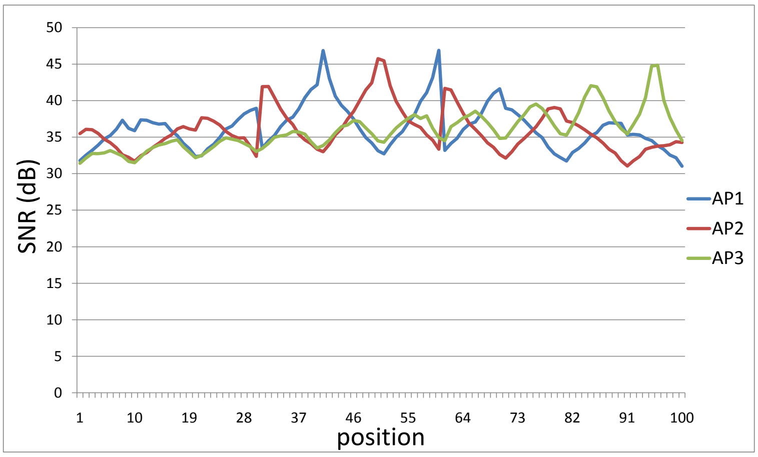

Figure 4.4: The SNR values of a group with the predefined trajectory

The group of 3 nodes moves on the predefined trajectory. Each node operates on a frequency of the AP corresponding. The graph shows the variation of the SNR values captured at each position. When the node approaches the AP, the SNR value increases and vice versa.

4.3.3 Simulation results

In Opnet, there are two ways to collect the statistical data: (1) collecting from individual nodes in the network (named object statistics) and (2) collecting from the entire network as a whole (named global statistics). In our simulation, object statistics are chosen to collect nodes' SNR information.

In order to evaluate the performance of the proposed algorithm 4, we consider two important factors that express the influence in the environment to the localization accuracy: the deviated time between groups (30s, 60s, ..., 300s) and the number of mobile nodes (72 and 102 nodes). By examining the radio conditions between the user's neighbors, we use the two proposed methods: the first method uses the minimum standard deviation, and the second method (Algorithm 4) does the comparison of number of valid locations in each room of the scenario. Both of them are responsible to determine the most capable users' locations in room-level accuracy. The all chosen locations from the two methods are utilized to evaluate their performance.

For each scenario, we perform three simulations, then, we obtain the mean value of three simulations for our evaluation. The comparison between the Algorithm 4 and the minimum standard deviation is illustrated in Figure 4.5 and Figure 4.6, respectively. As can be seen that the localization accuracy is decreased gradually as the deviated time increases. The reliability of the localization accuracy is highly appreciated to the deviated times is less than 90 seconds. The simulation results show the efficiency of Algorithm 4 that can achieve roughly 50% accuracy if the deviated times more than 120 seconds and it is better than the minimum standard deviation method.

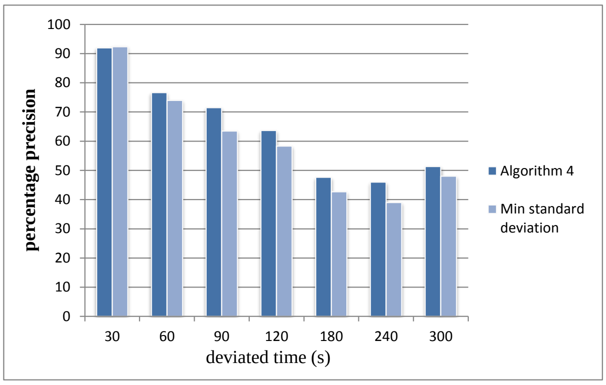

Figure 4.5: Comparison between Algorithm 4 and the minimum standard deviation method in the scenario of 102 nodes

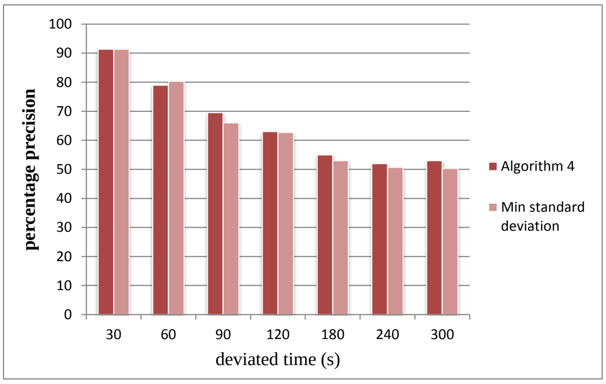

Figure 4.6: Comparison between Algorithm 4 and the minimum standard deviation method in the scenario of 72 nodes

Figure 4.7 presents the simulation results for two sets of mobile nodes (72 and 102 nodes). In the case of the deviated time is less than the threshold of 90 seconds, Algorithm 4 gives out the good results: with over 70% position accuracy. As the deviated time is extended, the percentage of localization accuracy is degraded. The results of the simulation with 102 nodes is slightly better than 72 nodes as can be seen in Fig. 4.7.

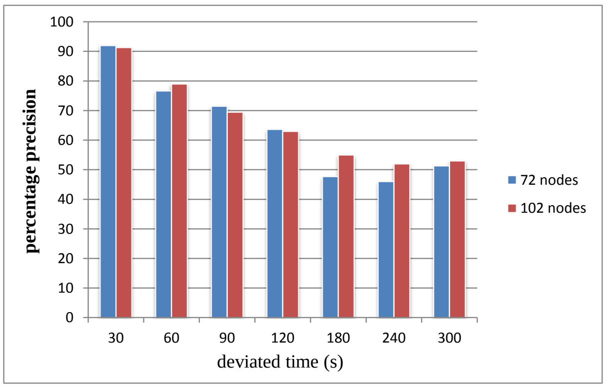

Figure 4.7: Simulation results of the proposed algorithm

From the obtained results, we can conclude that the density of nodes and the deviated time between neighbors significantly impact to the simulation quality. The mobile node's mobility leads to changes of radio conditions in the surrounding environment. Depending on the specific network topologies, a moderate density of nodes will not be strongly influenced the localization accuracy. Besides, the deviated time can affect the localization accuracy when it is extended. Furthermore, the simulation results have also proven that the performance of the proposed approach is not strongly influenced by the environment with a high density of nodes as well as the performance still remains good when the environment changes.

The next section will describe the implementation of our proposed localization approach using the similarity of radio conditions related to the user's neighbors.

4.4 Prototype evaluation

In this Section, we describe the implementing environment through testing the proposed signal-strength-based approach. This Section will be present the characteristics of the implemented approach and the experiment results.

4.4.1 Test-bed setting

Test-bed environment is established on the 3rd floor of the building E of the INRIA (National Institute for Research in Computer Science and Control) in the University of Rennes 1.

The test-bed setting categorizes the user's context into 3 parts:

1. Signal strength map: represents a map of rooms where each room is characterized by private features, such as identification, SNR information. The user's location is specified in room-level identification and it is determined from the Algorithm 4. The regular update of the signal strength map is a highlight of our

indoor localization system after a tagging. Thus, the signal strength map can adapt to the environmental changes.

2. Activity: is defined by two characteristics, including the user's movement and the NFC tagging. The user's movement is characterized by the user's activities, even arbitrary motions. The NFC tagging is an action that the user takes the smartphone close to an NFC tag to read an object's information.

3. Connectivity: describes the current network connection through the WiFi and NFC connection for data communication.

In the floor layout as can be seen in Figure 4.8, there are six rooms which are utilized for testbed. The floor layout is landmarked from A to I, corresponding to the inside rooms and the corridors. The dimension area of each room is around 4 x 5 m^2. The landmarks of B, E, and H are called corridors near the room entries.

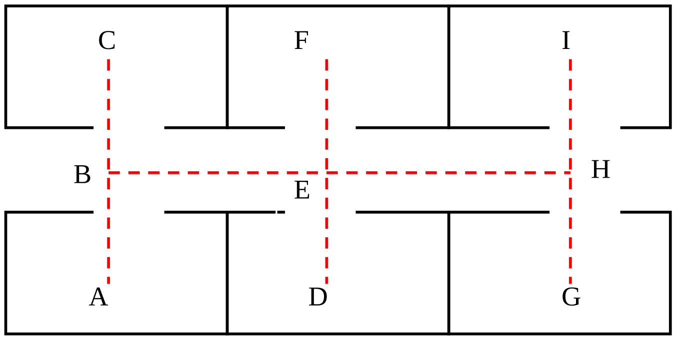

Figure 4.8: The floor layout of the testbed

In the experiment, we choose three WiFi networks: NETGEAR, iwifi-interne, and wifsic. The rest of this Section presents the Client side and the Server side. A smartphone SamSung Nexus S with the Android software stack is used as a Client device, and a laptop is used as Server for receiving data from Clients and for executing the localization algorithm. The test program is written in Java with Eclipse INDIGO and Android 2.3.3 SDK.

4.4.2 User side

On the User side, the proposed approach is implemented on the Android smartphone for executing the localization algorithm 4 by using the NFC tagging and the signal strength information on the WLAN. The NFC technology supports to get information from a Mifare classic tag. The NFC reader is already built in the smartphone. Thus, the user can use his smartphone to read the information on the NFC tag associated to the object/location in the predefined room. Moreover, each room disseminates the NFC tags in which contains the tags' actual location information. Figure 4.9 shows how our scheme can be able to update the signal strength information into the server's database. Whenever the user reads an NFC tag, the smartphone captures simultaneously radio conditions at the user's actual context. The signal strength information measured is associated to the actual location of the NFC tag. Finally, this information is sent to the Server.

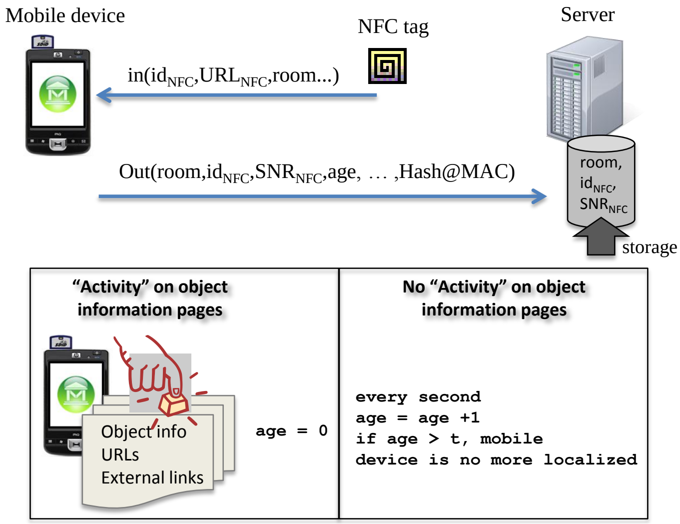

Figure 4.9: The updating signal strength information scheme on the Server database

Using a combination of NFC reading / WLAN connectivity, the system allows the Server to acquire the user's context (such as the signal strength information) at the NFC tag's location. A tuple *Out* is automatically published by the smartphone after capturing the user's context: $\text{Out}(room, id_{NFC}, SNR_{NFC}, age, ..., Hash@MAC)$ where

- id_{NFC} is identification of the NFC tag
- SNR_{NFC} is the signal strength describing the user's context
- URL_{NFC} is external link for getting more information
- $room$ is location parameter that points out the user's actual location
- age is a counter indicating if the user's location is still valid or not
- $Hash@MAC$ is a hashed value of the WiFi physical address of the device. Hash function is used to guarantee the user's anonymity (login is not used), and it is utilized by the Server to identify smartphones

In order to assess the mean variations in signal strength, we performed an experiment to measure the signal strength on a smartphone. The statistical data have been collected from 19:08 on 8 November 2011 to 19:12 10 November 2011 at the room A as in Figure 4.9. Each sample is an average value during 10 seconds. More than 17.000 samples have been collected from the smartphone SamSung Nexus S. The sensitivity of these Android phones ranges from - 45 dBm to -104 dBm. The signal strength is divided into 10 levels (from 0 to 9) by the function *WifiManager.calculateSignalLevel* of the Android library. Figure 4.10 shows the received signal level from three Access Points.

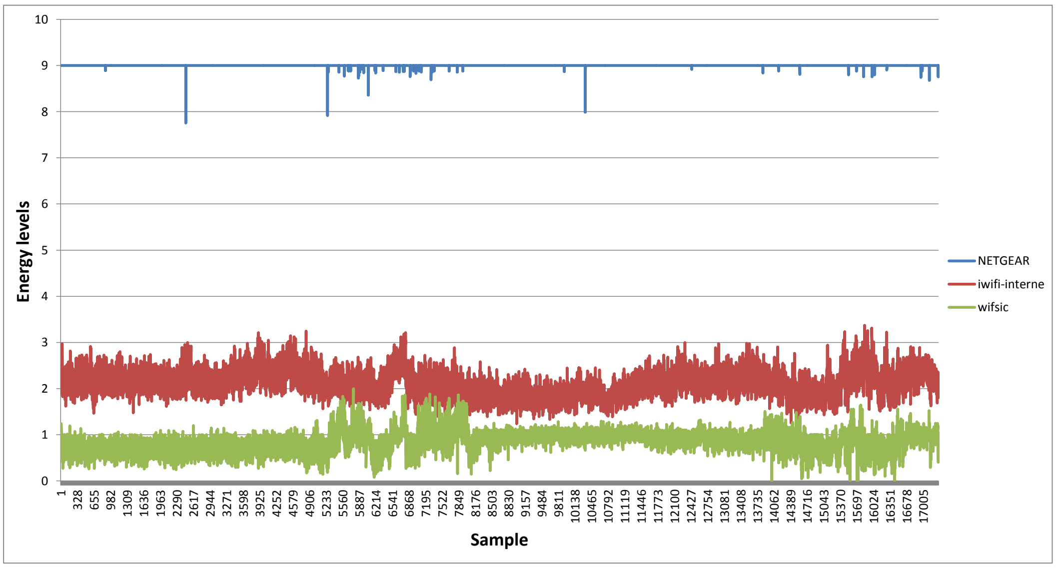

Figure 4.10: Signal strength level captured from the smartphone during the collection period

From the previous figure, it can be seen that the signal strength measurements keep stable during the absence of people. This happens in the hours between 19:00 on 8 November 2011 to 09:00 on 9 November 2011 and between 19:00 on 9 November 2011 to 09:00 on 10 November 2011. Furthermore, the variance in these periods of time is smaller than during the hours in which people walk around in the testbed areas. This indicates that the presence of people has a certain impact on the received signal level as the obstacles. Besides, note that the Access Point NETGEAR is placed in the same room with the measure device; hence, the received signal level is fully available because the measure device is closer to the Access Point NETGEAR than others.

(a) The screen of valid location

(b) The screen of valid location (the signal-strength-based approach)

Figure 4.11: The test program of the proposed system running on the Android smartphone SamSung Nexus S

As presented in the previous Chapter 3, after the program starts, the user interface shows an introduction screen which has two buttons: the button "Enter" and the button "Exit". The next screen contains an graph describing the acceleration information on the three accelerometer's axes and buttons "Start", "Map", and "Close". If the button "Start" is pressed, the monitoring daemon keeps running in background as a Service in Android. Whenever the user's smartphone reads an NFC tag, not only the accelerometer and the magnetometer are activated to capture data, but the system also measures the signal strength from three Access Points before sending them to Server. The duration of signal strength measuring process is 10 s. The data communication between Clients and Server is based on ELVIN publish/subscribe message, which will be presented latter. After pressing the button "Stop", the sensors will stop capturing and stores collected data in memory. At this time, the screen returns to the previous one (Fig. 3.17(c)). As presented in the previous chapter, when the user would like to know his actual location, he has three solutions from the NFC technology, the inertial-sensors-based approach and the signal-strength-based approach. After pressing the button "Map", the scenario layout will be displayed with the user's possible location determined from the two first solutions (the NFC-technology-based and the inertial-sensors-based approaches). If the system cannot give out a reliable location, the user can locate himself by pressing the button "Localizing" to choose the signal-strength-based approach. The system will capture the radio signals from the Access Points at the user's actual context and converts them into the signal strength data before sending a locating request to the Server. After processing the signal strength data, which is measured from the Client, the Server will reply the Client by the user's actual location. The user interface is illustrated as in the below Figure 4.11(b).

As can be seen in Figure 3.17(d), the NFC-tagging approach and the sensors-based approach determine the user at the Room F. As this location is invalid, the signal-strength-based system re-estimates the user's location which is Room D (described as the blue circle) as in Figure 4.11(b).

The connection between the Client and the Server is established through the WLAN. With the aim to maintain the temporary connection in terms of the energy issues and the user's mobility, we use a publish-subscribe event-based communication system for building an asynchronous communication between loosely coupled components. In practice, the publish-subscribe event paradigm is useful for decoupling information providers from consumers through a multicasting mechanism. A component can operate in the system without being aware of the existence of other components. It is required to know the structure of the event notifications in order for the component to issue the related subscriptions. For example, a mobile device can easily use a publish/subscribe-event-based communication to advertise its presence in a room and retrieve the services available there. Besides, it is possible to plug a component in and out of the architecture without affecting the other components directly. This communication system is useful for a traditional client/server model in mobile wireless networks since it is able to adapt to unannounced disconnection of components [45].

The publish-subscribe event-based communication system proposed in our implementation is Avis - an event router providing a fast publish/subscribe event routing service compatible with the commercial Elvin implementation [1]. Avis Event Router runs on a Java platform. Elvin is a publish/subscribe message bus that is used to synchronize entities. A message bus supports arbitrary communication topologies: unicasting, multicasting, broadcasting such as implementing traditional client-server request-reply protocols or message broadcast. Clients simply emit and receive messages on the bus where they've nominated an interest in if another client somewhere on the bus emits them [1]. Elvin supports the broadcasting messages between the Server and Clients. The messages are name-value pairs such as: ("RSSI", ID_{NFC} Room_{NFC} RSSI_1 RSSI_2 RSSI_3). We use a centralized architecture [49] where the Server is considered as a central Event Brokering storing all currently active subscriptions in the system. Every new event is published to the Server, which is responsible for matching it against all the subscriptions. Afterwards the event is forwarded to all Clients whose subscriptions match.

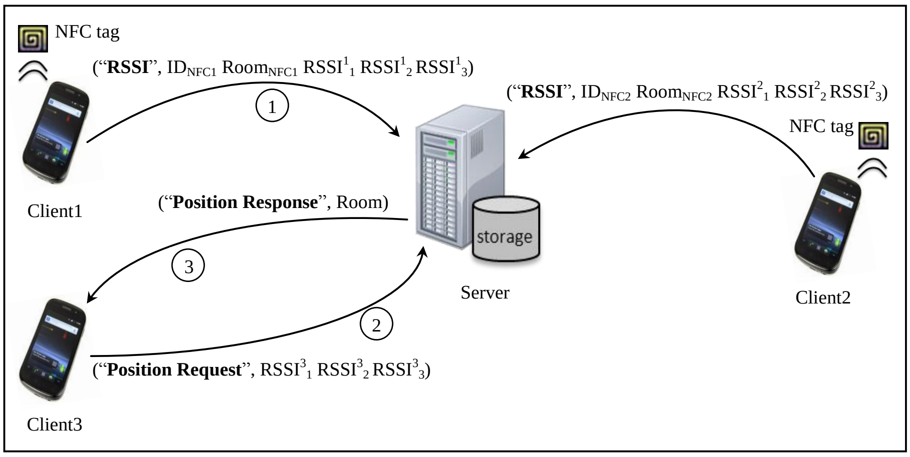

Figure 4.12: Content-based messaging schema using Elvin publish/subscribe message

In the process 1, after tagging an NFC tag, the two Client1 and Client 2 publish an event message named "RSSI" in the form of a notification. The notification encapsulates the NFC tag's identification and location and the signal strength values captured. The Server has one thread waiting for receiving an event message. When another Client would like to know his actual location, he creates and publishes a new notification named "Position Request" (process 2). At these situations, the Clients play a role as publishers and the Server is a subscriber. After executing the localization algorithm, the Server publishes a notification named "Position Response" which contains the location information of the user (process 3). At this situation, the Clients play a role as subscribers and the Server is as publisher.

4.4.3 Server side

On the Server side, a laptop Dell Latitude D630 [2] is used as the Server for receiving data from Clients and executing the localization algorithm. The laptop has the following configuration: the operation system Windows XP, Processor Intel Dual Core T8300 @2.40GHz and 2G RAM. The Server-side service has been programmed in Java. The laptop also has a WiFi communication interface to communicate with Clients by exchanging the Elvin publish/subscribe message through the "wifi-intern" network (see more the previous subsection).

The Server provides a localization service that can store and process data acquired from the all users' context. By capturing all "localization tuples" published by all users in Figure 4.9, the Server constructs a global signal strength map for executing the localization algorithm 4 as needed. Particularly, when receiving a positioning request from a user, the Server finds a most possible position whose the signal strength information has the best matches to the signal strength measurement which is taken by the user's smartphone. In order to maintain the stable accuracy of the signal strength information updated, the Server takes an average of the signal strength stored in the database and the new signal strength, which is sent from the smartphone.

4.5 Conclusion

This chapter presented the signal-strength-based approach using the similarity of radio conditions related to the user's neighbors. This approach combines the NFC tags disseminated in the indoor environment and the WLAN connectivity to improve localization accuracy with a high density of users. The procedure of capturing and sending the radio conditions to Server is described as in Figure 4.1. After that, the signal strength information, which is associated with the NFC tag's location, is stored into the Server database. When the two NFC-tagging and sensors-based approaches are no longer capable of determining the user's location, the signal-strength-based approach will be activated. After receiving the user's positioning request, the Server is responsible for locating the user by executing the Algorithm 4. The principle of this localization approach using the similarity of radio conditions related to the user's neighbors is summarized in Figure 4.13:

The OPNET simulation tool is used to simulate the signal-strength-based approach. Two important factors express the influence of the environment to the localization accuracy: the deviated time between neighboring nodes (30s, 60s, ..., 300s) and the number of mobile nodes (72 and 102 nodes). In order to evaluate the performance of the proposed approach, the two proposed methods are considered: the minimum standard deviation method and the proposed method based on the comparison of number of valid locations in each room. The comparison of these two methods is executed for two groups of nodes: 102 nodes and 72 nodes. The simulation results have proven that the reliability of the localization accuracy is highly appreciated as the deviated time between the user's neighbors is less than 90 seconds. However, the localization accuracy decreases gradually as the deviated time between the user's neighbors is larger and it satisfies with 50% accuracy. In conclusion, the simulation results show that the proposed signal-strength-based approach is suitable for the frequent changes of the environment as well as the presence of a large number of users.

The test program on the Client smartphone and the Server device are developed on the Android platform and Java, respectively. Implementation results show a good performance due to the simplicity and the feasibility of the proposed system compared to the RADAR and Redpin systems in the real environment.

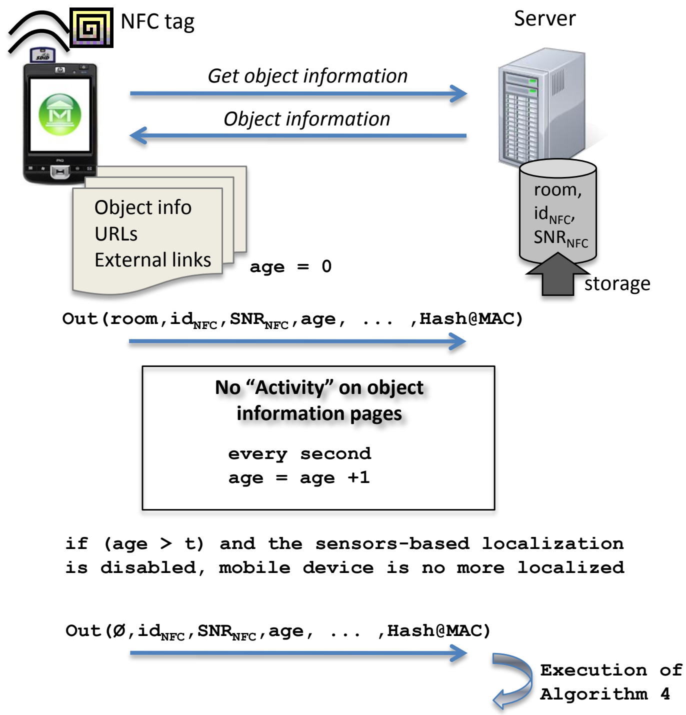

Figure 4.13: Signal-strength-based localization approach using the similarity of radio conditions related to the user's neighbors

Comparing the localization performance with the RADAR and Redpin systems

The Redpin system and our signal-strength-based approach are able to determine the user's location with the room-level accuracy. Meanwhile, the RADAR system also provides a localization accuracy of several meters.

The Redpin system only uses the accelerometer for detecting whether the device is stationary or moving. This principal does not perform the localization function; instead of that, it is utilized for the system to collect WiFi measurements. The signal strength measurements are done as the device is stationary and the user assign them to a fingerprint at each stationary place. In addition, the Redpin system proposes the conception of "Interval Labeling" that allows multiple measurements taken consecutively in a period of time before being added to the same fingerprint. Meanwhile, the RADAR system uses the fingerprint technique to construct a radio map. The construction of the radio map in the RADAR system requires manual measurements. The technicians have to walk along a predefined path, and measures the signal strength information at all corners of the building. The process of constructing the radio map in the RADAR and Redpin system is called off-line phase. In fact, the cost for the off-line phase and training time could rapidly increase as the scenario becomes larger. In summary, this empirical construction of the radio map requires much time and efforts and encounters some privacy issues as well as the radio map is not updated as often as the environmental changes.

The signal-strength-based approach takes advantage of the existing technologies in constructing a signal strength map for indoor localization. Instead of using the fingerprint technique of the RADAR system or "Interval Labeling" of the Redpin system, we use the similarity of radio conditions between the user's neighbors. The WLAN measures the signal strength information and the short-range communication NFC is responsible for reading a NFC tag, then, assigning the signal strength information measured to that NFC tag's location. The NFC short range communication helps the system to accurately capture the user's context before storing into the Server database. This combination allows the system retrieving the signal strength information from WLAN at the correct location without requiring any off-line phases as in the RADAR system. Based on the combination of the NFC technology and the WLAN, the experiment validates that the proposed system provides the signal strength map to be updated regularly and reasonable localization accuracy.

Chapter 5

Conclusions and Perspectives

In this last chapter, we summarize our research work including contributions and main results of the proposed indoor localization system. We also describe briefly some research directions for future work.

Conclusions

In the thesis, we have made the literature review of the common components of indoor localization systems including sensing technologies and communication technologies. After reviewing the existing measurement techniques and localization algorithms as well as analyzing fundamental knowledge and challenges of existing indoor localization systems, we propose a structure of the proposed system:

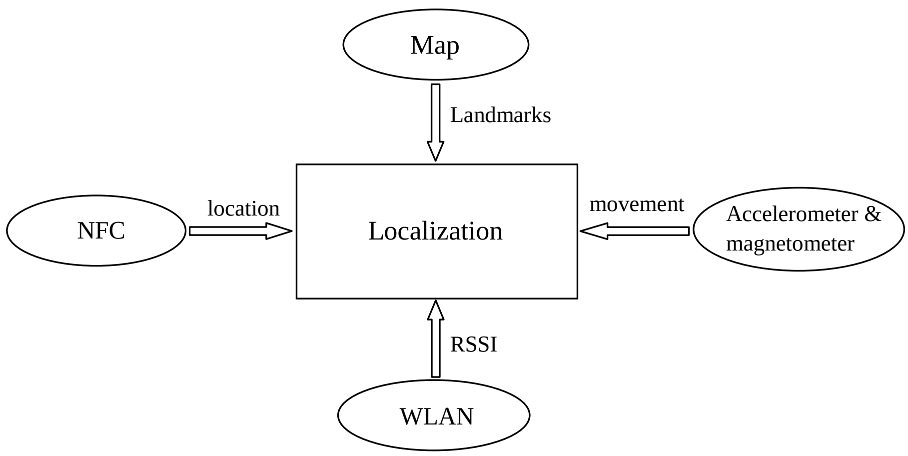

Figure 5.1: Structure of the proposed indoor localization system

It can be seen from the Figure 5.1 that the structure consists of technologies such as NFC technology, Wireless LAN and inertial sensors (accelerometer and magnetometer). Besides, a landmark is referred to a set of locations that correspond to an important place such as a room/corridor in a building. The map presents all landmarks together with their properties. The module Localization represents the system's operation by the proposed approaches.

Regarding some contributions of our research work to the field of the indoor localization, we propose three approaches as follows:

1. Firstly, we propose the NFC-tagging approach that provides a simple and effective service for an indoor localization. By tagging one of the tags disseminated in the indoor environment, the user can know his actual location that is at the same place of the tag. This approach is very practical since the localization is automatically done by closing the user's device to the tag. The NFC-tagging approach, however, requires the user to tag regularly since the location information could become obsolete if the user stops tagging for a long time. Our experimental results show that the location information is reliable within t seconds from the last tagging. The value of t seconds will be initially determined according to the implementing scenario.

2. We also improve the quality of the previous approach by developing the sensors-based approach that combines the accelerometer and the magnetometer to estimate the user's movement distance. This proposed approach can work as a stand-alone system without any infrastructure requirements. Inertial-sensors-based localization is a challenging issue since the precision of measurements on the handheld device is limited. Hence, many existing inertial-sensors-based navigation systems fix the sensors on the user's body or use many sensors at multiple positions to obtain measurements accurately. With the purpose of allowing the user to hold his mobile device conveniently in hand, the relative positioning scheme (such as the Dead Reckoning) is not a reasonable solution due to the growth of the drifting errors along with the user's travelled distance. Thus, the sensors-based approach provides a simple localization service which quantities the degree of the user's movement to identify whether the user is still staying at the same place from the last tagging. For a long trajectory, the user can use the signal-strength-based approach using the similarity of radio conditions between close neighbors.

3. Finally, when the two previous approaches cannot determine the user's location, we propose the signal-strength-based approach that uses the similarity of radio conditions between close neighbors.

Most of indoor localization systems have limitations in the installation cost and the complexity of the localization algorithms. Therefore, many existing indoor localization systems use WiFi technology due to its low cost equipment, coverage range, popularity and data speed. Their works mainly focused to the Location Fingerprint technique by using Received Signal Strength Indication (RSSI) to create an empirical radio map. Using such an experimental method, it forces the technicians to spend hours going to all places in the building to measure radio signal. However, developing a good radio propagation model for a particular building is not an easy thing. It is not capable for the model to flexibly conform to environmental changes. In short, many localization systems deployed usually adapt to a particular space model. Hence, constructing the radio map encounters the cost of time and efforts as well as it raises a privacy issue.

The closest related work to our solution of indoor localization is the RADAR and Redpin system. The RADAR system uses the fingerprint technique to construct the radio map; while the map is constructed by "Interval Labeling" technique in the Redpin system in which the user distributes his actual place to each fingerprint. Our contribution is to construct the signal-strength map in the simple way that the map can be updated regularly. The proposed signal-strength-based approach does not deal with fingerprint and data mining technique due to constraints of low data storage and processing capacity in the mobile devices. We proposed a combination of the NFC and WiFi technology to construct the signal-strength map: whenever the user reads an NFC tag, the tag's location and signal strength information will be updated on the server. By combining the location with signal strength information from the neighbors that has been recently updated on the server, the solution shows a correlation of signal strength information between the user's current location and the neighbors near-by. Moreover, the signal-strength-based approach does not require any off-line phase which is costly for recording radio conditions while still obtaining a good degree of accuracy for the indoor environment with frequent changes such as a high/low density of users, the opened/closed doors, the electromagnetic changes, etc.

The simulation results show that the localization accuracy is of the proposed signal-strength-based approach highly appreciated as the deviated time between neighbors is less than 90 seconds. The localization accuracy can be reduced gradually since the deviated time between neighbors is larger until reaching a stable value of around 50%. The results of the simulation also show that the signal-strength-based approach is suitable for the frequently changed environment as well as the presence of a large number of users.

In summary, we combine a simple NFC-tagging localization approach, sensors-based approach and the signal-strength based approach using the similarity of radio conditions between close neighbors to build the complete indoor localization system. The proposed system can ensure a positioning accuracy at room-level for multiple-user environments. Implementation results show a good performance due to the simplicity and the feasibility of the proposed system compared to the two related systems (RADAR and Redpin) in the real scenario.

Comparing the locating performance with other related localization systems

This sub-section will present a comparison of our proposed localization system to the two works that are the most related to. The comparison is described as in Table 5.1

System	NFC Technology		Accelerometer & magnetometer		Signal Strength	
	accuracy	valid time	accuracy	offline time	accuracy	offline time
RADAR	N/A		N/A		4.7m[103]	long
Redpin	N/A		N/A		room-level	short
Proposed system	high	$< t$ s	high	No	room-level	No

Table 5.1: Comparison the locating performance of the proposed system to the RADAR and Redpin systems

In the RADAR system, the radio map is constructed in a manner that the technician measures signal strength information by walking along a predefined path. The Redpin system also uses the empirical construction of the signal strength map. It proposes the conception of "Interval Labeling" that allows multiple measurements taken consecutively in a period of time before being added to the same fingerprint. The empirical construction requires much time and efforts and encounters some privacy issues. The cost of off-line phase and training time could rapidly increase as the scenario becomes larger in both RADAR and Redpin systems.

The proposed system provides a simple method of constructing the signal strength map. In fact, it takes advantage of existing technologies in constructing a signal strength map for indoor localization without mentioning an off-line phase. Instead of using the fingerprint technique of the RADAR system or "Interval Labeling" of the Redpin system, we use the similarity of radio conditions between close users. The WLAN network takes the signal strength and a NFC short-range communication is responsible for assigning the signal strength to a known location on the map. The NFC short-range communication helps the system to accurately get the location information. This combination can retrieve the radio signal strength data from WLAN at the correct location without requiring any off-line phases to record radio signal strength.

The signal strength map is not updated according to the environmental changes in the RADAR system. Meanwhile, the Redpin system only uses the accelerometer for detecting whether the device is stationary or moving. This principal does not perform the localization function; instead, it supports the system to collect WiFi measurements. The signal strength measurements are done as the device is stationary and the user assigns them to a fingerprint at each stationary place. The Redpin system allows updating the radio map during operation, but that is manually executed by users. In contrast, updating the radio map is automatically done in the proposed system. Using the combination of the NFC technology and the WLAN network, the proposed system permits the signal strength map to be updated regularly.

The experiment shows reasonable localization accuracy in the proposed system. The Redpin system and the proposed system are capable to determine the user's location with room-level accuracy. In addition, the accuracy of the proposed system is also enhanced by the support of the inertial-sensors-based approach. This approach is mainly used for determining whether or not the user is still staying at the same place from the last NFC tagging.

Perspectives

In the thesis, we proposed a simple, effective, and low-cost indoor localization system based on existing technologies integrated in recent smartphones without any additional infrastructures. The proposed system achieves an accuracy at room-level, adapts to environmental changes, and is able to be deployed in many kinds of scenarios. Although the implementation program is not a final product, the current application is just a prototype to prove the feasibility and the accuracy of the proposed system. More works need to be done to consolidate the security and scalability of the system. That is a part of future work to complete the indoor localization product.

In addition, the binding of approaches is still weak; we need more time to improve the stability of the proposed system. Besides, the complete localization system should be mentioned by combining with the existing outdoor localization system GPS to allow the user to move from an indoor environment to an outdoor one. Therefore, it is necessary to detect the transition point from indoors to outdoors and vice versa. In addition, we believe that more new technologies would be integrated into smartphones in the near future in order to develop new module and extend the ubiquitous usage of localization technology.

In the near future, we continue to improve the accuracy of the localization approach using accelerometer and magnetometer by employing the Map Matching technique with new observed data from supplementary sensors like gyroscope. With this combination, the approach could eliminate drift errors on a long traveled distance with unconstrained usage of a mobile device. Actually, we have some initial ideas for affecting this solution. The important point of the solution using Map Matching technique is to define Landmarks on the map and their features. A path connecting Landmarks is parameterized by the user's movement direction and distance. Each connecting path from a Landmark has two parameters: the Heading value and relative movement distance. Data captured from the gyroscope and magnetometer will be used for detecting turning moments. From that, Map Matching technique can correct position tracking on the map. In short, using the Map Matching technique can improve the accuracy by assigning objects/users to geographical locations (called Landmarks) on a digital map. From that the system can easily detect Landmarks the user has passed.

The proposed system does not deal with security issues like authentication before using the localization service; therefore, more work needs to be done in this direction to cope with these existing issues. This further improvement should be done to provide reliable solutions in the multiple-user context.

Annexes

Annexe A: The User side program described by the UML diagram

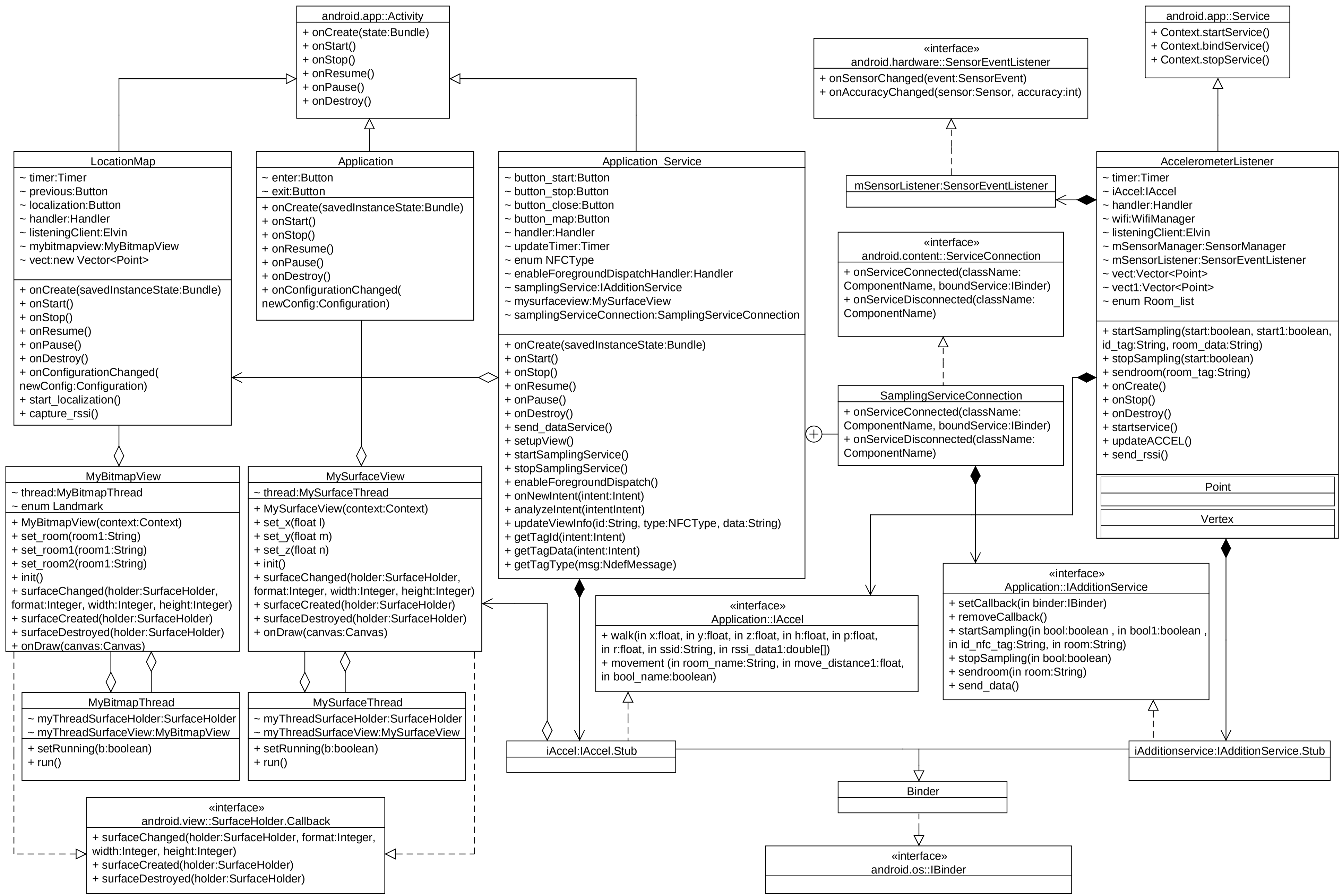

Figure 2: The User side program described by the UML diagram

Annexe B: Comparison between indoor localization systems

System	DR	No DR	Technique	Advantages	Disadvantages
RADAR	No	Yes	RF	accuracy	time of fingerprint map construction; sensitive to interferences
LANDMARC	No	Yes	RF	accuracy	not robust; the accuracy depends on the number of reference tags
Active Badge	No	Yes	Infrared	accuracy in room level	sensitivity to interference (sunlight and fluorescent light)
Active Bat	No	Yes	Ultrasound	good accuracy	required ceilling sensor grid
Cricket	No	Yes	Ultrasound	privacy and decentralized scalability	no central management and receiver computation
Dolphin	No	Yes	Ultrasound	a few of pre-configured reference nodes	receiver high cost
EasyLiving	No	Yes	Camera images		required high performance cameras and hogh processing power
Smart Floor	No	Yes	Physical contact	hight accuracy	not scalable for large applications
RedPin	No	Yes	Inertial Sensors and RF	self-contained; do not require an expensive training phase and location fingerprints	location labels attributed by users
Greenfield	Yes	No	Inertial Sensors		no precise movement direction

Table 2: Comparison between the existing indoor localization systems

Annexe C: Résumé de la thèse en Français

L'informatique ubiquitaire (ou informatique diffuse) est premièrement proposé par Mark Weiser dans son article intitulé "Some Computer Science Issues in Ubiquitous Computing" en 1993. La définition de l'informatique diffuse est à fournir un service informatique global où l'accès des ressources est effectué par les dispositifs embarqués de façon transparente aux utilisateurs. Généralement, l'informatique diffuse signifie que l'information est disponible et peut être facilement accessible à partir d'appareils fixes / mobiles tels que les téléphones, smartphones, tablettes, etc. Par exemple, Ubi-Bus et Ubi-Board fournissent des services basés sur le contexte de diffuser les informations nécessaires aux utilisateurs. Ces systèmes sont capables de traiter automatiquement les données spécifiques aux dispositifs particuliers, qui sont connus en avant, avec les propriétés des utilisateurs, par exemple, la langue parlée ou la personne malvoyant. L'utilisateur et l'application peuvent être en interaction les uns aux autres par l'intermédiaire des entités de contexte. Notez que ces entités peuvent être définies comme des informations de contexte afin de caractériser la situation d'une personne, un lieu ou une chose. En outre, la perception du contexte est classé à deux types de fonctionnement: (1) l'obtention de l'attribut de contexte qui est un processus / d'une opération de lecture sur les données dérivés par le contexte et (2) le déclenchement d'une opération lorsque une condition spécifique au contexte est satisfaite.

Motivations

L'interaction humaine en utilisant des terminaux mobiles est l'un des aspects prometteurs dans notre vie réelle. Premièrement, les fonctionnalités des terminaux mobiles sont plus intelligentes et plus diversifiée à travers le temps et, par conséquent, ils peuvent fournir des applications sensibles au contexte pour des utilisateurs mobiles. En effet, la localisation a été récemment étudiée en informatique diffuse comme une perspective potentielle. Les informations de localisation de l'utilisateur deviennent très importantes pour les systèmes nomades à maintenir le fonctionnement par rapport de la mobilité des utilisateurs. La conception d'une application originale intégrant la mobilité de l'utilisateur sera un point central entre les services dans l'informatique diffuse. Ce domaine demeure très attractif et permet d'offrir les applications innovantes.

Il est clair qu'un système de localisation est utilisé à fournir des services basés sur la localisation dans laquelle la position est un élément crucial du contexte. Les larges déploiements existants sont basés sur le système de localisation par satellite GPS qui est particulièrement adapté pour les applications extérieures. Ceux-ci comprennent des applications de service centré sur la position du véhicule tels que la planification de l'itinéraire et le suivi, ainsi que des autres applications intégrées dans les appareils portables GPS. Outre des applications spécialisées à l'usage militaire, des applications dans l'environnement intérieur sont omniprésentes pour les scénarios spécifiques. Par exemple, les services à la maison aident l'utilisateur d'allumer / éteindre les appareils ménagers en détectant la présence de l'homme ou supportent des handicapés et des personnes âgées pour des tâches quotidiennes. Les autres services sont à guider des visiteurs dans le musée ou surveiller des patients et aider à trouver le personnel médical en cas d'urgence dans les hôpitaux.

La précision de localisation dépend des exigences requises par l'application et aussi par la caractérisation de la technologie utilisée. Par exemple, la précision du système de localisation par satellite GPS est de l'ordre de plusieurs dizaines de mètres pour l'environnement extérieur, mais la dégradation s'est fortement produite dans l'environnement intérieur car le signal de satellites est bloqué par des bâtiments. Afin de localiser des objets ou des personnes à l'intérieur d'un bâtiment, un système de localisation en intérieur sur la base du contexte du terminal mobile doit être déployé. Toutefois, la localisation de personnes / objets dans l'environnement intérieur reste des défis importants. Plusieurs raisons expliquent pourquoi la performance de positionnement diffère grandement entre les systèmes de localisation en intérieur et en extérieur:

- Multipath / fading causé par la réflexion du signal entre des murs et meubles
- Signal Non-Line-of-Sight (NLoS) et une atténuation élevée en raison d'obstacles
- Changement de l'environnement tels que conditions climatiques, le déplacement de l'objet, ou le mouvement des personnes
- Haute exigence de l'installation et de la précision.

Afin de répondre au besoin de localiser les personnes / objets et de se situer dans l'environnement, plusieurs techniques ont été récemment utilisées. Les réseaux locaux basés sur des tags RFID/NFC, des Ultra-Sons, de l'Infra-Rouge, de WLAN (Wireless Local Area Network) ou bien encore de la vidéo peuvent être exploités pour le service basé sur location dans un rayon limité (quelques dizaines de mètres). Mais certaines de ces technologies ne sont pas adaptées à la localisation de l'utilisateur à l'intérieur à cause des problèmes de la mobilité, d'environnement ou d'interférence. D'autres technologies imposent des contraintes quant à leur déploiement. Certaine systèmes requièrent une grande densité d'équipements pour fournir en permanence la localisation raisonnable. Ces systèmes entraînent un surcoût soit au niveau de l'infrastructure soit au niveau du terminal de localisation. Alors, dans le cadre de l'environnement indoor, les technologies radio semblent bien utilisées grâce à leur capacité de traverser les obstacles qui sont nombreux à l'intérieur des bâtiments (murs, meubles, etc.). En plus, la réutilisation des réseaux radio permet d'avoir un support de localisation peu coûteux.

La plupart des systèmes de localisation en intérieur actuels utilisant des réseaux radio sont basés sur les approches de mesure de l'information d'intensité du signal. Les informations de la force du signal, qui est également appelé "empreinte", est reliée à la distance émetteur/récepteur. La technique de l'empreinte est représentée à construire une cartographie des empreintes radio qui illustre l'ensemble d'empreintes digitales recueillies à chaque endroit dans la cartographie. Cependant, il n'existe pas de formule idéale qui prend en compte de tous les facteurs environnementaux qui impactent sur le signal. Sans aucune caractérisation et modèle de captation empreinte précis, une grande quantité de données empiriques sont nécessaires pour évaluer la performance de la technique de l'empreinte. En effet, cette technique consomme beaucoup de temps et de main d'IJuvre à collecter des empreintes digitales dans le scénario de l'ensemble du réseau. Cela peut être très coûteux pour les grandes zones de déploiement. Par ailleurs, elle également rencontre des problèmes de la confidentialité, de la grande quantité de données, et des influences environnementales. L'utilisation d'outils de filtrage et d'apprentissage pour le traitement des données brutes est aussi un challenge pour les terminaux mobiles dont le contexte est complexe dans l'environnement intérieur.

En raison des limitations de la batterie, et la capacité de traitement et stockage de données des terminaux mobiles / smartphones, les systèmes de localisation en intérieur sont limités par des services stricts à travers le temps de calcul, la consommation de mémoire, la transmission de données, etc.. Au cours des dernières années, les techniques de localisation sont multiples. Une bonne maîtrise et connaissance et de diverses technologies et méthodes sont nécessaires afin de dimensionner proprement une solution de localisation. Parmi les technologies du signal RF à base de mise en IJuvre d'un système de localisation en intérieur, WiFi est une bonne alternative en raison de son déploiement à grande échelle de réseaux à haut débit. En plus, l'émergence des nouveaux matériaux ouvre des portes vers une localisation en intérieur plus fine dans les environnements dans lesquels ils sont déployés. La fusion des données de capteurs multiples et les méthodes représentant des données de localisation permettent d'élaborer de l'information contextuelle de haut niveau à partir de données de localisation.

Contributions

L'objectif de nos travaux de recherche est de concevoir une architecture simple et efficace veiller à deux exigences suivantes: (1) une grande précision (au niveau de la pièce) et (2) une adaptation aux plusieurs scénarios. La thèse contribue aux études pour les systèmes de localisation en intérieur en combinant des approches basées sur la caractérisation de mouvement, la communication courte portée et de l'intensité du signal. La combinaison de ces approches proposées permettent de minimiser la défaillance de chacune approche. En effet, notre système de localisation propose une combinaison des technologies qui sont actuellement équipé en terminaux mobiles, y compris la technologie de WLAN, NFC (Near Field Communication) et des capteurs (accéléromètre et magnétomètre). Voici nos trois approches proposées :

Premièrement, nous proposons l'approche basée sur NFC-étiquetage qui fournit un service simple et efficace pour une localisation en intérieur. En touchant une étiquette disséminées dans l'environnement intérieur, l'utilisateur peut connaître sa position réelle qui est même à celle d'étiquette. Cette approche est très pratique car la localisation se fait automatiquement en approchant le terminal mobile de l'utilisateur à l'étiquette. L'approche basée sur NFC-étiquetage, cependant, nécessite l'intervention régulière de l'utilisateur qui n'est pas prédictive et donc peut poser des problèmes sur la validité des informations. Alors, l'information de localisation n'est fiable que dans un certain intervalle de temps depuis le dernier étiquetage. La valeur de cet intervalle de temps (ex. t secondes) sera ajustée selon les scénarios de déploiement.

Deuxièmement, nous améliorons la qualité de l'approche précédente en développant la deuxième approche basée sur des capteurs qui combine l'accéléromètre et le magnétomètre pour estimer la distance de déplacement de l'utilisateur. L'approche proposée peut fonctionner comme un système autonome sans aucune exigence d'infrastructure. La localisation basée sur les capteurs est un challenge car les activités sur le terminal mobile sont imprévues. En effet, un grand nombre de systèmes existants de navigation basés sur les capteurs doivent fixer les capteurs sur le corps de l'utilisateur ou utiliser plusieurs de capteurs pour obtenir des mesures plus précises. Avec l'objectif de permettre à l'utilisateur de tenir son terminal mobile commodément dans la main, la deuxième approche fournit un service de localisation caractérisant le degré de mouvement à l'utilisateur pour déterminer si l'utilisateur est au même endroit depuis le dernier étiquetage. Pour une longue trajectoire, cette approche permet de détecter que l'utilisateur a déjà déplacé à un autre endroit. En plus, dans cette approche, le système permet à l'utilisateur de manipuler son smartphone en multi-positions, même lorsque debout, assis ou marchant.

Finalement, afin de surmonter les inconvénients de deux approches précédentes, nous proposons la troisième approche basée sur l'intensité du signal en utilisant la similarité des conditions radio entre proches voisins. Nous proposons une combinaison de la technologie NFC et WLAN pour construire la cartographie d'intensité du signal. Le réseau sans fil WiFi capte l'intensité du signal et la communication courte portée NFC est responsable de détecter la position actuelle de l'utilisateur. La communication à courte portée NFC permet au système d'obtenir correctement les informations de position. Cette combinaison peut récupérer les données de l'intensité du signal radio à et les attribuer à une position connue sur la cartographie, sans exiger de phases hors ligne pour enregistrer l'intensité du signal radio.

Conclusions et Perspectives

Le système proposé se compose de l'approche de l'étiquetage NFC et le soutien des approches basées sur des capteurs et sur l'intensité du signal radio en utilisant la similarité des conditions radio entre proches voisins. La précision de localisation est raisonnable au niveau des pièces. Notre système proposé ne tient pas compte de la technique d'empreinte ainsi que des algorithmes d'apprentissage en raison des contraintes de stockage de données et la capacité de traitement dans les terminaux mobiles. Au lieu de cela, nous désignons une architecture simple et efficace qui permet de prendre en compte la mobilité de l'utilisateur dans une grande zone de déploiement.

Les systèmes de localisation en intérieur les plus proches liés à le nôtre sont le système RADAR et Redpin. Le système RADAR utilise la technique d'empreinte pour construire la cartographie d'intensité du signal radio, tandis que la cartographie est réalisée par la technique "d'étiquetage de l'intervalle" dans le système Redpin dans lequel l'utilisateur distribue l'endroit réel de chaque empreinte. Comparé aux systèmes RADAR et Redpin, notre système proposé construit la cartographie d'intensité du signal de la manière simple en combinant de la technologie NFC et WiFi pour que la cartographie puisse être mise à jour automatiquement et dynamiquement en temps-réel. Chaque fois que l'utilisateur lit une étiquette NFC, les informations de l'intensité du signal à la position de l'étiquette seront mises à jour sur le serveur. En combinant les informations d'intensité de signal des voisins qui a été récemment mis à jour sur le serveur, la solution présente une corrélation des informations d'intensité de signal entre la position actuelle de l'utilisateur et celles de ses voisins proche. Car la cartographie d'intensité du signal est mise jour en temps réel, les mesures d'intensité du signal sont adaptés des changements fréquents de l'environnement tels qu'une haute / faible densité d'utilisateurs, l'ouverture / fermeture des portes, les changements électromagnétiques, température, etc. Les résultats des simulations montrent que la précision de localisation est de l'approche basée sur les forces signal de projet hautement apprécié que le temps dévié entre voisins est inférieur à 90 secondes. La précision de la localisation sera réduite progressivement lorsque le temps dévié entre voisins est plus grande et elle atteint une valeur d'environ 50%.

Dans un proche avenir, nous continuons à améliorer la précision de la méthode de localisation en utilisant l'accéléromètre et magnétomètre en employant la technique "map-matching" avec l'utilisation un capteur supplémentaires intitulé le gyroscope. La technique "map-matching" peut améliorer la précision de la trajectoire parcourue en attribuant des objets / utilisateurs à des endroits géographiques (appelées "Landmarks") sur une cartographie numérique. En fait, nous avons quelques initiatives pour réaliser cette solution. Le point important de cette solution est d'utiliser la technique "map-matching" qui définit les "Landmarks" sur la cartographie avec leurs caractéristiques. Le chemin entre des "Landmarks" est paramétré par la direction et la distance de mouvement de l'utilisateur. Chaque chemin dispose de deux paramètres: la valeur "Heading" et de la distance de mouvement relatif. Les données saisies dans le gyroscope et magnétomètre seront utilisées pour la détection des moments de tournant. Donc, le système peut facilement détecter les "Landmarks" que l'utilisateur est passé.

Acronyms

Acronym	**Expansion**
2D	Two Dimensions
3D	Three Dimensions
AGPS	Assisted GPS
AoA	Angle of Arrival
AP	Access Point
BS	Base Station
BSS	Basic Service Set
CSS	Chirp Spread Spectrum
dB	Decibel
dBm	Power ratio in decibels (dB) of the measured power referenced to one milliwatt
DR	Dead Reckoning
ESS	Extended Service Set
FM	Frequency Modulation
FP	Fingerprinting
GCC	Generalized Cross-Correlation
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System - a GNSS system
GSM	Global System for Mobile communication
HF	High Frequency (3 MHz to 30 MHz)
Hz	Hertz, SI name for cycles per second
ID	Identification
IEEE	Institute of Electrical and Electronics Engineers
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IR	Infrared
KF	Kalman Filter
KNN	K-Nearest Neighbor
LAN	Local Area Network
LBS	Location Based Services

LED	Light Emitting Diode
LF	Low Frequency (30 kHz - 300 kHz)
LoS	Line of Sight
MAC	Media Access Control (layer)
MEMS	Micro-Electro-Mechanical Systems
MIMO	Multiple-Input Multiple-Output
MM	Map Matching
MS	Mobile Station
MT	Mobile Terminal
NFC	Near field communication
NLoS	Non Line of Sight
OPNET	Optimum Network Performance
PDR	Pedestrian Dead Reckoning
PoA	Phase of Arrival
RADAR	RAdio Detection And Ranging
RF	Radio Frequency
RFID	Radio Frequency IDentification
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RToF	Roundtrip Time of Flight
RTT	Round Trip Time
SD	Standard Deviation
SLAM	Simultaneous Localization And Mapping
SNR	Signal to Noise Ratio
TDoA	Time Difference of Arrival
ToA	Time of Arrival
ToF	Time of Flight
UHF	Ultra High Frequency (300 MHz - 3 GHz)
US	Ultra Sound
UTMS	Universal Mobile Telecommunications System
UWB	Ultra-Wideband
WEKA	Waikato Environment for Knowledge Analysis
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network
WSN	Wireless Sensor Networks

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