POLITECNICO DI MILANO

Master of Science in Computer Engineering

Indoors Localization Based On Low Frequency RF Signals

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ABSTRACT

Indoor Localization of the person is actual issue nowadays. One of the main area in this field is localization based on radio frequency signals. There do already exist technologies, which perform indoor localization with different accuracy, but still there is a need for new technology, which can avoid common radio frequency problems whithout increasing the complexity or the cost of the system.

The goal of this thesis is to use benefits of low frequency (125KHz) in Indoor Localization. The main benefit of this technology is: robustness to the environmental obstacles in term of multipath propagation and power decay.

Different kind of experiments in different environments have been taken in order to understand the behavior of low frequency and used equipments to perform Indoor Localization. The proposed system uses RSSI provided by sensors stimulated by low frequency signals to estimate distances between some anchor nodes and subjects. Then performs multilateration using the obtained distances to estimate positions.

The preliminary results obtained by the built prototype shows that the idea of using low radio frequency signals can give advantages as previously mentioned with the ability to obtain a good localization accuracy reaching a mean localization error under 20cm.

SOMMARIO

Il campo della localizzazione di persone in ambienti interni è molto attuale. Una delle maggiori branche di questo campo è la localizzazione per mezzo di segnali radio. Esistono già varie tecnologie che permettono di attuare la localizzazioni di soggetti in ambienti interni con diversi risultati in accuratezza ma resiste comunque il bisogno di ricercare nuove tecnologie che permettano di evitare le problematiche più comuni legate ai segnali radio senza aumentare la complessità o il costo dei sistemi finali.

L'obiettivo di questa tesi è di sfruttare i benefici derivanti dall'uso di un segnale radio a bassa frequenza (125Khz) nel campo della localizzazione. Il principale vantaggio di questa tecnologia è la minor sensibilità agli ostacoli e di conseguenza un minor decadimento di potenza del segnale e una ridotta presenza di multi propagazione.

Il sistema proposto usa valori di RSSI letti da sensori stimolati da un segnale a bassa frequenza per stimare la distanza tra i nodi fissi e i soggetti da localizzare per poi applicare un processo di multilaterazione per stimarne la posizione.

I risultati preliminari ottenuti dal prototipo del sistema mostrano che l'uso di un segnale radio a bassa frequenza permette di sfruttare i vantaggi ipotizzati rendendo possibile l'ottenimento di una buona accuratezza nel processo di localizzazione mantenendo l'errore di localizzazione medio sotto i 20 cm.

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LIST OF ABBREVIATION

ILS – Indoor Localization System

UHF – Ultra High Frequency

GPS – Global Positioning System

IPS – Indoor Positioning System

RF – Radio Frequency

GSM – Global System for Mobile Communications

PDR – Pedestrian Dead-Reckoning

LM – Light-Matching

RTT – Round Trip Time

NTP - Network Time Protocol

LOS – Line of Sight

NLOS – Non Line of Sight

LAURA - Localization and Ubiquitous Monitoring of Patients for Health Care Support

CHAPTER 1

INTRODUCTION

1.1 Introduction

Localization is about the process of determining an object's location in space. Looking back to the history of localization, we can see that, sailors used primitive localization methods for a few thousand years, consequently they developed many specialized tools to provide more accurate localization, as the astrolabe, sextant and compass.

Despite the relatively long tradition, localization remains an active area of research. Especially nowadays localization plays an essential role in many ubiquitous computing applications, where location aware systems can be a very important component for many scenarios such as asset tracking, health care, location based network access, games, manufacturing, government, logistics, industry, shopping, security, tour guides and many others. Although the effective research and development efforts, the existing indoor positioning systems remain unsuitable for wide adoption. Currently, there is no de facto standard for an Indoor Positioning System (IPS) indeed this made development slow. There are several commercial systems on the market, but none of them is precise, affordable and unobtrusive at the same time [12].

Even if indoor localization systems can determine location, there is still need for additional information to determine which way a person or object is facing. Locating a person or device indoors is only half of the solution. For the location to be meaningful for navigation or other purposes, service providers need accurate indoor localization techniques [61].

Nowadays, different technologies have been developed for indoor localization, which will be introduced in the following section of this chapter.

1.2 Structure of the Thesis

This thesis work consists of eight chapters. First chapter is introduction, it is beginning chapter and gives general idea and purpose of the thesis.

The second chapter is the State of the Art; here presented different localization technologies and methods, which has been developed and used until now for realizing localization for indoor environments.

Third chapter is Similar Works; in this chapter we present the different most similar works to our work in indoors localization, which have done until now.

Fourth chapter is about devices, which we have used. In this chapter we give detailed information of device and its characteristics.

Fifth chapter is about methods, techniques, measurements implemented by us for realizing this thesis work.

In the sixth chapter we introduced the experimental results of our work.

In the seventh chapter we are comparing our thesis work results with LAURA results, which is localization technique implemented by using zigbee technology.

CHAPTER 2

RF LOCALIZATION METHODS AND TECHNOLOGIES

2.1 Problem of Localization

As briefly introduced, the ability to localize or track the position of an object or a person is very important in many application fields, the problem can be subdivided in these major fields: outdoor localization, indoor localization, and mixed type. In this chapter we will focus on the analysis of the most common techniques used in indoor localization.

Indoor localization can be defined as a technique that provides a precise position inside of a closed structure (e.g. shopping mall, hospitals, airport, a subway, and university campuses).

Different technologies can be used to perform indoor localization. In this section we will show some of the problems, which those technologies must face to obtain good performances. In this work we focus on Radio Frequency, but other technologies that uses different signals like sound, or light also have similar problems.

The main characteristic of the RF signal is that its measurable power decreases in relation with the increase of the distance from the signal source (Figure 1).

Knowing the relationship between distance and signal power allow the estimation of the distance of an object from the signal source given the measured power.

Such distance can also be obtained by measuring time required by signal to travel between two locations. Because after a certain distance the signals will eventually disappear a signal source can cover a limited area depending on the nature of the used signal.

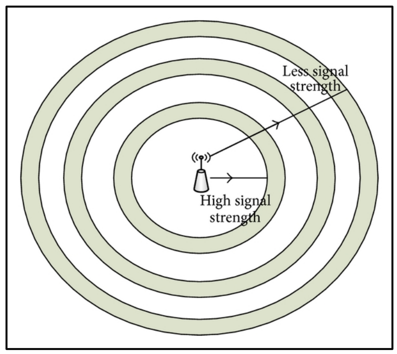

Figure 1: Signal strength pattern.

One of the main problems is that such signals are highly influenced by the environment. Even if RF can in general pass through concrete obstacles allowing communications in absence of line of sight, their signal is influenced by those situations. Once a signal has to pass through an obstacle some portions of its original power is absorbed by it and it get lost. This will decrease the range of the transmitted signal and the accuracy of distance estimation.

Other effects of obstacles on RF signals are refraction and reflection. Depending on the obstacles material and the signal characteristics once the obstacle is encountered the RF wave's direction can be modified by the collision. This will lead to multipath propagation problem.

In this situation the signal measured at a certain location will not be related to travel distance only, but it will potentially be distorted by unexpected change of direction

of the original signal or/and by the overlapping of different signals. Since reflection create a different number of signals derived by the original one it will also pose a problem on distinguish between the actual signal and the ones generated by the obstacles. This will also affect systems that rely on signal synchronization. Different technologies are affected by those problems in different measures so they deal with those problems in different ways. In the following we will present the main localization technologies and their characteristics.

2.2 Positioning Technologies

The Global Positioning System (GPS) is the de facto standard for outdoor navigation since more than twenty years ago. Consequently, the satellite-based navigation system has become the indispensable tool for anyone to determine their location outside of a building, in a car, on motorways, in the street. While even GPS can nowadays sometimes receive signals from satellites to determine a location inside a building, the resulting location is typically not accurate enough to be useful. This happens because of the signals from the satellites are attenuated and scattered by roofs, walls and other objects, beside all of these, the error range of GPS can be larger than the indoor space itself. Also, due to the signal attenuation caused by construction materials, the satellite based GPS loses significant power indoors environment affecting the required coverage for receivers. In addition, the multiple reflections at surfaces of objects cause multi-path propagation serving for uncontrollable errors.

So, because of this instead of using satellites, Indoor Positioning System (IPS) uses various optical, radio, or even acoustic technologies.
It is possible to identify the following main IPS categories, based on technology:

- Radio waves, based on radio communications between different devices to compute the position of the observed subject.
- Scene analysis based, extracting positional information from image analysis techniques.
- Sonic waves based, whose principles are similar to the radio waves family but using pressure waves (often in a not audible range).
- Physical contact based, getting measures from sensors acquiring data of presence directly from the tracked subject in a precise location.

Radio Frequency Localization technologies are commonly used since they are cheaper than other technologies, they can provide good coverage, they are simple to deploy, and in some cases they can work on top of already existent infrastructure. Those technologies are based on the measurement of radio waves characteristics and their analysis to estimate the position of a device. Since in the majority of the cases they need a device to be attached to the tracked subject most of those are invasive. In this category, systems usually differ from each other depending on the used frequency. This will impact on the systems performances, because the frequency will affect the behavior of radio waves especially in the indoor environments.
After briefly presenting the other technologies in this section we will mainly focus on radio based technologies, because it is the technique proposed in this thesis work.

2.2.1 Scene Analysis

Techniques in this category aim to solve the localization problem using the direct acquisition of images of the environment (typically by means of a camera) and compute the needed formation. For this reason visual occlusion is the major problem of such systems. To acquire information starting from a normal camera input, it is possible to use different image processing techniques, extracting information from an image in order to be able to recognize it later. The principal techniques for data acquisition are:

- **Visual on line data learning:** A set of fixed cameras observe the environment and at runtime the system build a set of visual features describing the moving objects in the view learning to recognize and track them across the location managing the shift of the object from the field of view of a camera to another. Examples of this type are [21,39,45]. The characteristic of those is that they can achieve a very good accuracy having means errors in position estimations under 10 cm [39].
- **Visual off line data learning:** In this method the visual features to be recognized are learned by the system before that the real tracking application is started, and then at run time the system only track such pre determinate Figures. Those methods are less complex in term of elaboration and can be used to perform proximity analysis or tracking with a system of fixed cameras or a moving camera placed on the subject to track [68].

Moreover light radiation can be used also in the frequency of infrared. This enables to use warm bodies (such as humans) as radiating sources to be tracked. This can be used in two main ways: simply as proximity information, or, thanks to more complex systems, providing more precise measurements [29,41]. Non-invasive infrared systems also exist.

Instead of receiving an infrared signal from some transmitter, they use the thermal information of a body to locate it into the space. An example of those shows the ability to track two people in a room with an error between 12 - 68 cm using four sensors to scan the area [29].

2.2.2 SONIC WAVES

Sonic waves localization technologies are based on the fact that the speed of sound in air is quite well known, robust with respect to the environment conditions. Distance between different locations can be computed from the measured traveling time from source to destination. Relative orientation is also available using directional antennas. With those

data it is possible to use techniques as time of flight or differential time of arrival (those techniques will presented in the next section) to obtain localization information. The used frequencies are usually above the audible spectrum, from around 20Khz to above 100Khz. Sonic waves suffer from the presence of obstacles both for attenuation of the signal and echoes condition, moreover noise coming from the surrounding can have a significant impact on the data accuracy. Some examples of such systems are [10,22,23,37,42], the proposed solutions vary in result obtained, but in general they show the capability of such techniques to provide a good accuracy. For example, the system proposed in [37], uses a microphone array to collect data from sources to locate, with an average error of 0.53 m on the worst axis.

Sonic waves can be used in combination with other localization techniques. As an example, they can be used together with dead reckoning to improve accuracy and precision, by periodically updating the position of the subject [52].

2.2.3 PHYSICAL CONTACT

Systems of this type use physical contact between the object or person to locate, and some kind of sensors. Those system's principles are simple but they may require a complex sensors arrangement and processing to obtain the most accurate results [40,43,44].

Different systems are developed based on different biometric characteristics of the human, such as gait, footstep and many others. For example of those systems in Figure 2 shown a system adopts the ubiFloor and identifies users by walking pattern.

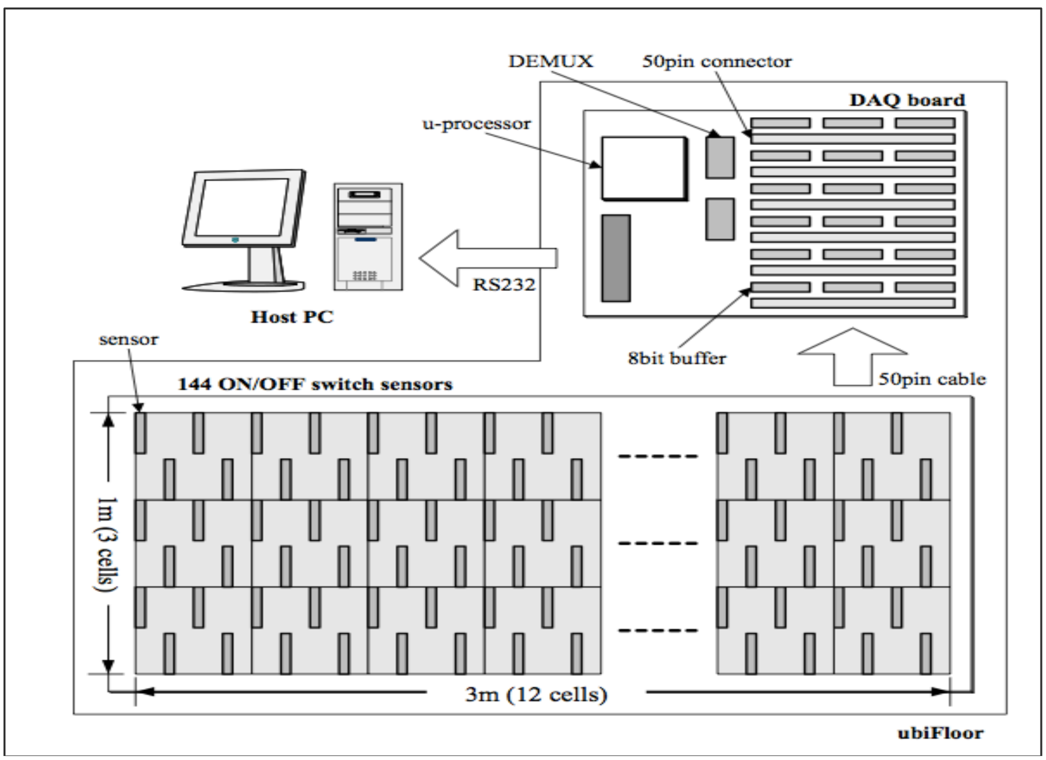

Figure 2: The structure of the ubiFloor system.

In this system by using of simple on/off switch sensors user's step positions are successively transmitted to a host PC in real-time which has software programs to identify the user based on received data sets. It uses the position of several steps as user's walking features [43].

Another example for this kind of system is a smart floor system based on footstep profiles, instead of the walking features, here used pressure of the step. Different user footstep profiles are dissimilar enough for the system to achieve reasonable accuracy. This helps creating an accurate system for recognizing a user's identity from their footsteps [40].

2.2.4 POSITION RECKONING

This technique is based on the principle of tracking the target from an initial known location and to continuously update its position, based on the data that a device can acquire, like speed and orientation. Most of the current systems use smartphone built-in sensors to acquire data as acceleration and orientation thanks to their high availability. Since devices built-in sensors may have different performances, localization algorithms of this kind have to be able to take this into account. Accuracy is limited by the sensor precision, magnetic disturbances inside structures, and unknown variables such as carrying position of the sensor and stride length. Such systems can be used alone to perform indoor localization without any data has been collected by a central system [18], also using peer to peer communication to improve the positioning, or used in mixed systems with other technologies, like Wi-Fi or RFID. This improves the accuracy obtained using the collected data directly by the device showing a considerable effect, increasing systems accuracy. [15,34].

For example, this article [34] studied how to improve Light Matching approach with additional sources. The light alone needs some time to converge and it is not always available. But with the additional sources (WiFi + Map + PDR (Pedestrian Dead-Reckoning) + LM (Light-Matching)) it is possible to reduce the larger errors that are caused by the delay of the convergence. The combination of matching approaches with absolute positioning techniques is always good, since all methods together eliminate multi-hypothesis and permit to reach sub-meter accuracy.

2.2.5 Radio Wave Technologies

Radio waves are electromagnetic waves, which have frequencies between 3 KHz and 300 GHz. They are used in many applications for example: fixed and mobile radio communication, broadcasting, radar and other navigation systems, communications satellites, and localization. In localization the most used are the shorter-range radio frequency waves, as RFID, Bluetooth, UWB, Zigbee and many others will be introduced in this section.

2.2.5.1 RFID

Radio Frequency Identification (RFID) is a technology that uses one or more fixed devices in known positions, to scan the environment, searching other devices. Such objects, called tags, respond to the input, giving the possibility to be localized. There are many different RFID systems that work on a very large variety of frequencies starting from 125 KHz to over 5 GHz.

RFID tags fall into two categories, active tags, which contain an internal power source, and passive tags, which obtain power from the signal of an external reader. Because of their lower price and smaller size, passive tags are more commonly used then active tags for retail purposes.
Because of the great variety of choice in terms of frequencies RFID have been used in many localization systems with different roles. They have been used for accurate localization [36]. For example, in [31] the system may estimate the position of the subject with error less than 20 cm. RFID can be used in proximity localization systems [13,30], with the possibility of unobstructed systems.

There are a number of relevant applications for this technology, for example the navigation of automatic guided vehicles (AGVs) for logistics applications. It is typically implemented by optical means using, for example painted lines on the floor, such as auto-tag in UK have demonstrated AGV positioning using floor mounted RFID markers. Another application is for RFID-based navigation system for blind people implemented in Swiss railway network provided with paving stones, which have a tactile feature distinguishable by the visually impaired using a cane. This allows the blind customers to navigate safely throughout stations [38].

2.2.5.2 Bluetooth

Bluetooth is a technology mainly developed to connect two or more devices to exchange data within a short range. Bluetooth stands in the 2.4GHz band. The benefits of using this technology for exchanging information between devices are: low cost, low consumption, and small size. Each Bluetooth tag has a unique ID, which can be used to tie localization information to a specific tag and its associated target.

The fact that Bluetooth has evolved to gain better performances and ranges gives the possibility to deploy localization systems with sub meter accuracy [54,56], although the major use in localization problem is to assist other technologies in mixed system (e.g., for synchronization purpose or in proximity techniques that do not aim to reach high localization accuracy) [55,56,57].

2.2.5.3 UWB

Ultra wideband (UWB) radio signal is a technology for short-range, high-bandwidth signals, characterized by a pulse, limited in time in the order of pico or nano seconds, on band typically larger than 500 KHz. The large bandwidth allows the signal to be more robust against interferences and frequency specific problems (like multipath or attenuations) directly caused by obstacles interactions. They have advantages also in term of signals interference since their energy is spread across a large frequency range and they are concentrated in time, and this less prone to be disturbed by (or interfere with) other signals. Like most of the radio technologies used in localization UWB needs base stations that collect the data of active tracked devices. Some usage of these technologies has shown its ability to reach high accuracy in tracking subject [12,14,19,20,67]. The cost of hardware makes it expansive for wide-scale use.

As an example, UWB location fingerprinting allows robust high precision localization in a rich multipath environment like an office. It has been performed to evaluate the location fingerprinting approach with real world measurement data including LOS (line of sight) and non-LOS situations. The performance has been evaluated with particular focus on region size and amount of necessary priori knowledge. The presented evaluations prove UWB location fingerprinting allows precise indoor localization without the necessity of synchronization.

An average positioning error of 4 cm can be achieved using regions with width less than 10 cm without encountering ambiguity between neighbor regions [26].

2.2.5.4 ZigBee

This technology is based on one of the most widely utilized standards for Wireless Sensor Network, with low power, low data rate, low cost and short time delay characteristics, simple to develop and deploy, and providing robust security and high data reliability. It is supported solely by the ZigBee alliance that uses the transport services of the IEEE 802.15.4 [47] network specification. ZigBee devices are very low consumption and they typically use 1mW (or less power) in sleep mode and only about 30mW for data transmission. They still provide range up to 150 meters in outdoors achieved by the technique called direct sequence spread spectrum (DSSS). It works in the 868 MHz (Europe), 915 MHz (North America and Australia) and 2.4 GHz (available worldwide) ISM band with up to 20 kbps, 40 kbps and 250 kbps data rate respectively. Other reasons to use ZigBee are its reliability, the possibility to easily implement network self-healing mechanism, the support for large number of nodes, and the availability of different models with different characteristics, and remotely upgradeable firmware. Because of its low cost and, its low power consumption and the fact that the needed infrastructure is relatively simple to deploy these systems are also successfully used for indoor localization, obtaining accuracy errors in the range of 1-3 meters [58,59,60].

2.2.5.5 Wi-Fi

Wi-Fi is a wireless network technology operating on 2.4 GHz and 5 GHz developed to provide high bandwidth data connection in local areas, like homes and offices. Thanks to its high availability and relative little cost the Wi-Fi signal has been used in indoor localization systems. Due to the nature of its signal, the device to be tracked needs to be active. Its main problems are that its frequency is relatively high (and it suffers from attenuation and multipath problems), and the tracked device has a high power consumption compared to similar systems. Wi-Fi localization can be used to obtain 1-2 meter error range results using metrics as the RSS [1,2,3,35]; more complex metrics from the radio signal such as signal to noise ratio, multipath information, phase and frequency offset in order to limit the multipath and interferences problems [1,3,11].

Some systems have improved their results by using fingerprinting (a localization helper technique; explained in the next section) techniques based on the Wi-Fi signals [1,2,3,4,5,6,25] or other independent radio signals like FM broadcast frequency [1,2,3,8] showing the possibilities to obtain accuracy in the range of few meters [1,2,3,25] which is good for room localization to more accurate results [4,5,6,8,11,35].

2.2.5.6 GSM and FM radio

Global System for Mobile Communications (GSM) and Frequency Modulation (FM) radio signals are low frequency signals (900-1800 MHz and 87.5 to 108.0 MHz) used for telecommunications and radio broadcasting [3,7,8].

They are widely spread on the territory and their frequencies and signal design allow a good penetration in indoor environment. Thanks to this they can be used in an indoor localization system.

The idea is to use those already present signals to perform localization instead of creating a local radio source. These technics also have the advantage that their tracking devices are quite simple and consuming low power. Many studies have shown the possibility to use FM radio signals as an independent fingerprint indicator to be used in mixed system [1,2,3,8]. There is a possibility to reach good result when they are used alone [8,9,17], with results that vary from room level [9,17] to sub-meter [8] accuracy. GSM signal is also used to perform indoor localization in several studies [4,7] showing accuracy in the range of 3-5 meters using different fingerprinting techniques. The main problem related to this kind of approach is that, using an independent broadcaster it is impossible to control the signal source changes in its characteristics can invalid the fingerprint information.

2.2.5.7 GPS

GPS is a tracking system based on satellites broadcasting microwave signals sending their positional information with respect to the earth. Those data are then elaborated by the receiving device to compute it's position. Because of the used high frequency, GPS signal is not suitable to be used in indoor environment. However usage of receivers, especially designed to work in indoor condition, showed the possibility to use such signal achieving a mean accuracy error around in the range of 4.5 - 8 m [28] at the cost on an initial outdoor tuning, or an average one of 9.6 m [16].

This level of accuracy is similar to the one of the GPS in outdoor condition but still not enough to be used for indoor localization. The idea of using GPS signal in indoor localization has also produced some attempt to mirror the original signal in indoor locations by means of different channels.

2.3 RF Localization Algorithms

To estimate the position of an object in the environment it is needed an algorithm computing such position, starting from the raw data collected by the system sensors. Because each system can collect different kind of data there are different kind of algorithms with different approaches based on the available information. Some of the most common algorithms will be shown in this section.

2.3.1 RECEIVED SIGNAL STRENGTH BASED ALGORITHMS

This technique computes the position of an object starting from the distances between it and some reference points. Radio equipment is placed at each reference location and a signal is used to communicate between those and the equipment associate to the person to locate. In order to estimate such distance the received signal power is measured at the object location. Knowing the relationship, typically logarithmic, between the distance and the received power of a signal is possible to estimate the distance. To compute the position of the object three different distances related to different known fixed locations are needed to perform localization by multilateration. Since we are only interested in the distance between each pair, it is not relevant which sensor is the transmitter or the receiver.

For example in Figure 3 shown a trilateration process (a multilateration performed with 3 reference locations) with three fixed sensors and a moving transmitter to be located. When the distances from three different sensors are known, the location ideally is at the intersection of the three circles centered in each sensor with the radius being the calculated distance. Imperfect measurements create a region of uncertainty in which the transmitter is contained.

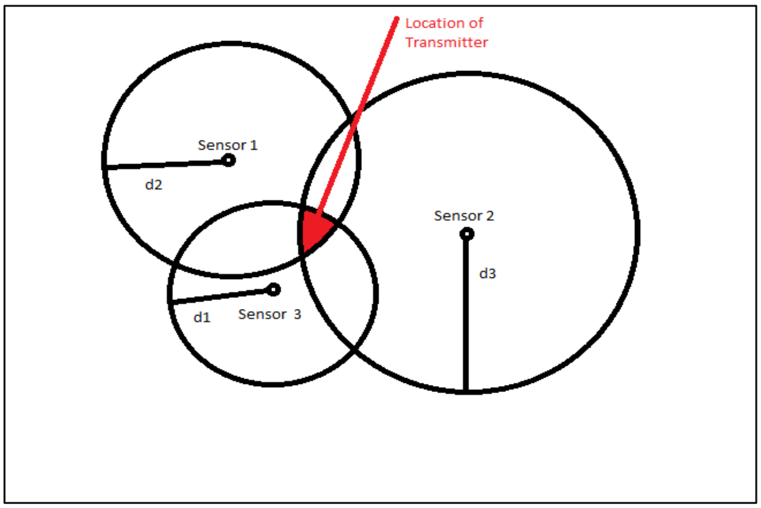

Figure 3: Example of trilateration.

2.3.2 TIME OF ARRIVAL (TOA) METHOD

Time of Arrival is time-based method. This method is based on the accurate synchronization of radio communication devices.

It uses the measure of time a signal takes to travel between two locations in order to estimate their distance. This is possible because the speed of the radio waves in open air is stable and well known. The accuracy of this method relies on the precision of synchronization between all radio communications device, especially considering the high speed at which the signals travels, this can be hard to obtain. Also, as with any time sensitive systems, there is also the possibility of significant hardware delays that must be accounted for to calculate the correct distances. Once at least three different distances are computed it is possible to estimate the position of the object using multilateration technique like in RSS method.

2.3.3 Time Difference of Arrival (TDOA) Method

This technique, like TOA method, is based of the time of signal arrival but it does not require the tracked object to be in synchronization with the other devices. With TDOA, a transmission with an unknown starting time is received at the various receiving nodes, with a time shift requiring only the receivers to be synchronized. Each measurement produces a hyperbolic curve in the localization space on which the location of the mobile node lies. The intersection of multiple hyperbolic curves specifies the possible locations of the client, so at least three different receivers are needed.

2.3.4 Angle of arrival (AOA)

AOA is a method, which uses simple triangulation method to compute the location of the receiver. The receiver measures the direction of received signals

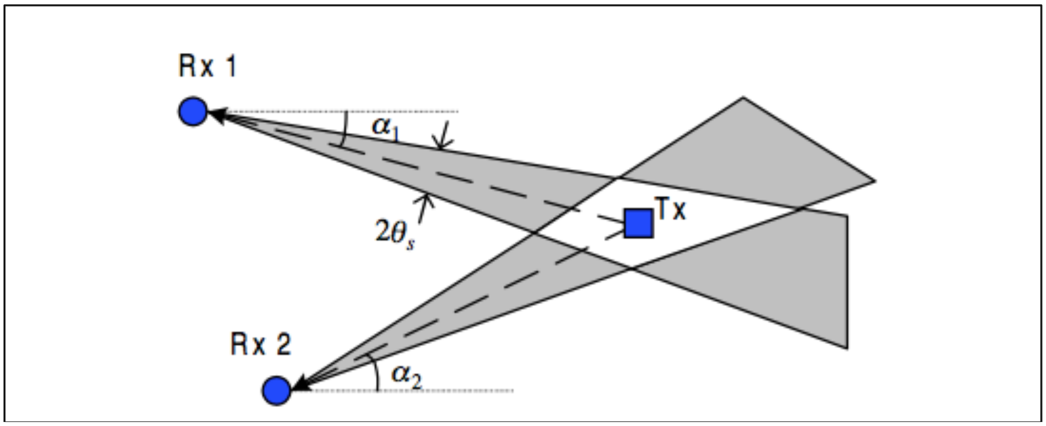

Figure 4: Angle of Arrival method.

(Emitted by the target transmitter) using directional antenna arrays. By using two receivers as shown in Figure 4**,** it will received the position of the object T regarding to angle a1 and a2. Also, as it is visible from the Figure, the accuracy of these measurements depends from the position of the transmitter with respect to the receiver. In case the transmitter lies between two receivers, AOA method will not be able to calculate an accurate position. So, in such case at least three receivers are needed to provide a valuable position. This method has good performance when there are not obstacles between the transmitter and receivers suffering from signals distortions like refraction or multipath propagation caused by obstacles.

2.3.5 FINGERPRINTING

This method estimate the position of an object comparing the real-time signal measurement with historical record of such measures collected before. In this sense, this is not a direct measure but instead lookup data comparisons with some live data measurement and some historical record of the same data. Since the historical measures also contains at where they have been registered, it is possible to estimate the current position of a receiver, finding the most similar measure in the historical data and look at the associated location. The historical data collection can also be time variant due to the environment conditions, so it is needed to periodically re-collect them in order to keep the system tuned. For the reason of needing a pre run phase to collect the lookup data, the use of this method is not always feasible or convenient. A difficulties with fingerprint approach is that the devices used at on-line stage for localization can measure different values in regard of the one used at off-line training potentially decreasing the system accuracy.

This method is often used to support other localization algorithms that compute the position using live data to increase their accuracy.

2.3.6 PROXIMITY DETECTION TECHNIQUE

This technique is sometimes referred as fingerprint because it can identify the presence of a subject in a space, but is not related to the fingerprinting technique described before. It estimates the position of an object by associating it to the area covered by a sensor. Since it provides only Boolean information about the presence of the target object, its accuracy is limited.

This method is used in several wireless positioning technologies, as RFID, Bluetooth, Wi-Fi and custom radio devices. It is one of the simplest positioning methods to implement by providing coarse location information, associated with sensors placed in keys locations [33].

2.4 Performance Metrics in Localization

When dealing with different systems: built with different technologies and operational logics that aim to the same goal, it is important to have some common metrics to compare them and evaluate their fitting under particular circumstances.
In the localization field performance metrics can be classified as the following [27]:
Accuracy: Accuracy (or location error, also called the area of uncertainty) of a system is an important requirement in positioning systems. Accuracy can be described as an error distance between the estimated location and the actual location. The system is always better if accuracy higher.
Precision: Precision measures the ability of the system to produce the same output given the same input. This can be interpreted as an indicator of the internal stability of the system (not related to external changes).
Scalability: The scalability of a localization system is an ability to maintain its capabilities while increasing the coverage area and/or the number of object to locate. A scalable system should be able to manage a change of needed coverage (supported by opportune infrastructures) or a change in users without special maintenance effort.
Responsiveness: Responsiveness is the measure of the ability of a system to reflect real world changes (input) into position estimation (output). This will also affect the maximum refresh rate of the output.

Coverage: The coverage of a localization system indicates the dimension of the area on that it can operate. A system with good scalability should not have any problem in providing the needed coverage in any situation.

Adaptiveness: Performances like accuracy, responsiveness and coverage can be affected by environmental changes. The ability of the system to deal with these changes is called adaptiveness. This can be an important metric especially if the system is supposed to be deployed in different locations under different environmental situations (climatic, spatial and others) without particular tuning.

Cost and Complexity: The cost of a positioning system is the sum of different aspects. The major costs are: the cost of the needed hardware, the cost of the deployment of such hardware in order to operate and the cost of the system maintenance which can heavily depend on his complexity in term of infrastructures and human effort.

CHAPTER 3

RELATED WORKS

In this section we will analyze previous works done in Low frequency indoor localization by different authors. And we will show the results of their works.

3.1 Low frequency indoor radiolocation

(By Matthew Stephen Reynolds [46])

In this work the author presents an indoor localization system based on 2.0 MHz radio signal. The frequency was selected because the author believed that it can be less influenced by obstacles, in terms of propagation path and attenuation, with respect to the usually GHz range frequency adopted.

The proposed system aims to provide a constant update (at 1KHz rate) at the position system with sub-meter accuracy. It was composed by a series of fixed transmitter installed at the edge of the building, and some mobile receivers inside it. The transmitters communicated to each other by means of cable connections in order to keep synchronization. Once the receiver received the signals from the transmitter it can compute its position without the need of any further communication. To achieve this, a radio map of the test environment was built with a technique similar to fingerprinting. This clarified the propagation of radio waves at the selected frequency and to increase the system accuracy.

The positional information is derived from analyzing amplitude and phase of the received signals from fixed references radio stations. Since amplitude and phase analysis require time synchronization between transmitter and receiver, a wire connection has been used during the test phase. The environmental noise has also been observed to have a visible effect on the quality of the obtained measurements with the difficulties of depending on the time, changing day by day its influence and being totally uncontrollable even if measurable.

Lower frequency poses a problem in terms of multipath signal interferences because of the large wavelength. Used multipath propagation model that pointed out the ground-ceiling effect of trapping the radio wave reflections in a space between two surfaces, did not explain all the anomalies observed during the measurements. The author thinks that a better model can avoid the problem.

The idea of the author was to use two both amplitude and phase as independent indicators to estimate two distances from the same signal. This was meant to understand which indicator was the more reliable and understand if they could be used together. Due to the values of the phase indicator collected in the test were very different from the ones expected only the amplitude indicator have been used. The tests collected were good the mean error was 0.10 m with a standard deviation of 1.68 m in the first and with a mean error of 0.05 m and standard deviation of 0.71 m in the last one.

3.2 Range Estimation Technique Using RSSI Low Frequency Waves

(By Kenichi O., Yuji Abe, Tomohito Takubo, Yasushi Mae, Tanikawa,Tatsuo A. [66])

In this study the authors investigate the benefit of using low frequency (125KHz) radio waves for indoor range estimation in terms of robustness against obstacles attenuation and reflections.

In the experimental phase they compare the using of such frequency to a ZigBee system measuring RSS in different distances and situations. While the ZigBee shows sensibility to obstacles the proposed system respond with high signal stability and almost no influence by metallic and non-metallic obstacles. They also conduct some test to investigate the effect of the angle between transmitter and receiver on the measured RSS at different distances. This revealed that at the maximum distance the power is received at the same level for every angle having a sphere shape, while the more the distance decrease the more the RSS tend to have an eight-like shape being stronger on two opposite angles and weaker on the other two.

In the range estimation measurements the mean error were above the expected value being around 0.5 m at the distance of 5 m and 3 m at 7.5 m. This is because in those test the observed propagation model was not considered; instead a uniform propagation was used. Even if the signal maintains great stability at long distances the difference in RSS per meter was too low to avoid the problem that different orientation in respect to the transmitter produce different RSS values for the same distance and similar RSS values at different distances.

3.3 Rethinking Indoor Wireless: Low Power, Low Frequency, Full-duplex

(by B.Radunovic, D.Gunawardena, A.Proutiere, N.Singh, V.Balan, G.Dejean [48])

In this paper, the authors investigate the possibility to substitute the normally used radio frequencies in local Wi-Fi networks (2.4 or 5 GHz) with lower ones (900 MHz) for the advantages in avoiding attenuations, reflections, and general environmental interferences and to decrease power consumption. They have presented a novel design paradigm for indoor wireless networks, which claims that the indoor wireless should use low carrier frequency, low transmit power and full-duplex communication in a single band.
Their work shows that those assumptions were, at least in part, true. In fact the proposed system was able to use a 900 MHz radio signal to operate a local wireless network with the same performance of a standard 802.11g (2.4 GHz) network (in terms of bandwidth and coverage) with the benefit of significant lower power consumption.

3.4 RFID Indoors Positioning based on Probabilistic RFID Map and Kalman Filtering

(by Abdelmoula Bekkali, Horacio Sanson and Mitsuji Matsumoto [62])

In this paper, authors presented a new positioning algorithm for RFID tags using two mobile RFID readers with 915Mhz frequency for indoor localization. The method proposed is analytical, estimating the location of the unknown tag by using multilateration and probabilistic RFID map based technique, with Kalman Filtering.

Their model based on RSS measurement for the location estimation, but it suffered from the fluctuations of the received signal strength. Those fluctuations were generated by the RF environment, but also by the RFID antennas orientation and radiation pattern, particularly when the RF tag was placed onto a lossy dielectric object or a metallic surfaces. In order to reduce the effect of those fluctuations and parameters and to improve the accuracy of the location estimation, an Adaptive Kalman Filter applied. For experiments, 500 RSS sample values were generated for each data point.

The result suggested that the estimation error in term of mean and variance of the estimation error increased as the distance from the readers increase. Hence, the measurement error is not uniform inside the reader's coverage area. An optimal resolution or distribution of landmarks and the short distance between the readers and the target may increase the location accuracy and precision.

After all, the results shows that proposed algorithm were able to provide good performance in accuracy, with a mean error in the range of 0,5 - 1 m and scalability.

3.5 A Standalone RFID Indoor Positioning System Using Passive Tags

(By Samer S. Saab and Zahi S. Nakad[63])

Authors of this paper proposed a standalone Indoor positioning system using with 865Mhz radio frequency. The idea based on an object equipped with an RFID reader module, reading low-cost passive tags installed next to the object path. As in the previous paper [62], authors propose the use of Kalman filter, designed to decrease the error of the reader location estimation.

Block diagram of the positioning system is described in the Figure 5.

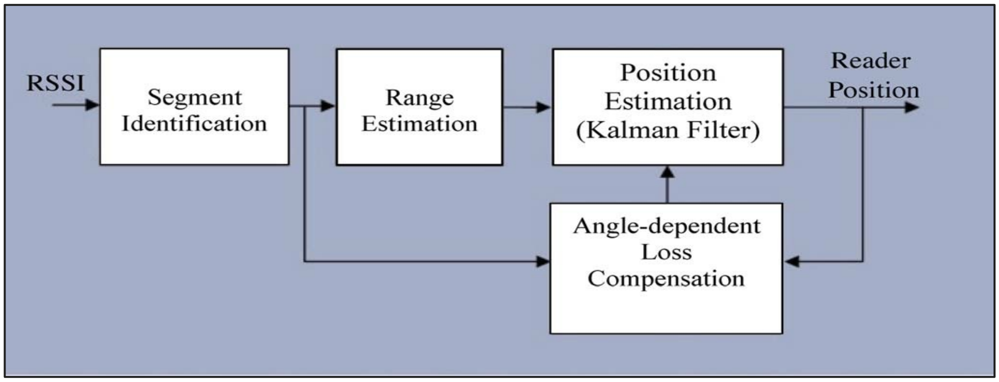

Figure 5: Block diagram of the positioning system proposed by authors.

The Kalman filter was developed for estimating the RFID reader position based on the instantaneous RSSI measurement received from the neighborhood's tag readers. At the end of the experiments, the proposed filter worked well with constraints relative to the path constitution. The average absolute position error was about 0.1 m, and the average of the absolute tag reader distance error was about 0.055 m.

The authors conclude that, a standalone passive tag RFID system promising good results in Indoor Positioning System (IPS).

3.6 Improving Accuracy for 3D RFID Localization

(By Jinsong Han, Yiyang Zhao, Yan Shun Cheng, Tse Lung Wong, Chun W. [51])

In this paper, authors presented active RFID tag for 3D localization. Actually, the work extends the RFID-based localization from 2D to 3D space and refines the location regions from pervious works. The authors used the frequency range 433 MHZ, for active tags.

To simulate practical scenarios they used an empty classroom. The design of the whole system is as following: system deployment, RSSI data collection and analysis, tracking targeted tags, and refining the location of targets. They developed an efficient algorithm for 3D localization based on the signal strength track targeted tags.

A grid of reference tags is used to acquire reference data to be compared with the moving tags attached to the person to locate. In this way the received RSSI values are compared at real time with other values associated to well known positional information. The initial RSSI values collected were noisy and with poor stability. Because of this reason they filtered the raw data. The associated read value with the average position of the most similar reference values giving priority to the area where similar results were denser.

In the system there are two antennas on each reader, thus the reader is reporting that two RSSI values for each tag, one for each antenna. In case the signal cannot be detected due to the interference, they have developed a policy to maintain a good estimation of the RSSI. If both antennas report values, they take the average, if only one of the antennas provides a value, they take it as the resultant value, and if both antennas do not provide a value, they assigned -1 as a label and tag as not detected.

The estimation error was higher when the distance between the readers and the tracking tag became larger; the average estimation error of 8 tags is 0.54 m.

In the 3D grid, each reference tag is assumed to be placed with a 1-meter distance with its adjacent tags. The obtained results are acceptable for an efficient indoor localization use but pose the problem of install such dense grid of reference tags.

3.7 Low-Frequency RFID Based Mobility Network for Blind People

(By Lorenzo Faggion, Graziano Azzalin [64] and Electronic white cane for blind people navigation assistance by Faria Jt., Lopes St, Fernandes Ht, Martins [65])

Both paper present system that use passive low frequency (134 and 125 KHz) RFID technology to provide localization information to visually impaired people. The two systems aim to create safe paths to reach some point of interest. Those are realized by passive RFID tags containing positional information in the ground along the interested path. The user can then follow those paths by using a special cane with a built-in RFID tag reader. Due to the nature of the tags the reader can only detect them in a range of 20-40 cm. The cane can give positional information to the user by collecting the tags information, compute them and send a feedback to the user using acoustic or haptic signals. Using those systems peoples can follow safe path between different points of interest possibly receiving additional information about them and have the environment react to their presence.

Both papers proposed the use of this technique to perform indoor localization and guidance and as helper for GPS based information to improve their accuracy. A great effort was made to make the hardware suitable to the real case scenario by make the proposed cane as similar as possible to those already used by visually impaired people. Performed tests proved the effectiveness of such systems, under the condition of an appropriate tags positioning (in order to maximize the possibilities for the user to find them when needed).

CHAPTER 4

DEVICE DESCRIPTION

Since the main goal of this work is to investigate the usage of low frequency radio signal to perform indoor localization there is a need of radio devices with such capabilities. The radio equipment chosen to realize this thesis is composed by two different kinds of devices: tag and base station, which have different capabilities and different roles in the localization process.

4.1 Description of the device

The system based on active RFID radio technology and can be used for different purposes, including indoor localization. It is composed by two main components:

- The control unit, called base station, is board device that control the low frequency (125kHz) antenna. It is programmable and can send low frequency radio signals in the surrounding area. It can also receive radio signals on the 2.4GHz frequency that is used to receive responses of stimulus outputted on the low frequency channel.
- The tags are small devices that can be activated by the low frequency signal emitted by a base station, operate some basic routine and return a response on the 2.4GHz frequency channel.

Both of the devices are able to communicate on two radio frequencies (125kHz and 2,4GHz) but those channels are used in a different way by the two devices.

The base station emits signal on the lower channel and receives messages on the higher one while the tag does the contrary. This configuration allow the usage of a low radio frequency without need to implement an antenna emitting on this frequency also on the tag allowing to contain its size and power consumption. This asymmetry still acceptable, because the RSSI value is computed on the tag device using the received low frequency signal and only transmitted back on the higher frequency.

RASPBERRY PI

The raspberry PI is a low power consumption device, low cost computer on a board with limited computational power based on an ARM core.

For using base stations there is a need for another control device to communicate commands and receive results on a serial port. For this purpose each base station is coupled with raspberry PI, which manages the serial port communication with the base station and also provide the capability to synchronize the work of more base stations connecting the relative Raspberry PIs with a standard WI-FI network. In Figure 6 shown the schema of the Raspberry Pi.

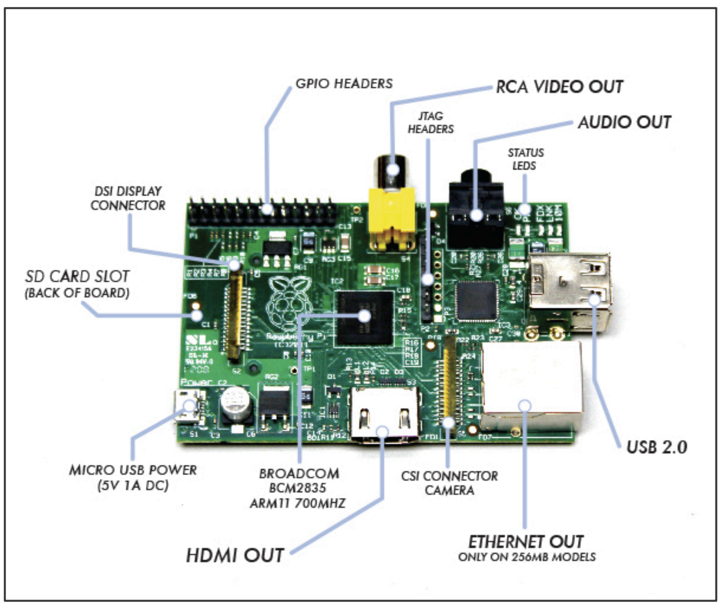

Figure 6: Raspberry PI schema.

4.2 Working principle of devices

TAGs, while turned on remains in a state of very low power consumption. Thanks to their full programmability they can perform all normal operations of a typical microprocessor as read sensors, keep time, acquire data, react to certain events.

The base station transmits a coded signal at low frequency (125Khz) in this way it stimulate the tags in a surrounding area with a diameter greater than 15 meters as declared by manufacturers.

When a tag receive the low frequency signal, it detects the ID of station, it perform the requested operation and respond on the 2.4GHz channel providing the requested data.

4.3 Device characterization

In order to use above-mentioned device to perform localization we need to estimate the distance between base station and the Tag. To compute distance we need to know characteristics of the signal in different environments and find a fitting model between RSSI data and distance.

4.3.1 RSSI Measurements

It is important to estimate the range of the antenna signal in which the tag can be detected in order to know exact area a single base station can cover.

In order to obtain the model that estimates distances using RSSI values, different data acquisitions has been done. For each data acquisition session we took RSSI measurements at different pre-defined distances. Such measurements have been done in indoor and outdoor environments and obtained different results.

Measurements have been taken to cover the area of maximum range of the emitting device, which is identified as the distance where the tag was detected with minimal power value. For each distance measurements were taken in different environments with different orientation of the tag and base station, to investigate the coupling of two device's antennas in different configurations. The tags are capable to detect different RSSI values for the three different axes (x, y, z) of their antenna.

Only maximum value between them has been used. The maximum value has been chosen because received RSSI power values are logarithmic so even a little change between RSSI values means great difference in an actual received power. Because of this the lower RSSI values do not carry much information to add to the strongest one. Also the two weaker RSSI values are not always detected, so they cannot be used as reliable indicators.

Both base station and tag antennas have three different orientations represented with the x, y, z-axes. In the Table 1 presented different RSSI values collected by using different base station – tag coupling. In the first column there is the tag name, the bas station orientation and tag orientation. Each pair of base station and tag axes means that the two antennas have been placed to face each other specified orientation.

BS-TAG-Coupling/ Distance	0,6	0,7	0,8	0,9	1	1,2	1,5	2	2,5	3	3,5	4	4,5	5
2003 x y	31	29	27	26	25	23	21	16	14	12	9	7	5	0
2003 x x	31	27	26	25	25	22	19	15	12	10	8	6	4	0
2003 x z	31	29	27	26	25	23	20	16	13	11	9	7	5	0
2003 z y	31	26	25	23	21	19	17	13	10	8	6	5	3	0
2003 z x	31	27	25	23	21	19	17	13	10	8	7	5	3	0
2003 z z	31	25	24	23	21	18	16	12	10	8	6	4	3	0
2003 y y	31	25	24	23	21	18	16	12	9	7	5	3	1	0
2003 y x	31	27	25	24	23	20	17	13	9	8	6	4	2	0
2003 y z	31	27	26	25	23	20	17	13	10	8	6	4	2	0

Table 1: RSSI data acquisition table.

From the table we can see that x axes of the base station emits more power than other axes. Also it seems that there is no big difference between received RSSI values regarding to orientation of the tag.

Tags comparison

To understand if all the tags report the same values under the same distance and orientation RSSI data sample has been collected in eight different locations for each tag.

In Figure 7 the orientations of base station and tag antennas are represented as a pair of references that indicate the position of the tag in respect to the signal source (y meaning

90 °, x meaning 0 °) and the orientation of the tag in respect to it using the same axes label as before.

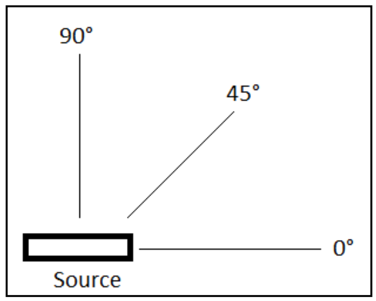

Figure 7: Tag angle orientation.

For understanding and evaluating better the characteristics of the devices we have made different measurements at 1m and 3m. As shown in Figure 8 at 1m the results are almost the same for each tag except for the tag number 2020 that seems to always report lower values than its pairs.

The result shows the tendency to get higher values at zero degree locations and even higher in the case of a tangential orientation. The tag orientations seem to have no effect at the ninety-degree position.

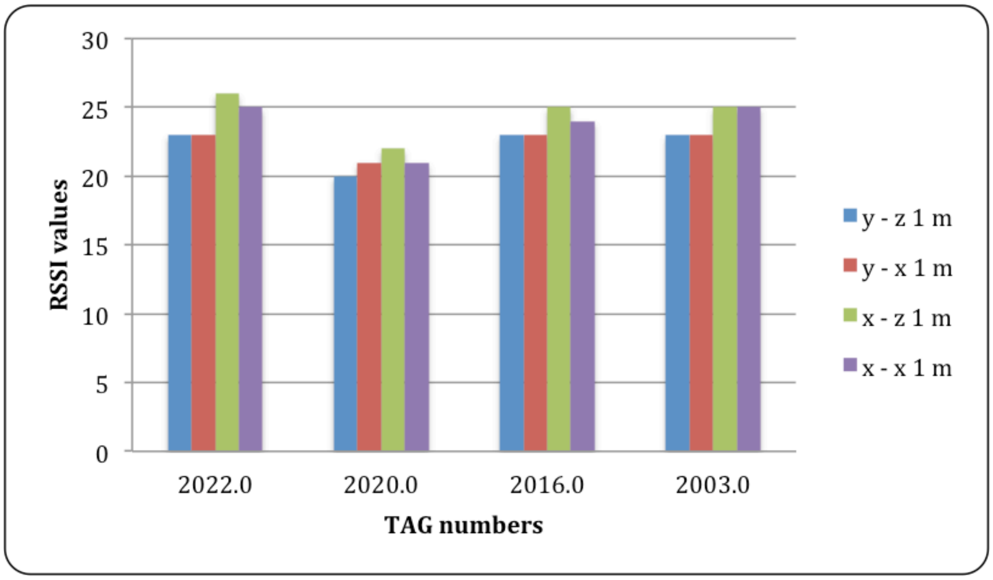

Figure 8: Different TAGs RSSI comparison at 1 m from signal source.

At the distance of three meters the results are seem quite aligned with only tags 2016 and 2003 showing very similar results as seen from Figure 9. Again a tendency of getting higher values at zero degree location can be observed.

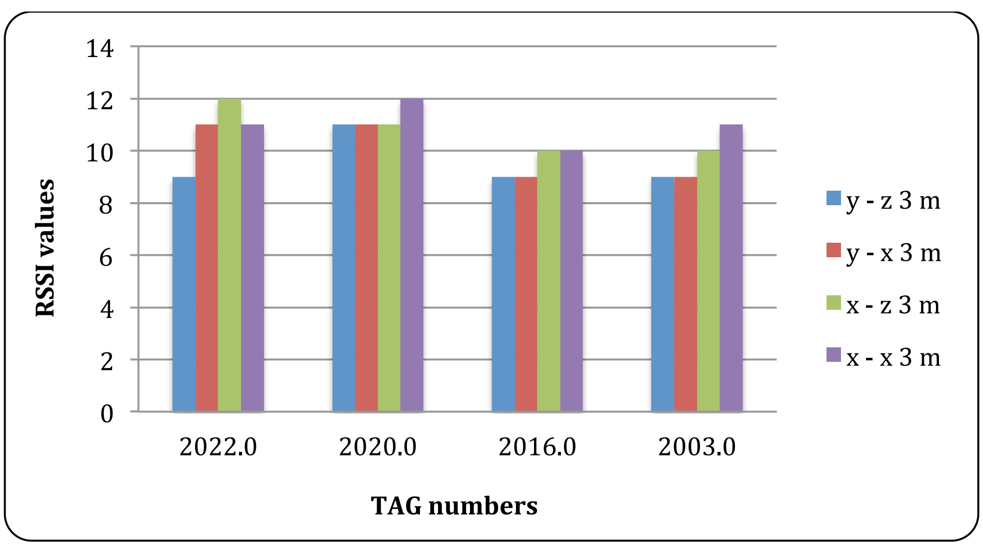

Figure 9: Different TAGs comparison in 3 m.

From above figures we can observe that in x axe of the base station antenna emits more power than other two axes.

Measurements of the different tag angles and orientations

Measurements at fixed distance (1 m) and different angles have been taken to understand the shape of the emitted signal and the effect of the tags orientation.

Two data series have been collected at seven different angles respect to the each source position, with a different tag orientation as shown in the following Figure 10.

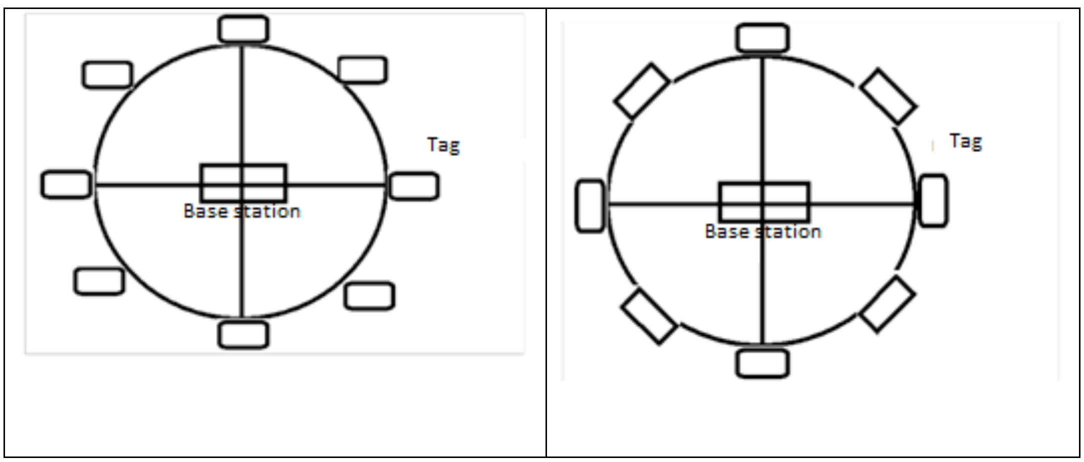

Figure 10: TAGs with different angle orientations.

All data has been collected using the same tag (2022). In the following Figure 11 we are plotting the results in term of median value for each series.

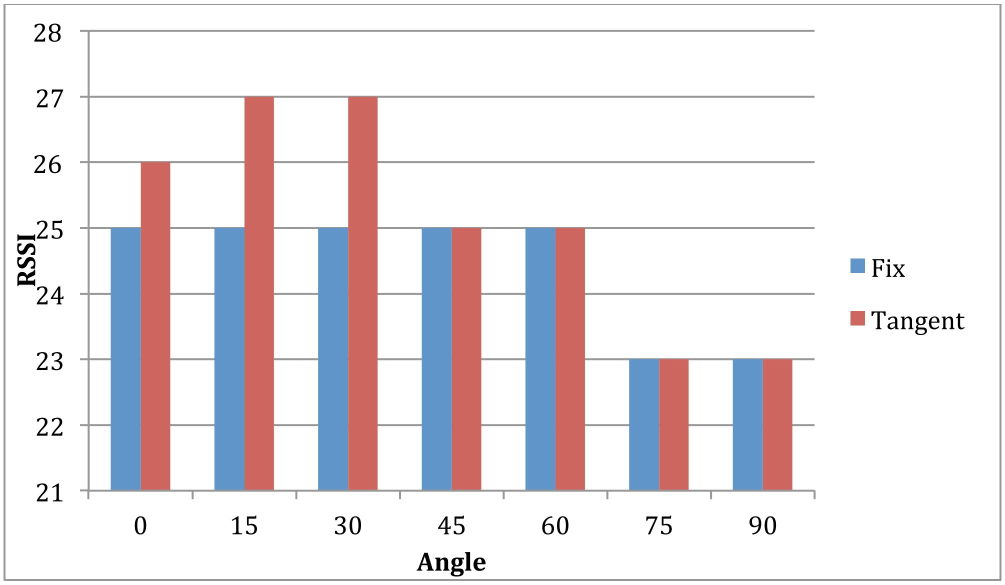

Figure 11: RSSI values comparison for different TAG angle displacement respect to the signal source.

The collected values show a tendency to produce higher RSS values as angle between the emitting antenna an the tag antenna moves from 90 to 0 degree. The orientation of the tag also seems to react to the base station signal with an increase of the received signal strength for the coupling between the x axes of the base station antenna and the z axes of the tag at the distance of one meter. As visible from Figure 16 this is no longer true at the distance of three meters, that coupling effect are probably also effected by distance between base station and tag.

From this and the previous series of data it is possible to observe that each tag responds in a slightly different way. The results are also influenced in a minor way by the tags orientation. Since the characteristic of the used tag and its orientation will not be in the control of the system at runtime this will introduce some errors in the position estimation process. It is not possible to take into account most of those source of uncertain in the final localization process.

The only action taken has been to use the base stations by placing them orientating the x axes, which is the one emitting more power in respect to the other two, in the vertical direction of the space. This will allow to have a circle around the base station on the plane around it at constant high from the ground minimizing the errors introduced by the differences between powers emitted by the base station antenna axes.

4.3.2 DISTANCE MODEL ESTIMATION

To estimate the position of the tracked subject there is a need of distance between it and the base stations. To obtain this a model to convert the received RSSI values to the correspondent distance has been used.

In order to obtain the model, RSSI measurements has been collected at given distances for three different base stations and different tags. Then for each distance the median RSSI value has been taken as reference and used to compute the resulting model.

Since power should decay in a quadratic way in relation with the distance we expected the model to be ruled by that relationship and to be similar to the curve as shown in Figure 12.

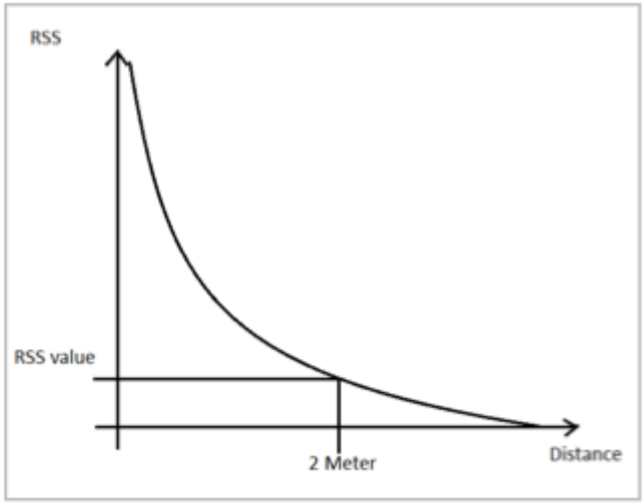

Figure 12: RSSI - expected model curve.

The RSSI values reported by the tags indicate the existence of an area near the base stations where they always report the maximum RSSI value or even no result at all, if they are to close to the signal source probably due to the detected power being higher than the maximum expected. As result there is an area near each base station where the tag are not detected with a diameter about ten to twenty centimeters depending on the base station, and an area where the RSSI is reaching constantly at its maximum value introducing a linear area in the actual sensor behavior, with a ray from the antenna of about 45 cm - 50 cm. To avoid the influence of the linear area the search of the curve that estimate the RSSI – distance relationship doesn't take in account the values collected there. As result an offset based on each base station has been added in the model leading to better estimation outside that area. Since the impossibility to tie the maximum RSSI value to an estimated distance those values has been ignored in the multilateration phase.
In order to understand if it was possible to improve the following (1) basic quadratic model a term of grade three was introduced in the fitting curve.

$$distance = a1 * RSSI^2 + a2 * RSSI + a0 + offset \qquad (1)$$

This addition did in fact improve the model in term of errors between real and estimated distances.

The reason of this improvement is probably related of the fact that it helps modeling the difference between the theoretical quadratic decay and the one that occurs in reality. Increasing the order of the equation doesn't show any improvement.

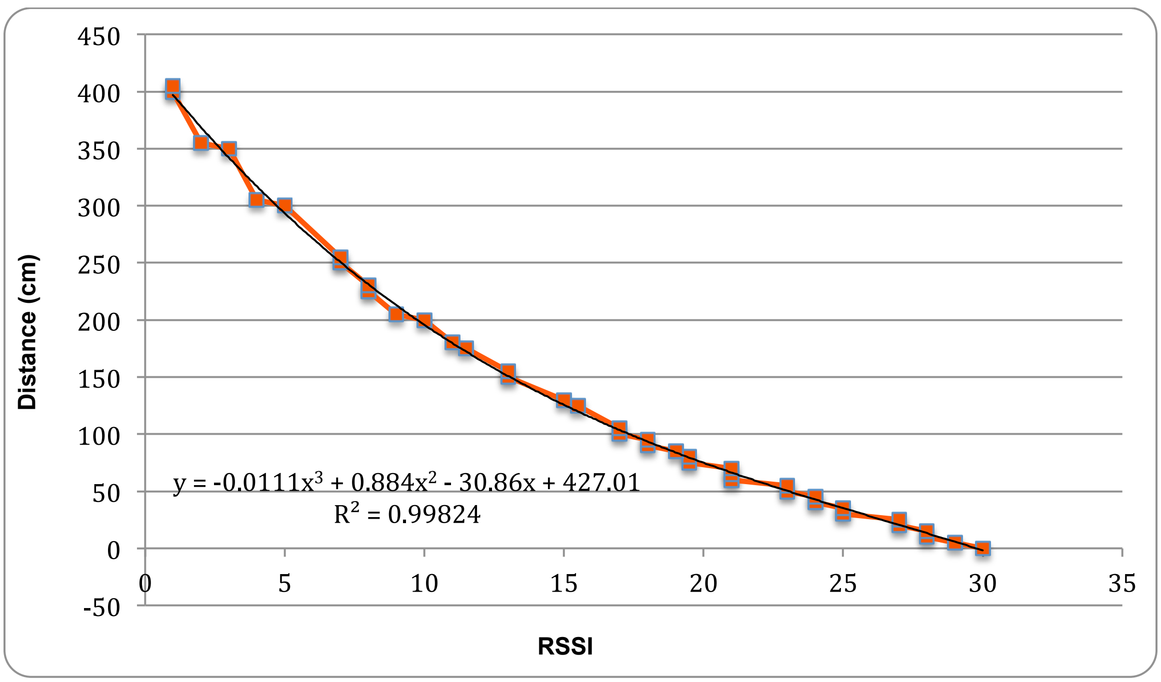

Figure 13: Estimated model-fitting curve with collected RSSI values.

In Figure13 distance/RSSI plot shows the line connecting the median of the collected RSSI values for each distance (in orange) and the cubic curve that estimate it. So as result the following formula (2) of this curve plus the base stations offset has than been used to convert the RSSI values into distances in the system functioning.

$$distance = offset - 0{,}011 * RSSI^3 + 0{,}884 * RSSI^2 - 30{,}86 * RSSI + 427{,}01 \qquad (2)$$

4.3.2 ROUND TRIP TIME (RTT)

Due to the characteristics of the used signal only one base station at the time can scan a given area to avoid interference. This means that even if there is a need to cover each area with at least three base stations to perform localization they cannot operate together at the same time. This means base stations need to operate in a sequential way and each one need to wait until the previous one has finish to emit the low frequency signal and has acquired the correspondent results.

To estimate the time needed by the system to acquire a whole data set from each base station it is necessary to find the time needed by each base station to obtain a single set of data. Such time is called round trip time (RTT).

RSSI data acquisition showed a RTT with a mean value of 0,43 seconds with a standard deviation of 0,0139 seconds with all the samples contained in a range between 0,4 and

0,46 seconds as can be seen from Figure 14 which reports the result of RTT taken with tags placed at the distance of two meters from the base station.

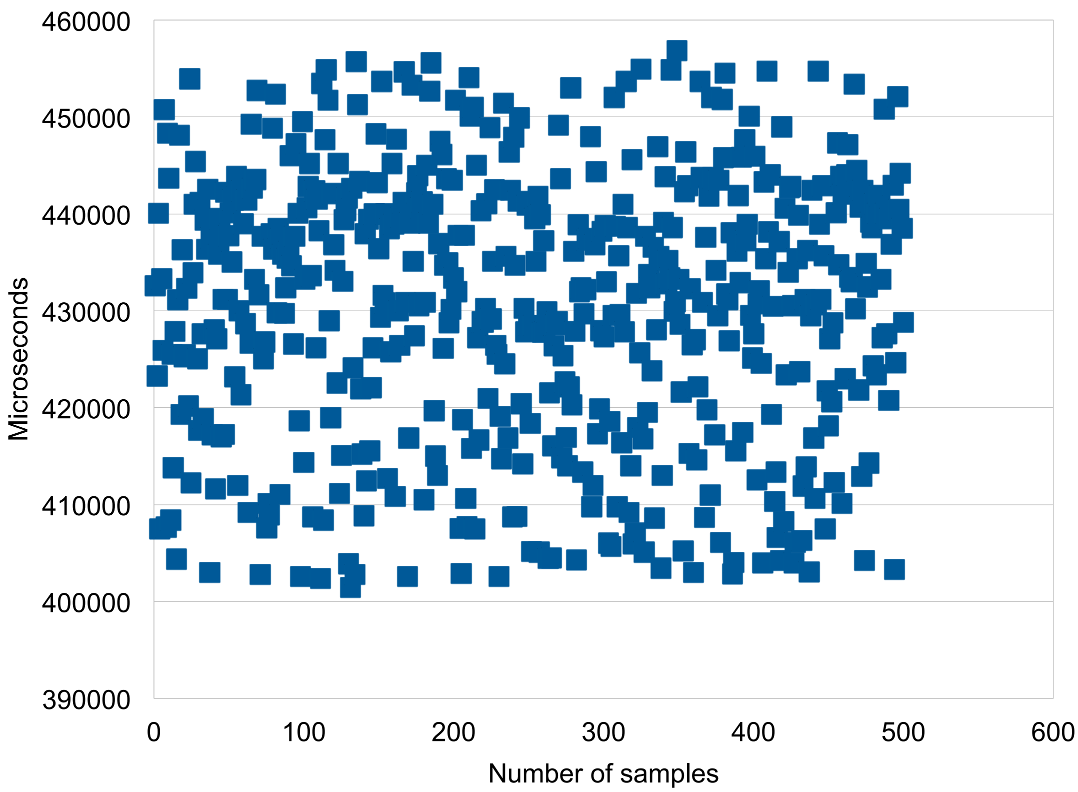

Figure 14: RTT values plot.

4.3.2 OBSTACLES EFFECT

Since in real indoor environment the system has to deal with obstacles such as walls and furniture different measurements have been done to understand the effect of those conditions.

Thanks to the frequency emitted by the used devices (125KHz) the expectation was to have little or no effect in respect to obstacles.

Measurements have been repeated for the same distances with and without walls and other furniture, to observe the differences in the collected RSSI values.

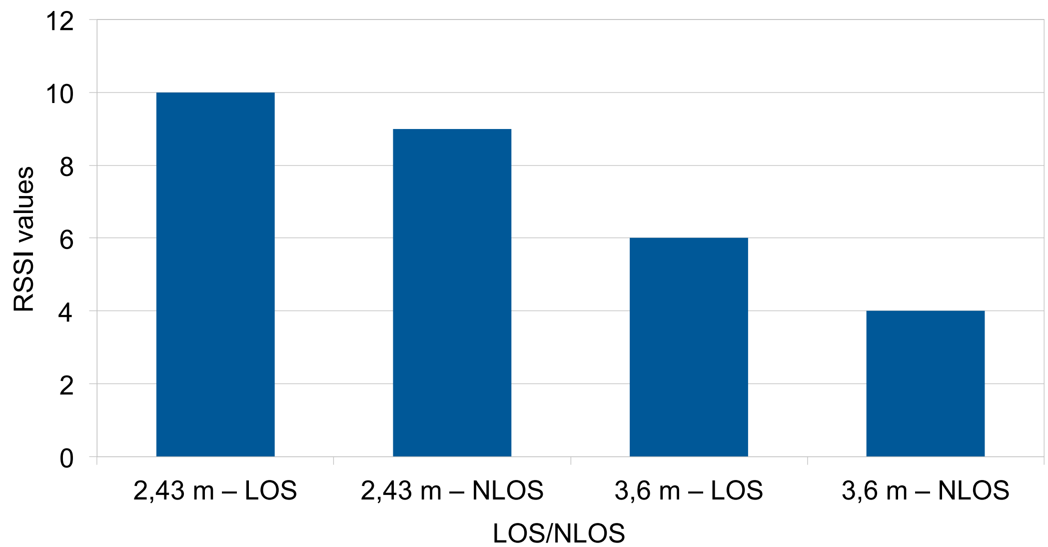

Figure 15: RSSI comparison in Line of Sight and Non Line of Sight conditions.

As the Figure 15 shows, the effect of obstacles is indeed limited but not irrelevant. In particular it is possible to observe that at higher distances the loss in RSSI seems to increase probably due to the fact that the absorbed power is enough to make a bigger difference in the logarithmic scale of the RSSI.

Since at greater distances each RSSI value cover a bigger space than at shorter distances, the fact that obstacles affect those RSSI values in a major way will bias the distance estimation. There are at least two techniques that can help limiting this obstacles effect. One is to take into account the obstacles in the environment as they are and include in a system a process to adjust the estimated distances knowing the precise map of obstacles present in the environment.

This solution has the disadvantage that a calibration is need to be performed for each different environment. A second solution could be to use a statistical model to cope with obstacle presence in relation with the estimated distance giving a probability to incur into an obstacle for each distance with the disadvantage to not reflect the real environment conditions.

At the moment none of the solutions has been implemented in the proposed localization system.

CHAPTER 5

IMPLEMENTED METHODS

In this chapter we are presenting detailed description of the system that performs indoor localization, estimating position with multilateration based on RSSI values. The steps for realizing the system are as following: data acquisition and elaboration, implementing the position method and configuring all steps together.

5.1 Acquiring and Evaluating RSSI data

For performing localization we started with acquiring RSSI data, in order to obtain distances between subjects and sensors. We compute the distance starting from raw RSSI values, provided by sensor and using distance model obtained during sensor study phase as explained in the previous chapter 4. For data acquisition, we implemented C++ code, which acquires RSSI data using commands provided by the device. The device is programmable by sending commands on the serial ports.

5.2 Position Estimation

To obtain the position of the tracked subject we need to implement multilateration algorithm to convert collected series of distances between the subject to be tracked and base stations, the given Base station coordinates.

For realizing this, after knowing the coordinates of the base stations and distances, between them to estimate the subject's position we use multilateration technique. This technique is explained in details in the chapter 2. As seen from the Figure 16 to get the position of the person using this method, he must be in the area where at least three base stations are reaching to his position.

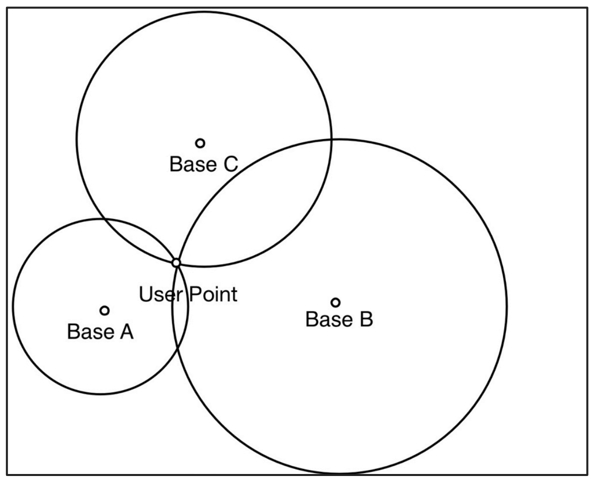

Figure 16: Multilateration with three base stations and one TAG (user point).

Since the acquired data are not perfect due to environment conditions and scan results stability, and because the distance model have to estimate the distances starting from a not continuous value as the RSSI, the estimated position will fall to an uncertain area. Which is created by the fact that the three circumferences having as centers the base stations with a ray equal to the estimated distance to tracked subject the do not intercept in one precise point.

To implement multilateration in coding level, we used the Levmar library, which is a mathematical library that allows to find the point in that area which minimize error on the estimated distances for each base stations.

The library implement the Levenberg-Marquardt iterative algorithm that uses a combination of gradient descend and Gauss–Newton algorithm to solve least square errors minimizing problems. This method uses the slower gradient descend technique to narrow down the area where the minimum lays, since Gauss–Newton don't guarantee to move in the minimum direction if the starting guessing point is very far from the actual minimum. Then switch to the faster and smoother, at least near the minimum, Gauss–Newton method to try to find it.

5.3 System Architecture

The system is composed of a series of at least three base stations working together to perform localization. Base stations communicate with each other on a standard WIFI network, using network capabilities provided by raspberry in order to exchange data.
The system activity is controlled by a server that organizes the scans for all the base stations, receive data from them and compute the position estimations for all the subjects found. Each base station shares the same code so they can act as server or client, depending on given configuration in the configuration file. At the system start up this is only active base station, then when other base stations turned on they sent a message to servers to register themselves.
After this, the server keeps a list of all base stations and decides the order for the execution of the scanning to find existing tags. Since it is important to minimize the time required to obtain data from all the base stations it is possible to configure the system to make base stations to run the scan command in parallel if the distance between them is enough to avoid interferences.

Each time the server receives the response from a base station containing new data about the distance from that base station and the tags in its areas, it recomputes the current tag position using the multilateration method mentioned above substituting the data relative to the current base station with the new ones and optionally writes the result to a log file.
One of the main issues in this system is time synchronization between all base stations. Since every scan result is labeled with a timestamp when it is recorded all the base stations must be synchronized with the same time. The timestamp is useful in order to use only new data to estimate the current position of a subject. For example if a base station stops to report its distance from a certain subject because it has moved out of its range the timestamp will ensure that the old distance information is not used to perform position estimation despite the fact that it is the last available for that base station. For this purpose the server runs an NTP (Network Time Protocol) server, possibly synchronized with an external source, so the clients can use it to adjust their time. The used NTP server in this system is chrony. Chrony is an easy to use and a free implementation of the NTP server available to different platforms. Figure 17 is described the system configured in the environment with the obstacles.

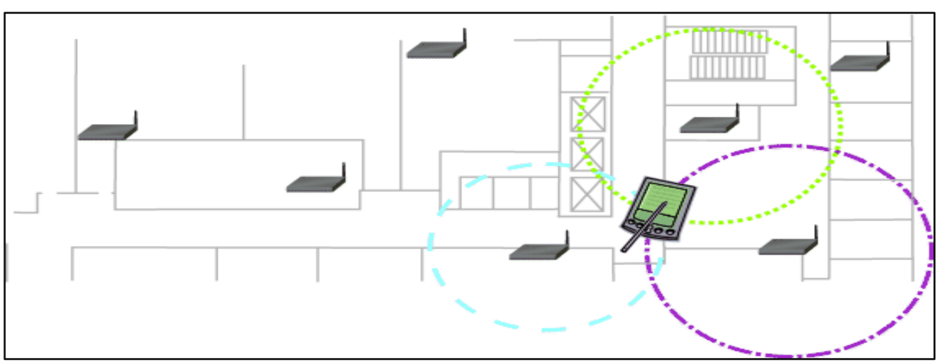

Figure 17: Localization System with obstacles.

5.5 Data Visualization

In order to observe the behavior of the system in real time, web based graphical interface has been developed. This interface can connect to the base station server to retrieve data about current base station in the system, estimated tag positions, and estimated distances between each base station and tag. After getting those data, application plots all those information on the screen as shown in Figure 18.

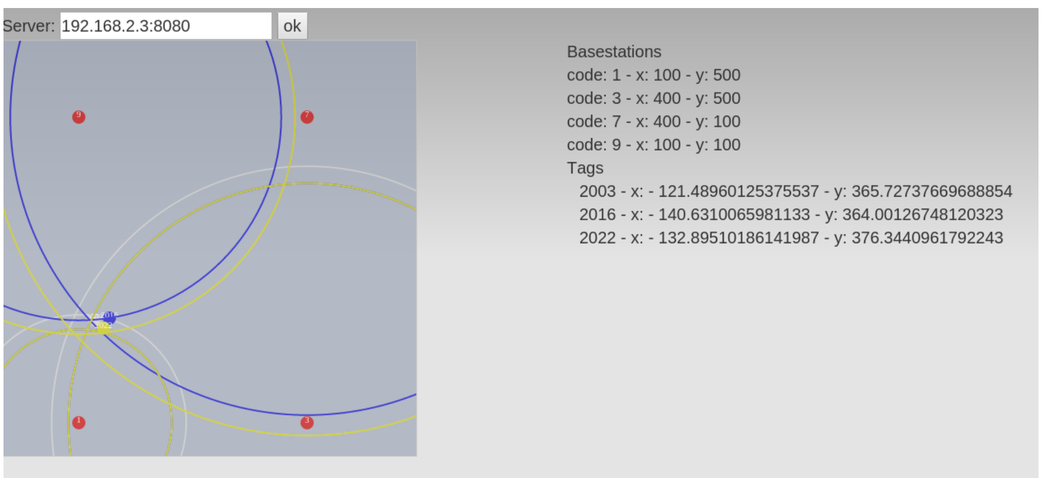

Figure 18: Graphic visualization of Localization System.

CHAPTER 6

EXPERIMENTAL RESULTS

In this chapter we will present our results of the localization system. For this reason we carried out different experiments under different conditions. First experiments are done in the space of the square shape, where tags placed in different fixed positions. Second series of experiments have done with moving tag in square shape space.
We are taking two kinds of series experiments because we need fixed position experiments, to understand accuracy of the system, and moving positions for testing how the system is good for tracking moving person.

6.1 Experiments with Fixed positions of the tags

As we mentioned above we need to take experiments with fixed positions of tags, to test accuracy of the system. Those test are set up by placing tags in the fixed position, and collecting offline RSSI values for a period of the time (3 min). In those preliminary tests the each base station has collected values independently from the others without the usage of a server since the objective was only to collect realistic data in order to understand the system accuracy.

First experiments carried out with user (tag) placed very near to two base stations (Base station 3 and Base station 7), and far from two base stations (Base station 1 and Base station 9) as seen from the Figure 19.

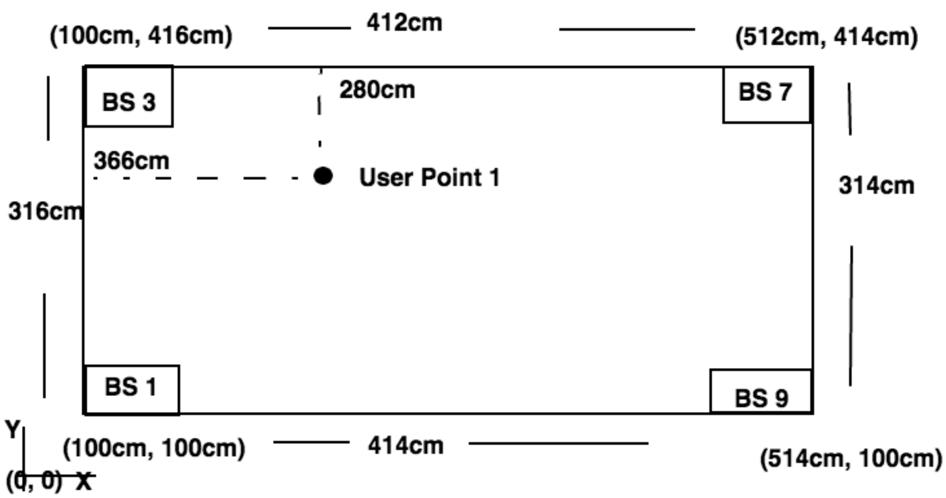

Figure 19: TAG placed at position (280cm, 316cm).

Similar experiments have done for the other User points2 and the 3 as following figures Figure 20 and Figure 21.

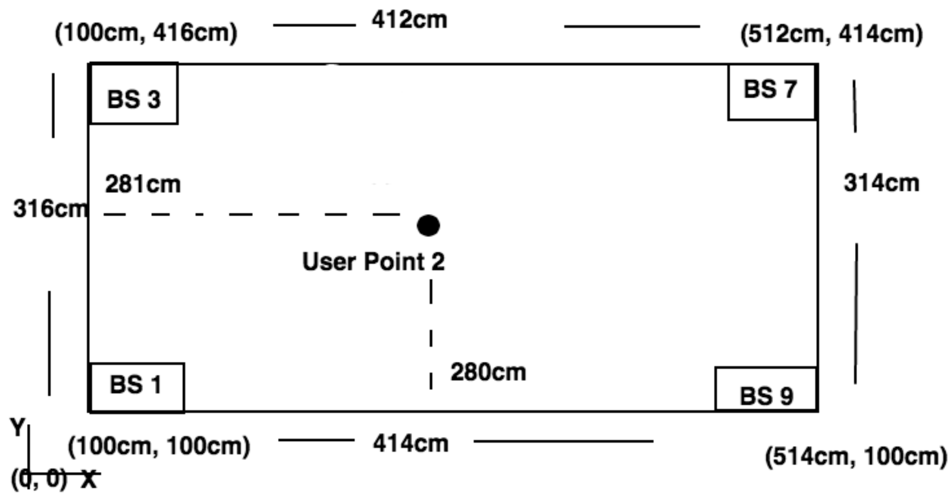

Figure 20: TAG placed at position (280cm, 281cm).

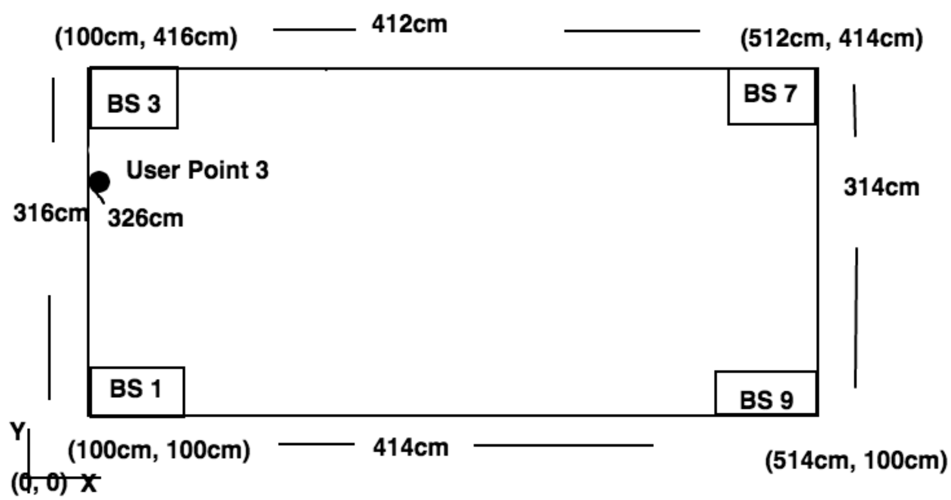

Figure 21: TAG placed at position (0cm, 326cm).

From our preliminary data we got the following mean error/standard deviation table. In the Table 2 Me is mean error, std is stands for Standard deviation.

TAG/ POSITION	2003 (me/std) in cm	2016 (me/std) in cm	2022 (me/std) in cm
User point 1	23,0331/7.78154	27.4581/7.47741	26.0486/5.52506
User point 2	6.58644/7.31135	10.5212/6.31804	11.2446/8.27724
User point 3	20.2005/11.5051	19.3201/10.9067	28.7803/9.89323

Table 2: The results of three user point's measurements.

The results of the three user points as seen from the Table 2 (me/std) shows the better accuracy when the tag placed at equal distance from each base station.

Once it became possible to test the system with online data while actually running it, a more complete test has been conducted testing the accuracy of the position estimation in more positions. A space of three by four meters has been divided in a grid of one meter by 1m spaces and measurements have been taken on each intercept, results are shown in Table 3. Then we subdivided three of such squares in spaces of 25 by 25 cm and collect other values, and results are shown in Table 4. The three spaces to subdivide have been chosen in a way that for similarity with other squares covers all the area.

As a result indicator, we used mean error of the estimated position and standard deviation. Table with measurements 400x300cm, by 100cm measurements is shown in following tables.

X / Y	100cm	200cm	300cm	400cm
100cm		29.24/36.84 37.47/55.85 20.12/33.73 27.96/42.24	43.75/23.12 30.11/22.98 37.17/21.98 36.88/23.36	
200cm	46.16/15.33 22.85/15.02 38.15/16.35 35.69/18.42	12.49/8.05 26.62/14.31 9.06/8.97 16.09/13.25	19.16/3.63 32.06/7.49 18.76/4.49 23.20/8.19	40.38/6.84 30.26/5.74 39.36/6.59 36.64/7.86 -
300cm	25.17/11.70 9.63 / 6.53 20.40 / 9.11 18.19/11.33	11.66/6.72 13.88/9.31 23.59/9.62 16.38/10.08	23.12/4.68 20.87/4.39 20.95/5.02 21.65/4.82	38.64/6.59 32.83/7.80 37.94/6.60 36.52/7.46
400cm	25.82 / 8.50 14.41 / 10.42 33.38 / 7.25 24.54 / 11.77	21.35/7.81 30.67/7.95 26.98/6.23 26.33/8.31	33.41/5.15 33.52/5.57 33.49/4.26 33.47/5.03	56.39/7.88 37.77/10.39 57.44/9.46 50.53/12.97
500cm		32.63/6.78 23.30/11.50 32.66/8.26 29.54/10.08	42.14/17.51 29.02/9.48 41.18/8.68 37.13/13.55	

Table 3: Mean Error and STD result of the measurements in distance of 100cm (TAG_2003: MERR/ STD, TAG_2016: MERR/ STD, TAG_2022: MERR/ STD, ALL_3_TAGS: MERR/ STD. Where MERR: mean error, STD standard deviation.)

x/y	100cm	125cm	150cm	175cm	200cm	225cm	250cm	275cm	300cm
300cm	25.17/11.70 9.63 / 6.53 20.40 / 9.11 18.19/11.33	16.32/6.13 9.72 / 6.88 22.77/9.87 16.27/9.44	13.34/5.22 9.22/6.61 15.48/4.29 12.68/6.04	14.22/4.55 9.00/6.88 13.70/5.60 12.38/6.18	11.66/6.72 13.88/9.31 23.59/9.62 16.38/10.08	11.71/13.40 12.77/11.45 7.84/13.21 10.77/12.89	19.57/8.65 15.13/7.90 17.35/8.72 17.20/8.60	11.46/5.89 14.81/8.97 18.96/9.66 15.01/8.85	23.12/4.68 20.87/4.39 20.95/5.02 21.65/4.82
325cm	19.05 / 7.61 14.05 / 9.06 17.11 / 8.84 16.77 / 8.77	8.50 / 5.20 22.07/8.28 13.66/6.86 14.74/8.88	12.61/5.32 17.56/6.98 9.07/5.08 13.02/6.79	7.14/4.07 14.04/6.38 8.53/5.43 10.04/6.20	7.96/6.28 10.87/7.22 13.60/12.25 10.81/9.27	8.12/7.47 10.49/6.37 6.91/7.45 8.50/7.27	14.94/5.34 20.80/6.75 18.73/6.17 18.16/6.58	7.80/2.81 18.23/6.12 9.81/4.24 11.88/6.41	13.19/3.62 17.99/4.15 22.99/6.91 18.07/6.48
350cm	16.49 / 6.24 15.43 / 9.14 23.58 / 7.65 18.41 / 8.56	11.74/5.35 15.05/6.84 16.39/6.32 14.20/6.49	9.62/5.45 9.10/4.99 11.79/5.25 10.17/5.36	6.46/4.84 12.26/7.31 7.20/5.39 8.64/6.47	10.08/3.65 7.18/10.05 17.51/6.17 11.58/8.35	8.65/4.32 13.75/7.17 10.35/3.95 10.91/5.74	15.80/5.82 28.00/5.34 24.17/3.76 22.62/7.20	13.72/5.75 30.06/6.05 14.63/6.01 19.45/9.56	17.53/3.02 16.28/4.15 20.83/5.57 18.22/4.75
375cm	11.64 / 6.76 16.66 / 8.52 19.42 / 8.70 16.04 / 8.68	11.29/4.69 12.32/6.36 13.47/7.20 12.36/6.24	13.68/7.21 31.13/10.25 13.85/8.71 19.77/12.11	5.08/4.70 32.38/12.66 7.19/3.88 13.46/14.05	11.55/5.07 7.32/5.92 15.04/6.03 11.22/6.51	7.92/3.63 9.11/4.28 17.40/7.94 11.48/7.02	15.06/1.53 19.49/6.03 10.41/3.77 14.98/5.60	14.50/6.27 16.94/4.77 9.01/4.13 13.55/6.11	18.22/3.95 15.98/6.20 25.63/6.79 19.90/7.09
400cm	25.82 / 8.50 14.41/10.42 33.38 / 7.25 24.54/11.77	12.65/6.63 15.95/7.07 18.55/5.42 15.72/6.85	13.97/5.91 12.45/6.73 10.52/5.50 12.31/6.23	17.48/4.04 13.59/6.33 10.61/5.52 13.89/6.08	21.35/7.81 30.67/7.95 26.98/6.23 26.33/8.31	10.49/3.82 11.42/7.56 18.70/6.52 13.53/7.17	14.03/5.81 30.38/7.93 17.95/5.97 20.79/9.63	11.92/4.36 23.82/7.44 16.59/3.15 17.44/7.22	33.41/5.15 33.52/5.57 33.49/4.26 33.47/5.03
425cm	25.30 / 5.82 15.93 / 9.88 24.22/13.22 21.62/10.75	16.73/8.36 18.26/7.56 16.25/5.77 17.10/7.38	18.59/5.37 11.95/6.86 8.27/6.04 12.87/7.46	24.58/4.96 16.73/5.84 7.39/5.33 16.24/8.85	26.38/4.64 14.74/5.59 11.12/4.36 17.42/8.14				
475cm			37.09/12.13 25.59/8.06 19.32/8.89 27.77/12.29	13.25/8.10 23.31/8.01 21.52/7.11 19.52/8.88	42.15/7.39 19.75/7.14 17.60/6.88 27.15/13.32				
500cm				25.95/6.82 39.01/10.68 21.20/11.39 28.48/12.38	32.63/6.78 23.30/11.50 32.66/8.26 29.54/10.08				

Table 4: Mean error and STD results of the measurements in distance of 25cm. (TAG_2003: MERR/ STD, TAG_2016: MERR/ STD, TAG_2022: MERR/ STD, ALL_3_TAGS: MERR/ STD. Where MERR: mean error, STD standard deviation.)

In the following table are reported the mean errors for each position with a gradient indication of their value. The more the color is intense the more the error is higher. Only the values in blues colors comes from actual measurements, the rest of the values, with white the background, are values reported by the blue area as expected from the mentioned symmetry. Position near the corners are not covered due to the fact that the distance from the nearest base station didn't allow for the tag to report the correspondent RSSI value as explained in detail chapter 4.

x/y	100cm	125cm	150cm	175cm	200cm	225cm	250cm	275cm	300cm	325cm	350cm	375cm	400cm
100cm				28,48	27,96	16,04	18,41	16,77	36,88	28,48			
125cm			27,77	19,52	27,15	12,36	14,2	14,74	16,27	19,52	27,77		
175cm	21,62	17,1	12,87	16,24	17,42	13,46	8,64	10,04	12,38	16,24	12,87	17,1	21,62
200cm	35,69	15,72	12,31	13,89	16,09	13,53	20,79	17,44	23,20	13,89	12,31	15,72	36,64
225cm	16,04	12,36	19,77	13,46	11,22	11,48	14,98	13,55	19,9	13,46	19,77	12,36	16,04
250cm	18,41	14,2	10,17	8,64	11,58	10,91	22,62	9,45	18,22	8,64	10,17	14,2	18,41
275cm	16,77	14,74	13,02	10,04	10,81	8,5	18,16	11,88	18,07	10,04	13,02	14,74	16,77
300cm	18,19	16,27	12,68	12,38	16,38	10,77	17,2	15,01	21,65	12,38	12,68	16,27	36,52
325cm	16,77	14,74	13,02	10,04	10,81	8,5	18,16	11,88	18,07	10,04	13,02	14,74	16,77
350cm	18,41	14,2	10,17	8,64	11,58	10,91	22,62	9,45	18,22	8,64	10,17	14,2	18,41
375cm	16,04	12,36	19,77	13,46	11,22	11,48	14,98	13,55	19,9	13,46	19,77	12,36	16,04
400cm	24,54	15,72	12,31	13,89	26,33	13,53	20,79	17,44	33,47	13,89	12,31	15,72	50,53
425cm	21,62	17,1	12,87	16,24	17,42	13,46	8,64	10,04	12,38	16,24	12,87	17,1	21,62
475cm			27,77	19,52	27,15	12,36	14,2	14,74	16,27	19,52	27,77		
500cm				28,48	29,54	16,04	18,41	16,77	37,13	28,48			

Table 5: Mean error (cm) for each position.

As a result we obtained, total mean error of the system about 19.69 and STD of the system about 14.20. From the first table it is possible to notice that the mean localization errors are higher in the borders of the interested area. Looking also at the x – y offsets for those locations is possible to see that the errors are largely due to the fact that the estimated position is placed toward the center of the area in respect to the real position. This is due to the fact that the more distant base stations placed on the opposite side are underestimating their distances from the tag dragging the estimated position in the middle of the area. The estimated distances for each base station in for that position reveal that the two base stations on the other side of the area are underestimating their distances from the tag of about 20cm. This introduces the fact that the estimated positions for that position are closer to the center of the area as elevated by the x axes offset. The same effect applies to all the positions closer to the border of the analyzed area with similar effects.

For the positions that are in the middle of area this effect is mitigated by the fact that the estimated distances are more precise because that reducing the distances also reduce the possible absolute error. In this way the major source of errors in this area, beside the fluctuations in the registered RSSI values, lies in the discrete nature of the collected RSSI. This implies that the estimated distances are also discrete. The multilateration algorithm will smooth those roughness interpolating the data by minimizing the error between the distance computed from the RSSI and the one computed from the estimated position for each base station but it can not solve the problem that for close positions is not improbable that some of the station will receive the same RSSI, an then estimated distance, for both the locations.

Despite all those source of inaccuracy the system still manage to have a mean error under 20cm, which is a fairly good result for the purpose of indoor localization.

6.2 Experiments with Moving tags

Since the system has been built with the purpose not only to find the position of static subjects but also to track their movements in the environment is important to test performance of the localization process of on moving subject.

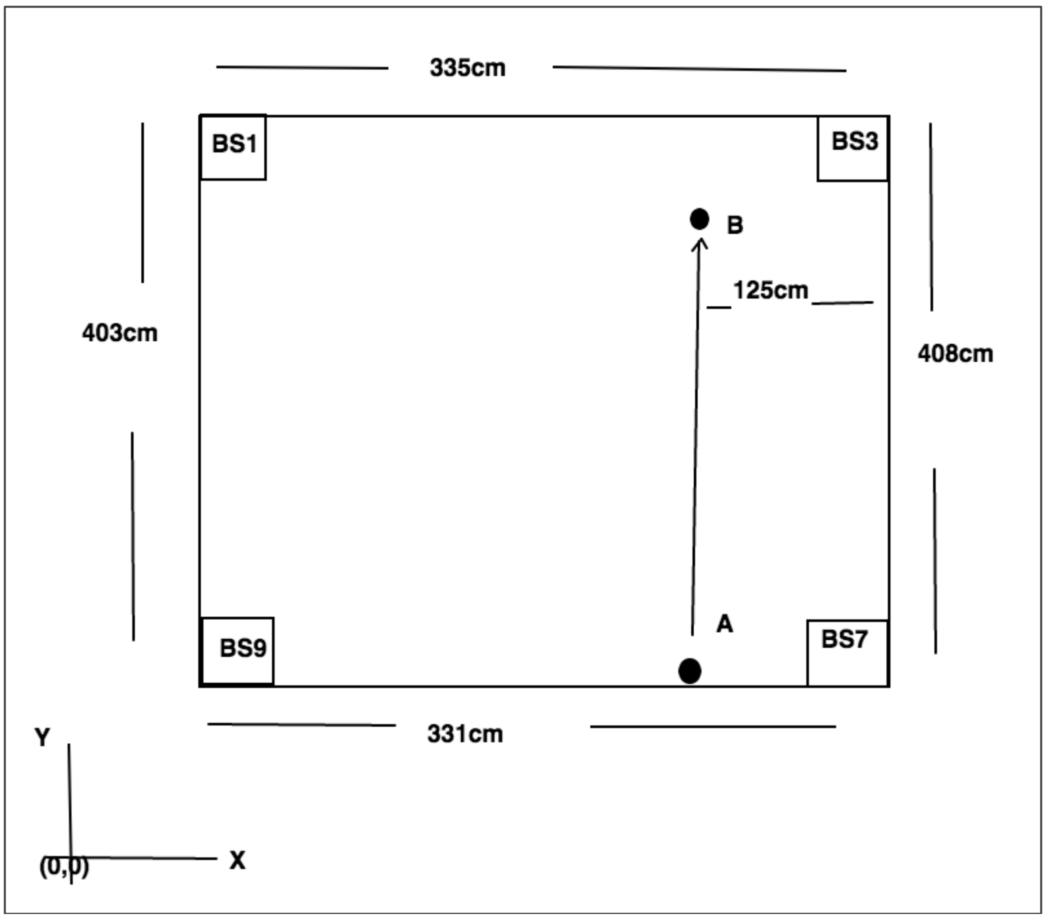

Figure 22: Moving TAG experiment.

As Figure show that those tests consists in continuously make the system estimate the position of a subject moving on a chosen path to make possible the comparison between the estimated data and the real position. Synchronization between real world data and estimated position has been provided recording a video of the subject so that knowing the time of the initial movement it was possible to get the estimated position at each time after that and make a comparison with the real position, even if not extremely precise, given by the figure.

From those measurements is possible to observe that there is a time delay between 0,5 s and 1 s from the moment in which the subject is in a certain location and the moment in which the system register the presence in the same position. In other term, for moving subject, the position estimated by the system is the one in where the subject was from half to a second before. This effect is due to the fact that only one base station at time can be active in a given area. This means that at each position update the system is mixing the most recent data from one of the base stations with older data from the other base station that were not allowed to scan the area concurrently. Using data collected at different times result in having the previously mentioned time delay because the localization process interpolates positional data relative to different times.

This delay is dependent on the trajectory and the speed of the subject, which in our experiments could be considered constant on a linear path. The given value is just a rough estimation of such delay since to exactly measure it is needed to have a better time synchronization and to remove the error of the system estimations. Those factors have been mitigated by number of different measurements taken but their presence could not been eliminated.

6.3 Comparison with LAURA

In this section we will compare our results with LAURA results. LAURA (LocAlization and Ubiquitous monitoRing of pAtients for health care support) is a system able to track several subjects and report some of their physical conditions. It composed by different modules, the one responsible for the localization process is called PLTS (Personal Localization and Tracking System). It is a localization system based on Zigbee technology (IEEE 802.15.4 standard). It is composed by a series of anchor nodes deployed to cover the interested area and some client nodes carried by the subjects to track. Each anchor node sends a message to each associated client node every 200ms. When the client receives the message it stores the associated RSSI value in a buffer. Periodically the clients compute a median of the last RSSI values for each visible anchor node. All the data from the client nodes are then collected to actually perform position estimation based on the collected RSSI values and the relative anchor nodes positions. The position estimation is based on the matrix containing the RSSI received respectively from and by each anchor node. Combined with the known positions of those nodes, this matrix is also used to estimate the relation between an RSSI measures to the correspondent distance.

In Figure 23 and Figure 24 presented the comparison between the cumulative distribution function of the mean localization error of LAURA PLTS and the proposed system.

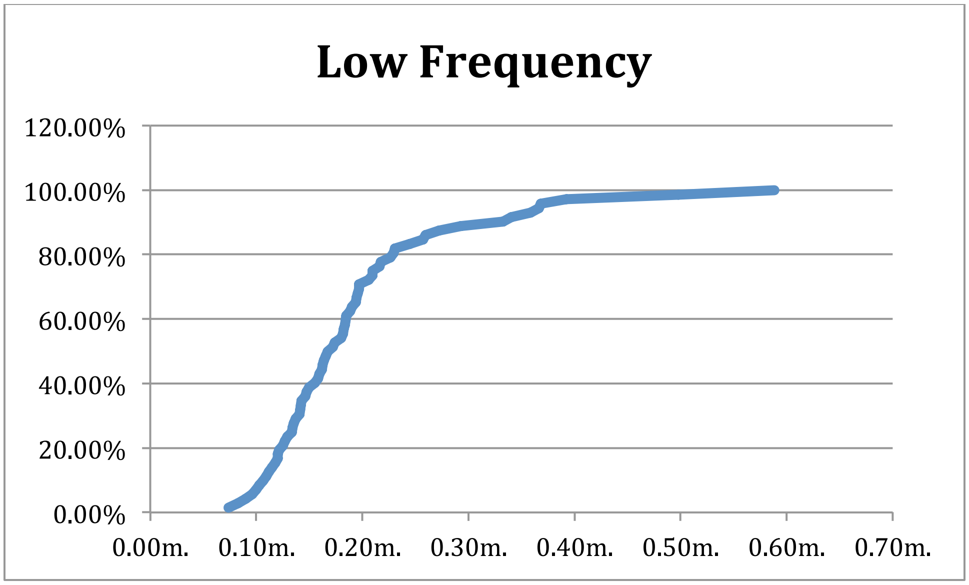

Figure 23: Low frequency results.

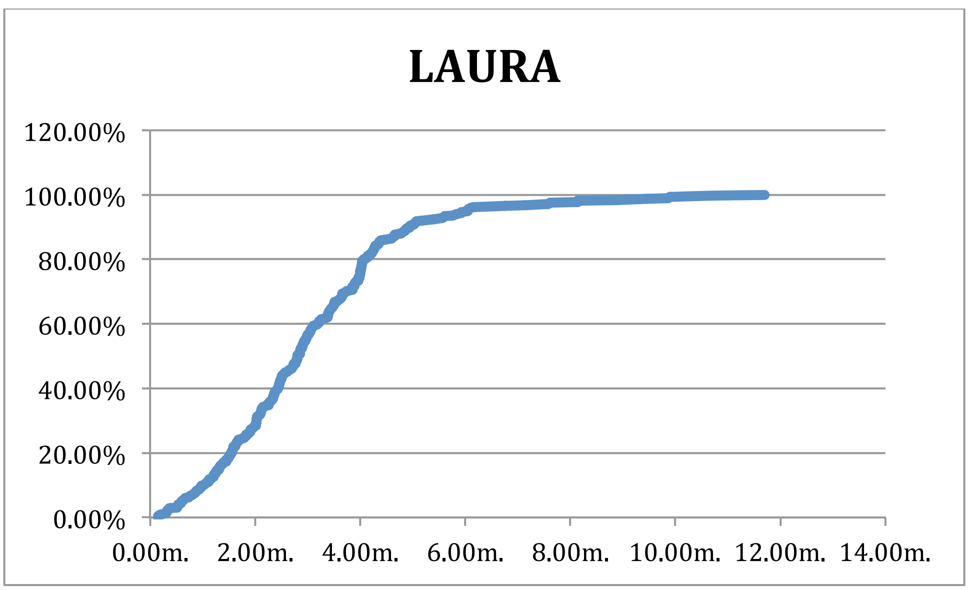

Figure 24: LAURA results.

The two data series has not been collected in the same environment or with the same exact methodology so this is not the result of a direct comparison between the two systems. Even so it can be noticed that the majority of the errors for the proposed system is accumulated between ten and twenty centimeters while for the PLTS system they lies in majority between one and four meters. This result, even accounting for the favorable test conditions for the proposed system shows the improvement in terms of localization accuracy that can result in the usage of the system based on low frequency in place of the PLTS.

CHAPTER 8

CONCLUSION AND FUTURE WORK

In this work we have researched the low frequency radio signal (125Khz) features in indoor environment. A localization system that uses such frequency has been built and tested. After this, the results compared with LAURA results, which is a localization system, based on zigbee technology. As expected, the results with low frequency have shown better results than LAURA as presented in chapter 7.

There are some areas that need focus for future development of the system. For example one improvement could be the development of an optimal positional map of how to place the base stations in order to cover a given area minimizing the time between each base station scan. This will help the system gaining performance in terms of decrease the delay between a movement in the real world and the consequent system response.

It may be possible to improve the estimation accuracy by using statistical interpolation to make adjustments on the computed position using the latest positions to limit errors given by spikes in RSSI values and smooth the delay given by old data in case of a moving subject.

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