POLITECNICO DI MILANO
Scuola di Ingegneria Industriale e dell'Informazione
Corso di Laurea Magistrale in Ingegneria Informatica

An adaptive indoor positioning system based on Bluetooth Low Energy RSSI

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Anno Accademico 2012/2013

This work was conducted in collaboration with:

Empatica

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Summary

Nowadays most of commonly used positioning and location detection systems, accessible via mobile phones, are usually targeted to open spaces, since adopted technologies are mainly based on GPS and satellite tracking, which are robust for outdoor environments. Only in recent years the focus has shifted to indoor venues where people spend about 80% - 90% of their time. The goal of indoor positioning in some applications, notably oriented to hospitals and malls, is to monitor people into a structure or provide navigation support; other applications want to use indoor positioning to better understand how customers behaves, enhance their satisfaction, branding and marketing for the venue, provide just-in-time information (for instance, intelligent audio guides for tours) or offer, by the means of location information, video or augmented reality experiences or connect people of interest in proximity to each another. In other words, indoor positioning systems (IPSs) enable location-awareness for mobile devices in ubiquitous and pervasive wireless computing systems. The need for connectivity, access and navigation has fueled research and investments in this field.

The absence of satellite signals in indoor environments clearly indicates the need for newer solutions: GPS does not work well in indoor spaces or in buildings surrounded by dense blocks of high-rise structures, since receivers require a clear view to communicate with satellites. Indeed, GPS signal is attenuated or scattered by roofs, walls, and other objects. In addition, GPS is only one-third as accurate in the vertical direction as it is in the horizontal, thus this makes impossible to be adopted in order locate a person or an object on the floors of buildings.

On the other hand, current IPSs require dedicated local infrastructures and, in some cases, customized mobile units. In practice, there are many different applications of IPSs and each application has its own requirements and there is no specific positioning system which suits all kinds of contexts, requirements and physical environments. As a result, the needs and constraints for every application must be analyzed separately to provide an individually tailored solution. Therefore it is important to assess the performance parameters of all the technologies capable of providing indoor positioning support and match them with the user requirements, which should be described precisely for each application.

From a technical point of view, most positioning systems can - at least theoretically - be adopted indoors as well as outdoors. From a general point of view, a high demand for precision and accuracy is required in both cases. However, in closed spaces, systems performances differ greatly, and this depends on many possibly distinct environmental configurations. To summarize, indoor environments are considered to be particularly challenging for positioning purposes, for several causes: strong multipath from signal reflection caused by walls and furniture, Non-Line-of-Sight (NLoS) conditions, slow temperature variations, high fading and signal scattering due to not negligible obstacles, rapid changes due to the presence of moving people or doors openings. On the contrary, indoor configurations facilitate, compared with outdoor contexts, positioning under many aspects. More precisely IPSs are concerned with small areas characterized by fixed geometric constraints derived from linear surfaces and orthogonality of walls, the extended presence of facilities such as electricity, internet access, walls (suitable for beacons' mounting) and object/people movements characterized by lower dynamics with respect to outdoor scenarios (slower walking speeds and no circulating cars).

In general, the architecture of positioning systems can be organized on a *transmitting infrastructure* and *mobile devices*. Infrastructure is the main component in the system offering support to location estimation, e.g., GPS satellites. In IPSs, infrastructure is usually composed by base stations, beacons (or anchors), transmitters etc. The mobile devices are receivers attached to the user whose location is to be calculated. e.g. GPS receiver, a listener or a receiver or a mobile device.

Some effective solutions require one to buy and install specific hardware, that can not be used with portable devices already available. The ideal indoor location technology, then, would be the one that requires no additional hardware to be added to mobile phones or devices to be positioned. As stated before, also the technology to be adopted is an important point of discussion: Although different solutions have been proposed, the most promising approach may be to use signals from mobile-phone networks (GSM) or wireless (Wi-Fi, Bluetooth Low Energy, etc.) hotspots. To remark this, on August 2012, a group of 22 technology companies, including some leaders in this field as Nokia, Samsung and CSR, formed the In-Location Alliance. This organization is concerned with the design and development of indoor positioning systems considering two main technologies: Bluetooth beacons and Wi-Fi signal mapping. Smartphones already encorporates the necessary radio receivers to manage these signals, which have the great benefit of being widespread in places where people spend most of their time: airports, offices, malls and city centres.

Unlike GPS, though, these signals do not contain positional information. Moreover, most commercial IPSs require a consistent installation process, with some on-place calibration surveys in order to adjust the specific parameters for the adopted positioning models. This means that systems are not easy to setup and require one to train the system after installation. As a result, a labour-intensive survey is required to take a digital fingerprint of the relative strengths of the signals present at multiple points within each venue. Software on a smartphone then collects RSSI values from surrounding beacons and tries to match this information with an on-line database, to calculate the phone's location to within few metres. This is the approach used by many companies including Skyhook[1] and by Wifarer[2]. A less intrusive approach may not require an offline survey of the location, but could be based on signal propagation models to be suitably tuned; the precision of these systems mainly depends on the proper model parameters selection. This estimation should be made dynamically and in real time in order to track for propagation model changes due to environmental changes.

A different and innovative solution for developing an indoor positioning system (IPS) can be based on the adoption of a low-cost transmitting infrastructure, based on a limited number of Bluetooth Low Energy (BLE) beacons, not requesting to the installer any effort (no on-site surveys) which uses a real-time and environment-adaptive signal propagation model, based on the evolution of Received Signal Strengths Indicator over time.

Accordingly, the present work aims at advancing knowledge about a feasible adoption of BLE for positioning purposes in restricted (room, offices, etc.) ranges. To do so, the evolution and stability of Bluetooth Low Energy signal is firstly evaluated in order to validate its relationship with respect to changing distances between transmiter and receiver. Secondly, a dynamic model based on Bayesian filtering techniques to detect model parameters is proposed. The biggest difference between the proposed Bayesian method and the traditional positioning methods lies in the fact that Bayesian method does not focus on obtaining a more accurate and stable RSSI signal from each beacon (which seems complex for this kind of signal), but on obtaining a more reliable sample collection, and through continuous updating of particles and related weights, eventually, it will converge to the most probable propagation model parameters distribution. Results show an increased accuracy with respect to other commonly widespread methods, based on linear regression on the curve describing the relation between measured power and distance.

[1] Skyhook Website - http://www.skyhookwireless.com/

[2] Wifarer Website - http://www.wifarer.com/

Prefazione

In un mondo dove la maggior parte dei più comuni sistemi di localizzazione e di rilevamento di posizione sono utilizzati in grandi spazi aperti, come quelli basati sul GPS, accessibili anche da telefoni cellulari, negli ultimi anni il lavoro di ricerca si è incentrato negli ambienti indoor, luoghi nei quali le persone trascorrono tra l'80% e il 90% del loro tempo quotidiano. Gli obiettivi di tale sistema di localizzazione sono molteplici e tutti di evidente importanza. In base alle diverse tipologie di utenza, essi sono spesso orientati ad ambienti, come centri commerciali ed ospedali, dove la navigazione interna può essere agevolata dalle informazioni di localizzazione, oppure mirano al soddisfacimento delle necessità dell'utenza, a rendere un luogo più interessante, a fornire informazioni in tempo reale, come quelle via audio durante i tour turistici, oppure a fini di condivisione tra soggetti connessi ed in stretta vicinanza.
Gli IPS, acronimo per sistemi di posizionamento in ambienti chiusi, sono quindi in linea con le recenti tendenze e sviluppi nell'ambito degli *ubiquitous computing systems* ed in grado di alimentare maggiormente la ricerca e gli investimenti in questo campo, entrambi mossi dalla necessità di connettività, accessibilità e navigazione a supporto dell'utente.
L'assenza di segnale satellitare in ambienti interni, infatti, rende evidente, in modo chiaro, la necessità di soluzioni più innovative; il GPS, ad esempio, non è in grado di soddisfare le richieste circoscritte agli spazi chiusi o ad aree urbane ad alta densità edilizia, poichè i ricevitori GPS necessitano di una chiara visuale per la comunicazione con i trasmettitori, i quali segnali sono attenuati o dispersi da materiali ad elevata densità o strutture costruttive, come tetti o muri. Inoltre, il valore della sua precisione verticale è pari solo ad un terzo della traiettoria orizzontale, tanto da non poter localizzare una persona o un oggetto a differenti piani in un grattacielo.
Un sistema IPS, però, spesso richiede un'apposita infrastruttura locale e, in alcuni casi, unità mobili personalizzate. A riprova di ciò, è possibile notare come esistono diverse soluzioni IPS, ciascuna delle quali con i propri requisiti e non vi è alcun sistema di posizionamento, considerato universale, che si adatti a qualsiasi tipo di applicazione o di ambiente. Da questo nasce quindi la necessità di analizzare separatamente tutte i possibili approcci adottabili nel caso di problemi di posizionamento. Per questo motivo, è importante valutare i parametri di efficienza di tutte

le tecnologie utilizzabili in ambienti chiusi e metterle a confronto con le esigenze dell'utente, che devono essere elicitate con precisione in ogni applicazione.

Da una punto di vista tecnologico, la maggior parte dei sistemi di localizzazione può, quanto meno sulla base della letteratura, essere utilizzato tanto all'interno che all'esterno, anche se, nel caso delle soluzioni indoor, le prestazioni dei differenti sistemi variano notevolmente tra loro, a causa delle molteplici differenze strutturali tra gli ambienti stessi. Gli ambienti interni, infatti, sono particolarmente complessi per il rilevamento di posizione a causa dei molteplici *path* seguiti dal segnale, che può essere riflesso dalle pareti e dall'arredamento o condizionato da situazioni di Non-Line-Of-Sight (NLOS) o attenuato e disperso a causa della maggior densità di ostacoli. Inoltre, rapide variazioni in ridotti intervalli di tempo, dovute alla presenza di persone e all'apertura di porte, possono notevolmente influenzare sia accuratezza che precisione complessiva.
La conformazione di tali ambienti, però, facilita, al contrario del caso outdoor, il posizionamento e la navigazione; questo è legato al fatto che un IPS si rivolge ad aree ristrette, con basse variazioni atmosferiche, cioè piccoli gradienti di temperatura e lenta circolazione d'aria, e per di più caratterizzate da vincoli geometrici derivanti da superfici piane e da muri ortogonali; anche la presenza di servizi, come accessi elettrici e ad internet, o di persone e oggetti caratterizzati da una minore dinamicità rispetto all'esterno, cioè a passo lento o a velocità inferiori rispetto a quelle di guida, facilitano - in alcuni casi - il task di posizionamento.
In generale, l'architettura generale degli IPS può essere organizzata su un'*infrastruttura di trasmissione* e su *dispositivi mobili*. La prima rappresenta la componente principale di tali sistemi e, solitamente, utilizza dei trasmettitori a posizioni fissate detti *beacon*, talvolta chiamati *access point* o *anchor*. I dispositivi mobili, invece, sono ricevitori spesso in mano all'utente finale, di cui si vuole valutare la posizione; essi possono essere, come nei sistemi GPS, ricevitori semplici o telefoni cellulari. In altri casi, l'adozione di soluzioni IPS possono comprendere l'acquisto e l'installazione di hardware specifico, che non può interconnetersi - in maniera nativa - con dispositivi e terminali di cui si è già a disposizione. La tecnologia ideale e desiderabile per un IPS, quindi, sarebbe quella in grado di non richiedere infrastruttura aggiuntiva. Infatti, sebbene siano stati proposti diversi scenari, l'approccio più promettente potrebbe essere quello incentrato su segnali derivanti dalle reti di telefonia mobile e dagli hotspots wireless (Wi-Fi, Bluetooth Low Energy, ecc.). Questa soluzione ha riscontrato una sempre maggiore attenzione da quando, nell'Agosto 2012, un gruppo di aziende leader nel settore della tecnologia, tra cui Nokia, Samsung e CSR, formarono l'*Inlocation Alliance*. Tale associazione si dedica alla realizzazione di sistemi di localizzazione indoor sulla base di due tecnologie: mappatura dei segnali Wi-Fi e beacons Bluetooth Low Energy. Gli smartphone, infatti, dispongono

già dei ricevitori radio necessari alla gestione di questi segnali, che hanno il beneficio di essere molto comuni in luoghi dove le persone la maggior parte del loro tempo, come ad esempio aeroporti, uffici, centri commerciali e centri cittadini. A differenza del GPS, tuttavia, i segnali adottati non contengono informazioni di posizionamento ed è necessario strutturare un mapping tra il valore del segnale ricevuto e la distanza dai trasmettitori. Inoltre, i sistemi attualmente commercializzati richiedono spesso un consistente processo di installazione, spesso seguito da alcune campagne di calibrazione atte ad adattare gli specifici parametri dei modelli di posizionamento all'ambiente in questione. Ciò risulta in sistemi non facili da installare e che richiedono una corposa preparazione al loro effettivo funzionamento. L'approccio maggiormente utilizzato, ad esempio nel caso di aziende come Skyhook e Wifarer, è incentrato su un processo intensivo di raccolta di *fingeprint* digitali dei livelli di potenza sentiti in differenti punti dello stesso ambiente. Il software installato su smartphone, quindi, consulta il database online associato, comparandolo con i valori di RSSI attualmente collezionati, al fine di calcolare la posizione finale dell'utente con una precisione di qualche metro. Un approccio meno intrusivo potrebbe non richiedere una calibrazione offine della specifica *location*, ma potrebbe essere basato su modelli di propagazione del segnale, da regolare opportunamente; la precisione di questi sistemi dipende, principalmente, dalla corretta selezione dei parametri per tali modelli. Questa valutazione dovrebbe essere effettuata in maniera dinamica e in tempo reale, per tener traccia dei cambiamenti nel modello di propagazione, dovute a variazioni dell'ambiente.

Una soluzione differente e innovativa potrebbe basarsi sull'adozione di un'infrastruttura di trasmissione *low-cost*, caratterizzata da un limitato numero di segnali Bluetooth Low Energy (BLE), in grado di non richiedere all'utente finale alcuna campagna di installazione *in situ*, definendo un modello di propagazione per il segnale in tempo reale e che si adatti all'ambiente di riferimento, basandosi sullo studio del Received Signal Strenght (RSSI).

In conclusione, il presente lavoro di tesi mira ad ampliare e studiare una possibile adozione della tecnologia BLE per fini di posizionamento in spazi ristretti. A tal fine è studiata l'evoluzione della stabilità di tale segnale per validare la sua relazione rispetto a differenti distanze tra trasmettitore e ricevitore. Inoltre, è proposto un modello dinamico basato su tecniche di filtraggio Bayesiano per determinare i parametri in grado di descrivere l'evoluzione di un'opportuna legge di propagazione. La differenza più grande tra un approccio Bayesiano e i tradizionali metodi di posizionamento, nell'ambito delle reti di sensori wireless, è riposta nel fatto che tali metodi non si focalizzano sull'ottenere un valore di RSSI più accurato per ogni beacon (che potrebbe risultare un task molto complesso per questo tipo di segnale), ma sull'ottenere una collezione più affidabile di campioni che, attraverso un continuo aggiornamento delle *particles*, sia in grado di convergere alla distribuzione più probabile per i parametri del modello. I risultati mostrano un'accuratezza migliorata rispetto ad altri metodi comunemente usati, basati su regressione lineare, al fine di migliorare la caratterizzazione della curva che descrive la relazione tra potenza rilevata e distanza.

Chapter 1

Introduction

1 Motivations

Location-aware applications play a fundamental role in identifying and studying user behaviors and interests by analyzing their activities and proactive interactions with other people or objects within a limited amount of time. Since most individuals spend the greatest part of their time and many of their daily-life tasks are performed in indoor environments or closed venues, indoor positioning systems (IPSs) are the ultimate technology adopted to solve the problem of locating and identifying targets-of-interest in closed environments. However, the ability to accurately localize and track an indoor object using existing GPS technology is bounded to limited performances, due to the absence of a direct view to three or more satellites at the same time and signal disturbance caused by obstacles between them and in-building receivers.

Indoor Positioning Systems (IPS) have led to increased efficiency in many types of contexts and organizations, and many companies - nowadays - are attracted from the new opportunities and intriguing capabilities found in a IPS solution. The development and use of IPS systems have increased radically in the last few years. This is related to the many areas of application in which IPSs could fit. For instance, they could be used in navigation, health care, logistics, in-home asset tracking, emergency services, visitor identification, security, and so on [3]. IPSs are designed in order to give the best performances, security and efficiency. The purpose of reaching these high-demanding results gives the technology behind the IPS systems several challenges and requirements. Research on the technologies used in IPSs is thus a continuous and ongoing process to always get the most out and exploit available features in existing technologies and solutions.

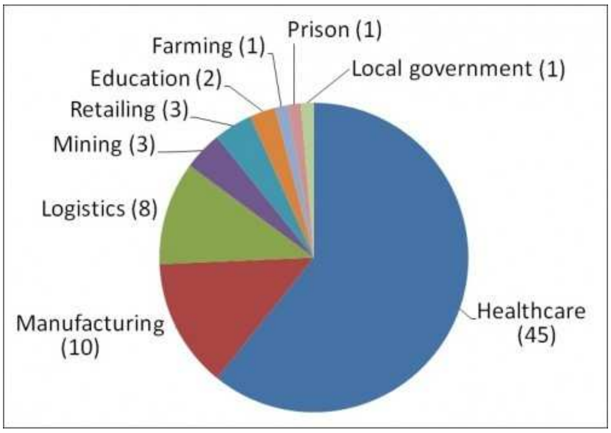

Figure 1.1: Survey of 74 case studies of IPS by application [4]

Furthermore, because of IPSs importance and extensive potential in offering new services and features, there is a significant interest in the industry for IPSs. The market potential for commercial IPSs are thus predicted to widely expand in the next years. According to a survey by Markets and Markets and a press release in The International News Magazine global indoor location market is estimated to grow from $448.6 million in 2013 to $2.60 billion in 2018. This represents an annual growth rate of 42.1% from 2013 to 2018. In terms of regions, North America is expected to be the biggest market in the near term, while the European region is expected to experience increased market traction in the longer term. In addition, different large companies are moving towards IPSs, such as Apple[1], Microsoft[2], Sony[3] and Google[4] because it will be a source of competitive advantage and of extra income in the mobile, smart watches and wearable technologies markets [4].

2 Technology Overview

Indoor Positioning Systems is a specific type of Real-Time Locating Systems (RTLS). The focus of RTLS is that of locating or tracking persons, or in some scenarios, objects in a real-time fashion. However, the idea of locating objects and people in buildings is not completely new. It was the 1990s, when RTLS entered the market. These systems allowed hospitals and medical centers to track equipment, warehouses to track merchandise, etc. These systems initially used active tags on objects and trackable items. In the following years, IT companies started providing RTLS using

[1] Apple Website - http://apple.com/
[2] Microsoft Website - http://microsoft.com
[3] Sony Website - http://sony.com
[4] Google Website - http://google.com

some sort of wireless systems in the building. First deployed systems were characterized by a high density of access points to allow the system to apply triangulation techiniques and used tags that were not so small as today. Generally, when talking about RTLS systems, they are simply being referred to as *Local Positioning Systems* (LPS), or simply Positioning Systems.

The spread of more wireless technologies is leading to additional features in systems capable of solving numerous tasks in organization environments. The extended set of services that IPSs can offer are the basis for their extreme success and growing interest in the recent years. A simplified structure of an IPS system is based on the periodical execution of different steps and the locating process is not done in a single and isolated moment. First, sensors or receivers receive signals from transmitting devices. Receiving sensors send the collected data values to a central locating engine. The task of the central engine is to setup and estimate parameters in order to calculate the approximate position of the device, using different and on-line adapted algorithms/models. Collected data values could be either related to the received power of signal (i.e. Received Signal Strength Indication, RSSI) or based on Time Difference of Arrival (TDoA) or Angle of Arrival (AoA). How accurate the results are, depends on the technology used in the system. Calculated results, expressed in x and y coordinates, relative to the venue, are then sent from the locating engine to a user interface (UI). UI is basically just responsible to show to the final user its position on a map. The most interesting aspect of modern IPS is to be able to adjust itself whenever there is a change in the environment, contemplating a small or no delay, for instance when a person or an asset has changed its position. If a moving person is being positioned, the position given to the user interface will often be slightly delayed in relation to the actual position because of the time it takes to collect data, calculate, and pass the information to the user interface.

3 Technical Challenges

The not predictable variation of RSSI in the indoor environment is the most compelling technical challenge for RSSI-based positioning systems. There are some main reasons that lead to the variation of RSSI. First, due to the structures of the indoor environment and the presence of different obstacles, such as walls, people and doors, the signal experiences multi-path and fading and the RSSI varies over time even at the same location. For this reason an evolving model to describe propagation properties should be taken into account. Moreover, the presence of human bodies also affects the RSSI by absorbing the signal, since they contain large amount of water. Finally, the orientation of the measuring devices also affects the RSSI, as orientation of antenna affects the antenna gain and the signal is not isotropic in real indoor environments.

Another challenge is providing a real-time system taking into account the transmitter/receivers battery life. To get as close as possible to real-time, device has to transmit its position as often as possible, but this results in high power consumption and a low battery life.

In order to provide a possible solution to this compromise, the technology adopted in this work is the Bluetooth Low Energy (BLE) standard. BLE beacons are part of the new generation Bluetooth 4.0 (or *Bluetooth Smart*) standard. Devices using Bluetooth LE wireless technology consume a fraction of the power of Classic Bluetooth enabled products. This makes BLE an excellent starting point for a real-time positioning solution. Since 2010, dual mode chips (i.e., able to work with Classic and Low Energy enabled Bluetooth) have been built into in an increasing number of smartphones, tablets or laptops. For instance, Apple has incorporated them in its products since the iPhone® 4S and iPad® 3. Currently they are in most new Android phones and Nokia[5] has started to incorporate in all its Windows phones. Moreover, Apple and Google (Android™) have released APIs for developers in order to integrate BLE capabilities in their apps. This has stimulated a greater collective effort in hardware design, including crowd-funded projects on sites like Kickstarter[6], where the majority of short-range wireless projects now use BLE. BLE is already present in hundreds of millions of devices. That number is projected to increase by 1 billion additional devices each year for the next few years as smartphone and tablet penetration increases. [5]

4 Scope and Contributions

The indoor localization system developed in thesis uses BLE beacons that are capable of providing received signal strength indication (RSSI). This indicator is used to determine the location of a target object or individual in indoor environments. A client equipped with a smartphone device scans the latest RSSI values from surrounding active beacons, and sends an HTTP Post request containing the collected values to the server. Accordingly, the software on the server, receives the request, generates the estimated location, and returns it to the requesting target object. In future works, movement and indoor activity analysis could be conducted using those data, which can greatly contribute in deeply comprehending individual behaviors and interests, social relations and activities within other research areas.

[5] Nokia Website - http://nokia.com
[6] Kickstarter Website - http://kickstarter.com

This thesis will focus on indoor positioning, and thus IPS using BLE technology. To summarize, the purpose of the work here presented is to:

- Propose the design of a new signal-based indoor positioning algorithm which should **(1) exploit only BLE technology**, **(2) be adaptive to the environment**, **(3) require minimal configuration**, **(4) use a limited amount of beacons in the room**;
- Validate in real life scenarios the proposed technique and show whether it performs better or, at worst, in a comparable way to other existing solutions;

The main outcomes are positive feedbacks about the reliability and efficiency of the algorithm and new insights about the chance of actually using BLE for positioning purposes.

5 Thesis Organization

The work is presented in three main chapters and their content is summarized as follows.

Chapter 2 - Indoor Positioning Basics and Bluetooth Low Energy

As the present work is based on experimental studies, the majority of Chapter 2 is focused on giving a complete and formal definition of the indoor localization problem and to better comprehend some of the adopted solutions, which will be described in the following parts. Signal-based indoor positioning system and, in particular, RSSI-based ones (which are the focus of this dissertation) are analyzed. This kind of systems are gaining importance among other indoor positioning techniques since signal strength informations are easily available on most of existing wireless equipments, at no extra cost. Also some measures for quantifying system performance and the definitions of *calibration* and *positioning error* have been presented. This measures include, for instance, *accuracy* and *precision*, that will be adopted in the validation and testing of the system (Chapter 4). Other localization system properties have been described. These are: *complexity*, *robustness* and *adaptiveness*, *scalability*, *cost* and *calibration effort*. This chapter, extending valid classifications proposed in other works [1], gives a complete overview of the different signal based localization methods that exist. In general the following classes of localization approaches can be distinguished: *range-based* or *range-free*. We provided a detailed description of the most adopted algorithms for each category. Finally, this chapter also describes different technologies which have been used, in past, for localization and provides a brief insight of future research directions. A broad distinction between these classes can be made based on whether they are based on radio-frequency (RF) signals or not. Bluetooth LE falls in this category. In the last part, a description of the Bluetooth Low Energy technology has given. Its main purpose, however, was to understand its underlying architecture, in order to explicitly outline how it can be used for localization.

Chapter 3 - Channel Characterization and Position Estimate

In Chapter 3 our methodology for indoor positioning is presented. In particular, our system is based on two steps, both performed on-line: a real-time *calibration* process and a *positioning* routine, which is called every time a user asks for position detection. The first step of the adopted approach is described: It starts from data collection and data processing in order to tune propagation model parameters for each beacon. The best setup for the calibration step is also described. The second step, positioning, is based on repeated scans for power strength indicators (RSSI), from surrounding BLE beacons in a closed environment; this is done in order to estimate distances between them and the user and, finally, evaluate his/her position. In particular, we carried out a feasibility study about how Bluetooth Low Energy can be used for positioning purposes and how the adopted metric (RSSI) varies through time and at different environmental conditions. Moreover, after having described, in details, what are the main factors that influence signal propagation in these spaces, we tested how signal practically evolves considering different real conditions: *antenna orientation*, *human presence* and small *scale movements*. In order to make the RSSI signal tractable in practice, some filters should be applied on the signal. Some of the most common filters described in literature are tested on our RSSI values flow and we observed which one gives us the best results to remove the *fast fading* component on the signal. On the contrary, *slow fading* (or shadowing) depends on obstacles present in the far field from the receiver. Their influence on the overall fading for the signal is expressed considering a lognormal distribution (Log Normal Shadowing, LNS). Our work aims to get a proper characterization of the signal, based on these assumptions. In particular, we tried to better describe - using stochastic approaches - how the relation between received power and distance can be adequately characterized.
As positioning algorithm we adopted the trilateration one, which tries to evaluate user position starting from the signal received from, at least, three beacons in a room. In particular, RSSI signal is converted into distance accordingly to the previously calibrated model.

Chapter 4 - Experimental Results

In Chapter 4, our deployed solution is illustrated. In particular an initial focus is oriented toward system implementation in its three main parts: *beacons*, *base sta-*

tion and *terminal nodes*. Since our solution is based on calibrations and interactions between each pair of beacons in a room, no commercially available solutions were found natively incorporating this feature, so we simulated beacons behaviour using BLE-enabled devices. Some implementative details are also provided in this part.
Subsequently, the analysis of the behaviour of this system is evaluated, based on comparisons between calculated outputs and another calibration model, using a linear regression calibration model, which is taken as a gold standard. Through properly designing experimental test, we show how this system was designed to suit fast-changing signal propagation conditions and to satisfy all requirements and constraints derived from noisy environments and specific particular fields of adoption. Our approach tries to mediate on major issues in this context, mainly due to the strong fluctuations of the RSSI values typical of a pair of wireless transmitter-receiver even in Line-Of-Sight (LoS) conditions or different antennas' orientations, using inter-beacons measures in order to estimate our chosen propagation model.

Chapter 2

Indoor Positioning Basics and Bluetooth Low Energy

1 Introduction

An Indoor positioning (or localization) system is a system that can determine the position of something or someone in a physical and limited space [6]. The effective implementation of a solution of this type, as it is understood today, can not prescind from the availability of a more or less extended network of wireless sensors (WSN). A WSN is a spatially distributed network of communicating sensors, designed in order to monitor and keep under control some environmental conditions (e.g. temperature, sound, pressure, position, etc.) and to cooperatively pass their data through the network to a main location [7] being able to reason and react to the world that surrounds them. In addition, the development of smart environments represent the next generation of technology applied to the automation in the field of building, utilities, industrial, home and transportation systems.

Mobile wireless sensor networks (MWSNs) are a specific class of WSN where mobility has a key role. More in details, in this systems, mobility enables sensor nodes to target dynamic and fast changing phenomena such as vehicles or clouds movements (outdoor) or furniture changes (indoor). Localization is a key aspect of such networks, since the knowledge of a target location is critical in order to better understand information originating from it.

RSSI-based methods, like the one proposed in this work, can be easily deployed in almost every MWSN platform, since its founding technology is natively supported by most of the existing embedded chipsets, with no extra hardware costs. Therefore, there is still a lot of interest in improving the performance of RSSI-based localization algorithms [34].

As the present work is based on designing an adaptive IPS, the majority of this chapter will focus on giving a complete and exhaustive overview of indoor positioning basics and commonly adopted technologies. Successively, a separate section will introduce Bluetooth Low Energy (BLE), its features and its underlying structure.

2 Problem Statement

Before analyzing several localization techniques that have been proposed in literature, a formal description of what an indoor positioning task is, is now presented. Indoor positioning can be defined as the process of finding the location of objects or persons in a closed and indoor space, within a limited time frame. Global Positioning System (GPS), which offers good performance levels in open spaces and outdoors is not capable of operating indoors, because of the large attenuation introduced by buildings' walls and ceilings; therefore it cannot represents a ubiquitous localization method.

Formally the positioning process can be defined as follows.

Definition 1 *Let* S *denote the indoor venue where an object is, organized on an infinite number of different locations. Given a set of observations* O *in a certain time period [t_{start}, t_{end}] and a target* T *which require to be localized in* S*, the positioning process is defined as the iterative evaluation of the following equation for a sequence of time periods.*

$$\hat{P} = f(\mathrm{T}, \mathrm{O}, \mathrm{C}) \tag{2.1}$$

where $\hat{P}$ is the location estimate for the target, evaluated on repeated measures. In particular, $\hat{P} \in$ S*. The function* f *is called the positioning function, which maps a given target and its collected observations to a set of a location estimates. In addition to parameters* T *and* O*, the localization function takes some extra parameters, defined as* C*, which represent calibration information for* S*. The choice of* C *is dependent on the approach being used to calibrate the considered environment.*

In general this definition, which could be extendend to a more generic localization problem, can be considered at a higher level of detail depending on the perspective; it can be related to a first person point of view or an external (third-person) point of view. In the first case, the localization process is used to estimate the location of the object itself, for example a user asking for his/her position in a shopping mall. In the second case, the localization process is concurrently locating more targets in the same localization process, for example elderly people monitoring inside a clinical structure [8].

Within this context, as previously introduced, we speak of *wireless indoor positioning* to refer to the case in which the positioning procedure is performed using wireless systems (WSN) and the focus is on indoor environments. Comparing our work with those previously presented in literature, the term wireless exclusively refers to systems based on radio frequency (RF) technologies, in particular Bluetooth Low Energy (BLE), which is used in distance estimations to determine the location of a target.

In addition, a distinction between static and dynamic indoor positioning should be outlined. In particular, static positioning is related to detecting the coordinates of an object which is supposed to be stationary (or characterized by minimal movements) while performing positioning. A dynamic positioning (or tracking) is related to a moving subject. In a broader vision, tracking can be intended as an iterated static positioning. In our work we are focused on static positioning.

3 Radio Signals

Signals transmitted over mobile radio channels are structured by a set frequencies within a bandwidth which is narrow compared with the centre frequency of the channel. Such signals are called band-pass signals and can be expressed in the form:

$$s(t) = a(t)cos[2\pi f_c t + \theta(t)] \tag{2.2}$$

where *a(t)* is the envelope of *s(t)*, *θ(t)* denotes the phase and f_c is the carrier frequency. Most of signal's information is contained within the phase and envelope variation.

In addition, given a continuous-time signal, we will define:

$$E_s = \int_{-\infty}^{+\infty} (|s(t)|)^2 dt \tag{2.3}$$

as the *energy* of the signal. This is graphically represented in Figure 2.1.

Moreover, *power* (or, better, *average power*) of a signal is defined as a time average of energy (energy per unit time). This is useful when the energy of the signal goes to infinity. Sometimes, $\sqrt{P}$ is used; this is called the *root mean squared* (RMS) power value. In particular:

$$P = \lim_{T \to +\infty} \frac{1}{2T} \int_{-T}^{+T} (|s(t)|)^2 dt \tag{2.4}$$

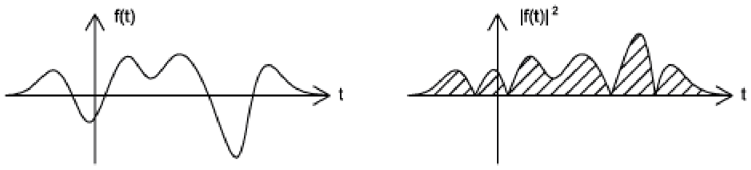

Figure 2.1: Graphical representation of Signal Energy

In a common and ideal scenario, a radio system support information exchanging between a transmitter and a receiver. The information is transmitted through an antenna which converts the RF signal into an electromagnetic wave. The transmission medium for electromagnetic wave propagation is free space. The electromagnetic wave is intercepted by the receiving antenna which converts it back to an RF signal. Ideally, this RF signal is the same as that originally generated by the transmitter. The original information is then demodulated back to its original form.

When a signal travels from the transmitter to the receiver in real cases, it undergoes an attenuation which results in a loss in power, known as Path Loss (PL) and it is expressed, in linear format, as:

$$PL = \frac{P_t}{P_r} \tag{2.5}$$

More precisely, PL is the loss of power of an RF signal propagating through space. In particular, P_t is the power level at the exit of transmitter's antenna, while P_r is the power level at the input of receiver's antenna. Usually PL is expressed in dB. Considering the transposition in logarithmic units of Formula (2.5):

$$PL_{dB} = 10log_{10}(\frac{P_t}{P_r}) \tag{2.6}$$

When transmitter and receiver see each other we are in line of sight conditions (LoS). Otherwise, this situation is called non line of sight (NLoS). NLoS happens when a radio transmission across a path is partially obstructed, usually by a physical object.

4 Signal Based Positioning

As described in Chapter 1.2, IPSs of our interest are based on positioning exploiting BLE-based beacons. Formally:

Definition 2 *A beacon is a fixed radio-frequency (RF) signal transmitter, usually placed on walls, near ceilings (to avoid obstacles), that broadcasts distinctive signals as a navigational aid.*

Previous works have shown how many different characteristics could be taken into account in the design of a signal-based IPS. Closely related to the adopted technology and its properties, some approaches use the signal's Angle of Arrival (AoA) also known as Direction Finding (DF), others its Time of Arrival (ToA) or, eventually, the signal's Time Difference of Arrival (TDoA).

4.1 Signal Measurement Techniques

Here a short description about widespread signal-based measures used in IPS development is provided.

- **Angle of Arrival (AoA)** is the angle from which a signal arrives at a receiver. By comparing the direction of signal arrival with a reference orientation, received angle can be measured. The receiver may also know its own orientation for better angle measurement. Target object can be found by intersection of several pairs of angle direction lines. In order to derive the 2D location of the target, at least two reference points and two angles are used. Usually, AoA exploits an array of highly directional sensors, thus the angle can be determined by which sensor received the signal. Measurements could be completely not time-synchronized. To extract this measure a large and complex hardware is required [35].

- **Time of Arrival (ToA)** is the amount of time a signal takes to propagate from transmitter to receiver. Because the signal propagation rate is constant and known (ignoring differences in mediums) the travel time of a signal can be used to directly compute distance. In a centralized architecture, a transmitter emits a signal to many receivers. All receivers then forward their signal arrival time to a centralized system for comparison. An alternative approach could include many transmitters at known positions and a single receiver. Systems which use ToA, generally require a complex synchronization mechanism to maintain a reliable source of time for sensors [36].

- **Time Difference of Arrival (TDoA)** is an improved version of ToA. It determines the relative position of the mobile transmitter by examining the difference in time at which the signal arrives at multiple measuring units (receivers). Theorically, the sender transmits a signal $s(\mathrm{t})$ which is delayed of τ_i to receiver i, according to distance to each receiver. Correlation analysis provides a time delay $\tau_i - \tau_j$ corresponding to the path difference to receivers i and j [37].

- **RSSI-based**. In this work, Received Signal Strength indicator (RSSI) is the feature used for the positioning system, as it can be obtained directly from existing beacons by any device that is equipped with a proper network adapter or antenna, without any additional hardware. This is clearly compliant with the required features of the system to be deployed, described in Section 1.4. The RSSI is used to evaluate distance between the receiving device (which needs to be located) and each beacon, accordingly to current parameters. It is implemented and widely-used in 802.11 (WLAN)/802.15 (Bluetooth) and Bluetooth Smart (BLE) standards. Received power can be calculated from RSSI [30].

Extending Definition (2.1), in the signal-based scenario, it is possible to better formalize the Observations (O) array, when using RSSI measures.

Definition 3 *Let* O *be the device collected RSSI values from* N *available beacons, periodically picked within the frame [t_{start}, t_{end}]. These online RSSI readings could be denoted as:*

$$\mathrm{O} = [r_1(t), r_2(t), ...r_n(t)] \tag{2.7}$$

Having $t_{start} < t < t_{end}$ and i *= 0, 1, 2, ..., N where the generic $r_i(t)$ refers to the RSSI reading collected from beacon* i *at time t. Note that the amount of collected RSSI could be limited by the device's antenna and hardware performances.*

Then, the proposed positioning and tracking system uses *r(t)* to compute the position estimate.

4.2 RSSI Measures in BLE

RSSI is an 8-bit signed integer that denotes whether the received (RX) power level is within or above/below the Golden Receiver Power Range (GRPR), which is regarded as the ideal RX power range. Any positive RSSI value returned by the Controller indicates how many dB the RSSI is above the upper limit, any negative value indicates how many dB the RSSI is below the lower limit. The value zero indicates that the RSSI is inside the GRPR. How accurate the dB values will be depends on the Bluetooth hardware; according to BLE specifications, RSSI shall have an accuracy of ± 6dB. The only requirement for the hardware is its capability to tell whether the RSSI is inside, above or below the GRPR. Communication Controller (BR/EDR), present in dual mode devices (See Section 2.7.1), are in charge for providing this information.

The RSSI measurement compares the received signal power with two threshold levels, which define the GRPR [31]. More formally, GRPR can be expressed as:

$$GRPR = [J_r^{LT}, J_r^{UT}] \tag{2.8}$$

Where:

- J_r^{LT} is the lower threshold level that corresponds to a received power between -56 dBm and 6 dB above the actual sensitivity of the receiver.
- J_r^{UT} is the upper threshold level is 20 dB above the lower threshold level to an accuracy of $\pm$ 6 dB.

The receiver sensitivity is defined in BLE as the signal level at the receiver for which a Bit Error Rate (BER) of 10^{-3} is achieved. The BLE specification mandates, at least, a sensitivity better than or equal to -70 dBm. Common values are between -87dBm and -93dBm [32].

Unfortunately, RSSI varies over time due to multipath fading and the level of fluctuation gets higher in an indoor environment. This instability degrades the localization accuracy. To overcome this problem, previous works measured RSSI for long duration and used the average values. Our proposal to deal with RSSI high variability, which includes signal filtering, is proposed later, in Section 3.2.

4.3 Positioning Process

A positioning process is based on three principal steps: *beacons placement*, *calibration* and *positioning*. These are the basis of the functioning of an IPS. They could be more precisely defined as follows:

- **Beacons Placement**: During this step, known also as *deployment phase*, beacons are placed inside the environment of interest. Beacons' deployment should take into consideration the size of the area in which localization is possible, number of reference nodes and desired localization accuracy [33]. Some problems could arise in the case of wrong beacon positioning. For instance when, in the case of a lateration-based positioning technique, some beacons could not be reachable from the target. This clearly influences the possibility to estimate its unknown position since, if we have information about the distance from only one reference station, we can only say that the terminal is somewhere around the circle with radius being equal to this distance. If we have information on the distances from two reference stations, we can limit our searching to two points resulting from intersection of two circles. To obtain unambiguous information about position of the terminal, information from at least three reference stations is required. In conclusion, beacons placement should be taken into account while evaluation system performances in real cases.

- **Calibration**: The goal of this step is to define and setup all the configurations needed to perform the next phase. In particular, depending on the localization techniques adopted, it can include propagation parameters' tuning (range-based) or on-site surveys to record RSSI at specific locations (range-free). Even in this case, it is possible to provide an overall formal description extending Definition (2.1), to better characterize the Calibration (C) parameter:

  Definition 4 *Let* C *be the calibration parameter for the adopted positioning function, periodically updated with a rate* $f_{calib} = \frac{1}{t_{calib}}$. *The time frame between two consequent updating steps,* t_{calib}, *is usually >> than the positioning frame [*t_{start}, t_{end}*]. In particular,* C *could also be expressed as:*

  $$\mathrm{C} = [c_1(t), c_2(t), ...c_n(t)] \tag{2.9}$$

  Having i = *0, 1, 2, ..., M where the generic* $c_i(t)$ *refers to the* i-th *calibration model's parameter.* M *also represents the calibration model complexity and varies, as well as* t_{calib}*, from the adopted positioning technique.*

  For instance, in the case of a range-based positioning algorithm, generic c_i(t) represents one of the model's parameters that is able to describe propagation dynamics into an indoor venue (e.g. path loss at a reference distance, PL_{d0}). In this case, t_{calib} should be set in order to reflect in the model parameters any change happening. On the other hand, in the case of range-free solutions, c_i(t) may represent a generic pair ($\hat{P}$, RSSIs) which maps a specific position with an array of estimated to-be-listened RSSIs from surrounding beacons. In this case, t_{calib} is very extended: when using this approach modifications in the environment require a RSSI remapping of the venue and, thus, they are not supposed to happen frequently.

- **Positioning**: The goal of this step is to provide to the final user the location of the target T to be positioned (See Definition (2.1)). Since our work is intended to be applied in the case of two-dimensional environments (i.e., not considering multiple floors), position could be denoted as:

  $$\hat{P}(t) = [\hat{x}(t), \hat{y}(t)]^T \tag{2.10}$$

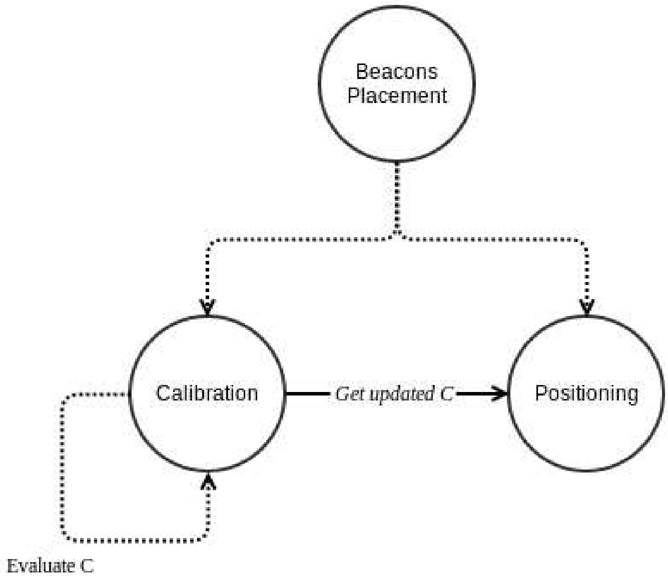

Figure 2.2: Positioning Process

Having $\hat{x}$(t) and $\hat{y}$(t) being the Cartesian coordinates of the estimated position at time t. In particular, $\hat{P} \in S$. This means that, describing the considered environment S, where target could be located, with a quadruplet $< x_{min}, x_{max}, y_{min}, y_{max} >$ representing the venue perimeter, that should satisfy:

$$\begin{cases} x_{min} \leq \hat{x}(t) \leq x_{max} \\ y_{min} \leq \hat{y}(t) \leq y_{max} \end{cases} \tag{2.11}$$

It is important to state that the order of the last two steps is not fixed. They may be repeated over time (e.g., a calibration step could be performed multiple times in a range-based approach). Consequently, the only step that may be intended as static, over the two positioning techniques, is the *beacons placement* one, since beacons re-placement may require a new setup for the entire system. *Positioning* and *calibration* events are completely not time-syncronized. This is illustrated in Figure 2.2.

4.4 Positioning Algorithms

According to literature, two main categories for localization algorithms using RSSI could be identified. They are:

- **Range-based**: Range-based algorithms make use of the RSSI to estimate the distance between nodes, using signal propagation models. Practically, at higher distances, signal strength becomes weaker by attenuation of path.

Using this metric, distance can be approximated based on the relationship between transmitted and received signal strength (the transmission strength is a constant given by the antennas being used), as long as no other error contribute to faulty results. Then, different techniques, such as lateration, triangulation or statistical inference, are used to estimate the position of target nodes with respect to the beacons. Unfortunately, the interior of buildings is not *free space* (ideal propagation), so accuracy is significantly impacted by reflection and absorption from walls. Non-stationary objects such as doors, furniture or moving people make RSSI have very large fluctuations due to the unpredictable radio propagation behavior. On the other side, these methods, unlike range-free solutions, do not require any configuration step or on-site survey. This provides an easy installation process and a reduced time interval between beacons placement and a fully working system. In addition, range-based methods could be considered as auto-adaptive, in the sense that - when the positions of some assets in the environment change - propagation models are able to modify their parameters based on new RSSI readings accordingly and thus fix any errors in positioning.

- **Range-free**: In Range-free algorithms, localization is still performed by exploiting the RSSI values that, however, are not used to estimate the distances between target and beacon nodes or to calibrate propagation models. Good results have been obtained by RSSI-mapping techniques which however require to preliminary perform an accurate measurement campaign aimed at constructing a map of the received radio signal strengths in the area of interest. This process could be, for instance in case of large venues, very expensive in terms of time and human resources. Moreover, when some changes happen within the mapped environment (e.g., furniture replacement), a new mapping process is required, which sometimes could be unfeasible.

In this work we adopted a Range-based method, considered the most suitable choice according to our requirements (explained in Chapter 1.4). Thus the focus in our dissertation is to precisely describe the RSSI-distance relationship for each beacon, so that user's location can be consequently estimated simply considering collected RSSIs.

To better describe indoor positioning techniques, some of the most used approaches are here proposed [1]; *Lateration* and *MinMax* are described for the range-based methods and *Scene Analysis* and *Proximity* for the range-free methods:

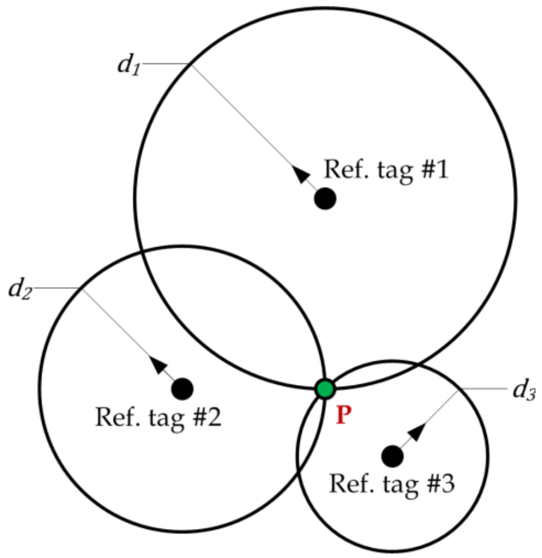

Figure 2.3: Lateration Approach

- **Lateration**: RSSI can be translated into a distance from a particular beacon according to a theoretical or empirical signal propagation model. Then, with distance estimates from at least three non-collinear beacons with known positions, lateration can be performed to estimate the target location. Distances between beacons and the unknown target location can be considered as the radii of the circles with centers at every beacon location (See Figure 2.3). Thus, the unknown location is given by the intersection of all the circles.

  This approach does not give the most accurate estimate, related to the fact that the indoor radio propagation channel is strongly variable, but requires no efforts in configuration and calibration steps, as already explained. In addition, this method does not require changes if something within mapped environment changes since, using an adaptive approach, propagation model's parameters are evaluated continuosly at a regular base. This means that, in lateration-based approaches, both calibration and positioning steps are performed *on-line* and setup time is, thus, minimized. This is the method adopted in this work.

  Additionally, distance measurements between reference stations and target node are, because of the strong RSSI variability, noisy. The amount of noise (i.e., its variance) depends on the strength and types of signals used and environment surrounding reference stations, which caused a distance measurements error. Distance is shown as ring around the station. As a result of considering at least three rings, we can indicate circles' intersections where the target is likely to be localized. This area is called the *area of uncertainty*. To make beacons perform at their best during positioning attempts, they should be placed higher and in the room's corner.

More formally, considering the case of N ($N \geq 3$) beacons listened, the target node (T) position, $\hat{P}_T = [\ \hat{x}(\mathrm{t}), \hat{y}(\mathrm{t})\ ]^T$, can be located using the a priori known coordinates of the reference nodes ($P_1, P_2, P_3, ..., P_N$) and their corresponding estimated distances using the adopted propagation model ($\hat{d}_1, \hat{d}_2, \hat{d}_3, ..., \hat{d}_N$) with respect to T. From a geometric point of view, having defined $P_1(x_1, y_1)$, $P_2(x_2, y_2)$, $P_3(x_3, y_3)$, ..., $P_N(x_N, y_N)$, this can be analitically represented as the following non-linear, overdetermined, quadratic system:

$$\begin{cases} \hat{d}_1^2 = (x - x_1)^2 + (y - y_1)^2 \\ \hat{d}_2^2 = (x - x_2)^2 + (y - y_2)^2 \\ \hat{d}_3^2 = (x - x_3)^2 + (y - y_3)^2 \\ ... \\ \hat{d}_N^2 = (x - x_N)^2 + (y - y_N)^2 \end{cases} \tag{2.12}$$

Ideally, if circles intersect in one point, the target coordinates $\hat{P}_T$ are obtained by considering the unique solution from the system above. Of course, as previously described, a problem could be represented by the fact that the intersection will not result in a single point and an area of uncertainty is then defined. In the latter case, the goal then becomes finding the most likely position for the unknown node, $\hat{P}_T$. Some possible solutions has been proposed to overcome this issue [38]. They are:

– **Nonlinear Least Squares (NLLSQ)**: A possible first solution to the uncertainty problem can be using a least squares method (LSQ), that is, minimizing the sum of the squared residuals between the estimated ranges $\hat{d}_i$ and the evaluated distances $\|P_T - P_i\|$. More precisely:

$$\hat{P}_T = \underset{P_T}{argmin} \sum_{i=1}^{N} (\|P_T - P_i\| - \hat{d}_i)^2 \tag{2.13}$$

The minimization problem can then be solved by using any Newton type optimization algorithms. This class of iterative algorithm starts from a point $x_0 \in R^n$ and generate an infinite sequence of points x_k that converges to a point belonging to a set that has an assigned property. This class of algoritms starts from an initial guess for the solution and then performs a number of iterations. Each iteration gradually improves the estimated position at each iteration, evaluation the optimal length of displacement along the chosen search direction until a local minimum for the objective function is found. The Gauss-Newton algorithm [63], for instance, can be adopted. It can be seen as a modification of Newton's method for finding a minimum of a function. Levenberg-Marquardt algorithm [62] could also be used to get the final solution.

– **Linear Least Squares (LLSQ)**: An alternative solution can be obtained by linearizing the proposed system and then solve it in least-squares sense. This can be achieved by subtracting one of the equations given, from each of the remaining N-1 equations. The complete linear system, using as pivot the *N-th* equation in the system, can be expressed in the form:

$$A(P_T) = b \tag{2.14}$$

Where:

$$A = \begin{bmatrix} x_1 - x_N & y_1 - y_N \\ x_2 - x_N & y_2 - y_N \\ ... & ... \\ x_{N-1} - x_N & y_{N-1} - y_N \end{bmatrix} \tag{2.15}$$

$$b = \frac{1}{2} \begin{bmatrix} x_1^2 - x_N^2 + y_1^2 - y_N^2 + \hat{d}_1^2 - \hat{d}_N^2 \\ x_2^2 - x_N^2 + y_2^2 - y_N^2 + \hat{d}_2^2 - \hat{d}_N^2 \\ ... \\ x_{N-1}^2 - x_N^2 + y_{N-1}^2 - y_N^2 + \hat{d}_{N-1}^2 - \hat{d}_N^2 \end{bmatrix} \tag{2.16}$$

Solving in the LLSQ way requires to minimize the quantity: $\epsilon^T \epsilon$ where $\epsilon = (A(P_T) - b)$. The solution in the LLSQ sense is expressed as:

$$P_T = (A^T A)^{-1} A^T b \tag{2.17}$$

– **Adaptive Lateration (AL)**: This approach tries to estimate the position of an unlocalized target using circle intersections. Furthermore, AL aims to reduce the computational overhead involved with matrix calculations in LSQ based methods. This solution consists of three steps: *intersection and elimination*, *first estimation* and *refinement*. At the first step two intersecting circles are arbitrarily chosen. These circles may intersect at one or two points. If there is more than one point, the location with the larger distance to the third beacon is eliminated. At the first estimation step, the previously computed intersection point is moved to the middle of the line connecting it with the closest point of the third beacon's circle. This is done to compensate the errors introduced by range measurements. At the last step the position can be further refined. Therefore, beacons that were not used in the previous steps are added to the position estimation process with the same principle utilized in the estimation step.

- **MinMax**: MinMax (or *bounding-box* based) is one of the most used algorithm for localization due to its easy implementation [40]. THe target node measures the RSSI values received from surrounding beacons and estimates its distance $\hat{d}_i$ to each one, using the collected RSSI values, based on the corresponding propagation model. The algorithm main idea is to construct a bounding box for each beacon using the calculated distances and then determine the intersection of these boxes. So a square $2 \cdot \hat{d}_i$ wide is drawn around each beacon node. The target lies within the overlapping area of all of the squares drawn around all beacon nodes. This algorithm requires a less computational effort if compared to lateration-based ones but may have some increase in error, caused by geometrical reasons, as it uses bounding boxes rather than circles, giving a wider area measured from each beacon [39].
  Using a formal approach, we are considering the case of N ($N \geq 3$) beacons listened, the target node (T) position, $\hat{P}_T = [\ \hat{x}(\text{t}),\ \hat{y}(\text{t})\ ]^T$, can be located using the a priori known coordinates of the reference nodes $(P_1, P_2, P_3, ..., P_N)$ and their correspondant estimated distances using the adopted propagation model $(\hat{d}_1, \hat{d}_2, \hat{d}_3, ..., \hat{d}_N)$ with respect to T. The target node computes the maximum and minimum values, and it identifies a square having corner coordinates, D_{low} and D_{high}, defined as:

$$\begin{aligned} D_{low} &= [max_{x_i - \hat{d}_i}, max_{y_i - \hat{d}_i}] \\ D_{high} &= [min_{x_i + \hat{d}_i}, min_{y_i + \hat{d}_i}] \end{aligned} \tag{2.18}$$

  The estimated position searched, $\hat{P}_T$, is the average of both corner coordinates, D_{low} and D_{high}. This is graphically represented in Figure 2.4.

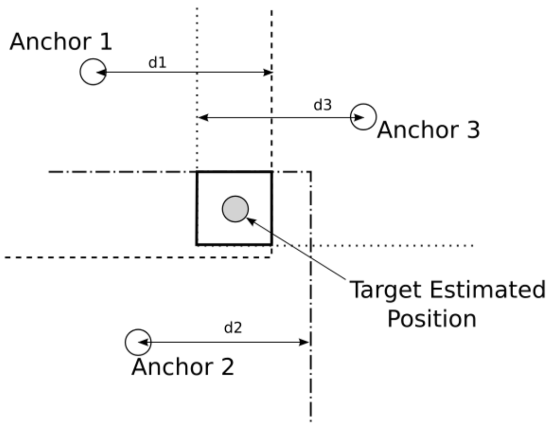

Figure 2.4: MinMax Algorithm

- **Scene Analysis**: RSSI-based scene analysis refers to the type of algorithms that first collect features (*fingerprints*) of a scene and then estimate the location of an object by matching online measurements with the closest location fingerprints. RSSI-based location fingerprinting is commonly used in scene analysis. In other words, this includes techniques that match the fingerprints of some of the characteristics of a signal that is location dependent. Fingerprinting approaches do not assume that a relation exists between RSSI and distance, but instead assume that there is relation between RSS and location. This means that at a certain location the distribution of the RSS values is assumed to remain constant as long as the target does not move and there are no changes in the environment affecting signal propagation. Since this is a range-free method, it is based on two stages for location: offline step and online step. During the offline stage, a site survey is performed; measured RSSI samples at a certain location are converted and labeled into a fingerprint. This is done for a certain number of locations in the venue and the set of fingerprints is called the radio map. Construction of the radio map is often referred to as the training phase. During the online step, a location positioning technique uses the currently observed signal strengths and previously collected information to figure out an estimated location. More formally, defined $RSSI_{target}$ as the RSSI values collected from the target T whose location, in a space S, is to be estimated, F_l is the fingerprint (collected RSSI values in calibration campaign) for location l and c is a cost function having as domain the set of all possible RSSI readings for surrounding beacons, position estimate $\hat{P}_T$ can be described as:

$$\hat{P}_T = \underset{l \in S}{argmin}\ c(RSSI_{target}, F_l) \tag{2.19}$$

This problem may be solved using different pattern recognition technique: probabilistic methods, k-Nearest-Neighbor (kNN) [42], neural networks [41], support vector machine (SVM) [43], and smallest M-vertex polygon (SMP) [44]. The main challenge to the techniques based on location fingerprinting is that the received signal strength could be affected by diffraction, reflection, and scattering when propagating in indoor environments. Accuracy of fingerprinting based localization methods depends on the granularity and distribution of the fingerprinted location. Increasing the number of fingerprints also increases the accuracy. However, increasing the number of fingerprints does not necessarily improve localization accuracy [45].

- **Proximity**: Proximity algorithms provide symbolic relative location information. Usually, this method exploits a dense grid of antennas, each having a well-known position. Nodes which receive signals with a higher strength are located closer to the target device, compared to nodes which receive lower strength signals. This information is used to define a relative ordering of nodes based on their proximity to the target. Such systems do not make an actual estimate of the distance between the nodes and the target; they rely on the relative ordering to geometrically define an area in the mapped space, which contains the location of the target. After having identified this area, the centroid of the area is then usually taken as the estimated location of the target. The simplest proximity-based localization method is to select the location of the node with the highest signal strength. However, this method, to achieve the highest accuracy, requires a dense deployment of beacons which makes range-based approaches more appealing since with the same amount of nodes they can provide better behaviour. On the other hand, differently from standard range-free techniques, these methods do not require calibration; they are relatively simple to implement and can be deployed over different types of physical media (e.g. RFID, BLE, Wi-Fi, etc.).

5 Performance and Evaluation Metrics

In order to evaluate the performance of an IPS, different definitions could be found. As previously remarked, one of the most often cited work in literature is, probably, the one of Hightower and Borriello [1]. In their paper, they define some metrics to assess the actual behaviour of a system, considering the difference between the indoor and outdoor cases. The most relevant measures to take into account when evaluating an IPS are *accuracy* and *precision*. However, other secondary metrics (e.g. *cost*) need to be considered when providing a complete overview for a system. In the following, exaustive definitions for the previously cited properties (and others) are provided.

5.1 Error Evaluation

System performances are strictly related to two types of error:

- **Calibration Error,** $\varepsilon_{calibration}$: This error is dependent to the evaluation of the parameters in the calibration model. In particular, in range-based approaches $\varepsilon_{calibration}$ is related to the periodical update of the signal propagation model's parameters and it is strongly time-related ($\varepsilon_{calibration}(t)$, to highlight time relation). In range-free approaches, where calibration parameters (i.e. fingerprints) are pretty stable, $\varepsilon_{calibration}$ is considered as the resulting error in wrong fingerprints' labeling.

- **Positioning Error,** $\varepsilon_{positioning}$: This error is dependent to the adopted positioning algorithm.

Both errors include an additional noise related to highly-variable RSSI measurements. Thus the overall system error, ε_{IPS}, is given by a combination of the just described errors and it is usually characterized by a Normal distribution.

$$\varepsilon_{IPS} \sim \mathcal{N}(\mu, \sigma^2)$$

5.2 Accuracy

Accuracy (or location error) is probably the most important requirement of an IPS. Usually, accuracy is quantified by the *mean positioning error*, that is the average of the Euclidean distance between the estimated location, $\hat{P}_T$, and the true location, P_{Treal}, over N positioning attempts. Formally:

$$\bar{\varepsilon}_{IPS} = \frac{1}{N}\sum_{i=1}^{N}(\|\hat{P}_T - P_{Treal}\|) \tag{2.20}$$

Obviously, the higher the accuracy, the better the system; however, there is often a tradeoff between accuracy and other characteristics. Some compromises between suitable accuracy and other characteristics is needed.

In addition, also the accuracy of a single calibration step could be described. In particular:

Definition 5 *Considering* M *beacons placed in a venue and let the estimated distances between a specific target* T *and the* M *beacons, using the adopted propagation model, be* $(\hat{d}_1, \hat{d}_2, \hat{d}_3, ..., \hat{d}_M)$ *and the correspondent real distances defined by* $(d_1, d_2, d_3, ..., d_M)$*:*

$$\bar{\varepsilon}_{calibration} = \frac{1}{M}\sum_{j=1}^{M}(\hat{d}_j - d_j) \tag{2.21}$$

5.3 Precision

Accuracy only considers the value of mean distance errors. In addition to that, precision is a measure describing the variance of the distances between measured points and the reference point. Hence, the value of accuracy is directly influenced by the value of precision as the percentage of sensor readings within a certain diameter directly influences its radius (increasing the value of precision results in lowering accuracy).

Usually, the cumulative probability functions (CDF) of the overall error (ε_{IPS}) is used for measuring the precision of a system, accordingly to its distribution. When comparing two IPSs, if their accuracies are comparable, in this work, we prefer the system having the CDF which reaches high probability values faster, because this means that its distance error is concentrated in small values. In practice, CDF is described using the percentile format. For example, if one system has a location precision of 90% within 2.3 m (the CDF of distance error of 2.3 m is 0.9), and 95% within 3.5 m; another one has a precision of 50% within 2.3 m and 95% within 3.3 m. We could choose the former system because of its higher precision [30].

5.4 Complexity

Complexity of a positioning system can be considered from hardware or operational perspective. Complexity has a direct effect over other parameters, for instance, cost. The more complex is the system, more it is expensive. For what concerns hardware, a complex system requires a higher number of beacons to be deployed inside the environment or a huge number of connections to work. Since our work is focused on the positioning of a beacon inside an indoor space, the infrastructure complexity could be expressed as:

Definition 6 *Let's consider* M *beacons placed in a venue and let* S *be its surface area, expressed in* mq^2*. Infrastructure complexity (or beacons density) can be defined as:*

$$C_{infrastructure} = \frac{M}{S} \tag{2.22}$$

Operational complexity refers to software complexity (related to the specific algorithms chosen or calibration techniques). For instance, if the computation of the positioning algorithm is performed on a centralized server side, the positioning could be calculated quickly due to the powerful processing capability and the sufficient power supply. If it is carried out on the mobile target, the effects of complexity could be evident since most of mobile device are not characterized by a strong processing power or a long battery life.

From another point of view, operational complexity is related to the computational cost of the positioning algorithm. Since, it is difficult to derive the analytic complexity formula of different positioning techniques the computing time is usually considered. While, from an overall perspective, system's complexity takes into account both positioning algorithm complexity and, if needed, calibration complexity in order to evaluate the propagation model's parameters (only in the case of range-based methods).

5.5 Robustness and Adaptiveness

A positioning technique with high robustness could function normally even when some signals are not available. Sometimes, the signal from a beacon could be totally blocked. More in general, some changes in the environment may affect the localization system. The ability of the localization system to cope with these changes is called, more specifically, *adaptiveness*. A system that is able to adapt to environmental changes can provide better localization accuracy than systems that cannot adapt. An adaptive system can also prevent the need for repeated calibration, thus reducing the required effort calibration. Range-based methods, as clearly stated before, are much more adaptive than range-free ones.

5.6 Scalability

The scalability feature of an IPS allows it to provide the normal positioning functions when the target area gets large. In other words, it is the ability to easily extend the positioning coverage (i.e. mapping new rooms in the same venue). Positioning performance, due to the RSSI nature, degrades when the distance between the transmitter and receiver increases. Extending the coverage area, on the other side, may affect other parameters as infrastructure complexity.

5.7 Cost and Calibration Effort

The cost of a positioning system may depend on many factors. Important factors include money, time, space, weight, and energy consumption. The time factor is related to installation and maintenance of the overall structure. Mobile units (targets and beacons) should be small, lightweight and easy-to-carry. Beacons density is considered to be the most influencing factor when evaluating space cost. For what concerns money, beacons' cost should be evaluated. BLE beacons can have a cost varying from few dollars for not branded solutions, to five dollars Qualcomm's *Gimbal* beacons[1], arriving at more than twenty-five dollars for Estimote[2], GeLo[3] or Kontakt[4] solutions. As described, many localization systems need to be calibrated to make location estimates with reasonable accuracy. The amount of effort required for the calibration process can have a big influence on the usefulness of a system, especially if a lot of effort is required. Another factor to consider while evaluating calibration effort is whether it is intended as a process that needs to be performed only once or repetitively. This is one of the most remarked difference between range-based and range-free approaches.

6 Enabling Technologies

In the last years, the remarkable growth of interest in mobile, portable or wearable devices equipped with wireless technologies, accordingly with an increasing market focus by some of the most important IT firms, has paved the way for the development of positioning systems relying on the measurement of different location-related parameters from the wireless signals.

For instance, *signal strength* of an RF link is usually considered as dependent on the distance between transmitter and receiver, according to a law whose details describe the propagation model of the physical environment where communication occurs. In a similar way, RF signal *propagation time* depends on the distance between the communicating devices, and can be determined by knowing the signal propagation speed in the medium. Furthermore, the angle at which RF signal arrives at the receiver contains important information about the position of the transmitter, and can be related to the transmitter-receiver range as well. Accordingly, distance can be indirectly determined from the measurement of such parameters, and later processed by means of appropriate methods to estimate the position [9].

A number of classification schemes are used in the literature to inspect indoor positioning systems. In this section, we classify the systems based on their enabling technology in order to better comprehend how Bluetooth Low Energy could help achieving our final goal. Although in this section we offer a broader overview of some developed systems, the main focus of this work is mainly on the RF based

[1] http://www.qualcomm.com/solutions/gimbal/beacons
[2] http://www.estimote.com
[3] http://www.gelosite.com/
[4] http://kontakt.io/

Positioning System	Accuracy	Signal	Principle	Range	Cost	Data rate
Active Badge	7cm	Infra Red	T/TOA	5 m	moderate	0.1 Hz
Active Bats	9 cm	Ultrasound	T/TOA	50 m	moderate	75 Hz
Cricket	2 cm	Ultrasound	T/TOA	10 m	low	1 Hz
Dolphin	2 cm	Ultrasound	T/TOA	Room	moderate	20 Hz
Radar	2-3 m	RF	R/RSS	Room	moderate	4 Hz
Wave LAN	3 m	RF	R/RSS	Room	moderate	4 Hz
UWB	10 cm	RF	T/TOA	15 m	moderate	1 Hz
LANDMARC	1-2 m	RF	R/RSS	50 m	moderate	70 Hz
SpotOn	3 m	RF	R/RSS	Room	low	2 Hz
CLIPS	0.5 mm	Camera images	Image process	36 m2	high	30 Hz

Figure 2.5: Accuracy comparison between some of the proposed technologies [25]

ones, because, differently from other signals such as ultrasound, infrared or visible light, RF waves can penetrate obstacles and thus are suitable even in NLoS conditions, which are particularly inherent to indoor environments.

A tabular overview of the characteristics for some of the described solutions is presented in Figure 2.5.

6.1 Ultrasound

Ultrasound is an oscillating sound pressure wave with a frequency that is greater than the upper limit of the human hearing range. Ultrasound devices operate with frequencies from 20 kHz up to several gigahertz. Ultrasound signal is characterized by a slow propagation speed, a negligible penetration in walls and a low cost of the transducers (See Figure 2.6). Characteristics of the ultrasound signal are interesting for use in indoor positioning systems (IPS) since achievable precision by ultrasound may be of few centimeters. With this technology, time-of-flight (TOF) of the signal in its propagation from a transmitter device to a receiver device is used to evaluate the distance between them taking into account, in this case, the propagation speed of sound. This requires a correct temporal synchronization of the network nodes. [10]

Active BAT A real application could be the Active BAT[5] localization system, designed by researchers at AT&T Cambridge that provides 3-D position and orientation information for the tracked tags and which is meant for accurate indoor localization [11] [13]. It proposes the use of ceiling mounted beacons - connected to a central station - placed in order to maximize likelihood of line of sight to beacons.

[5] Active Bat Website - http://www.cl.cam.ac.uk/research/dtg/attarchive/bat/

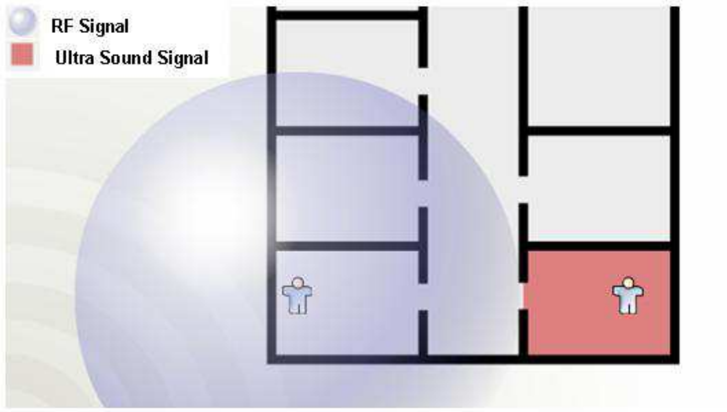

Figure 2.6: Coverage comparison between RF and Ultrasound

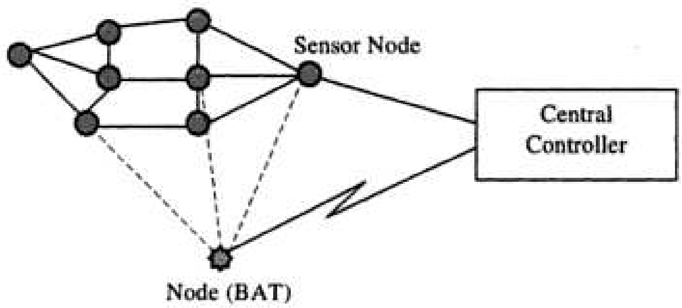

Figure 2.7: Active BAT Architecture

The system works by equipping target objects with a badge that emits ultrasound pulses. Deploying a large number of sensors on the ceiling in each room is a time-consuming task, which degrades the scalability of this system. One of the risen problems in adopting Active BAT is related to a lack of scalability, since multiple tags need to be well separated and correctly placed to be queried concurrently without the risk of interference, which results in complex and costly installation. [12]. A bat's position is queried over an out-of-band radio channel, which is also used by bats to notify the system of their presence (this is known as registration). When a bat receives a query it responds by emitting an ultrasound pulse that is detected by ceiling-mounted receivers. If the pulse is detected by three or more ceiling-mounted receivers then the position of the bat is calculated on the central station, using multi-lateration. Each communication between sensors and target device is then reported to the central station. However, the performance of this technology is influenced by the reflection and obstacles between tags and receivers, which degrades system accuracy. [2]

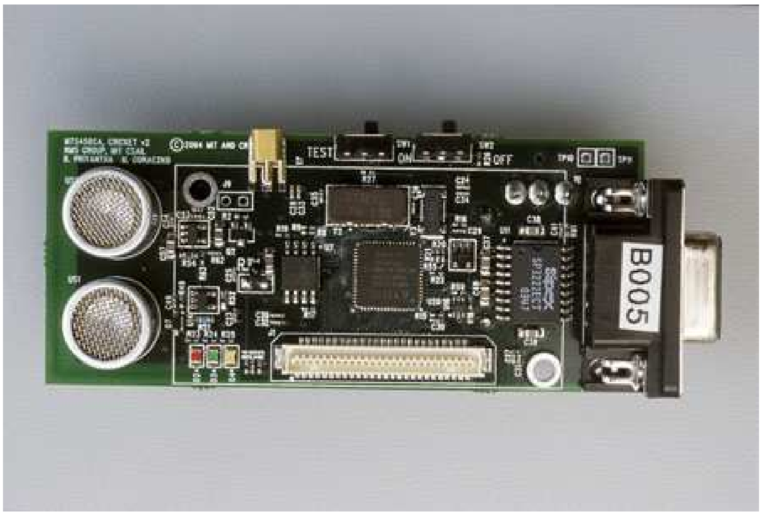

Figure 2.8: A Cricket listener. It can be attached to the target device using an RS232 serial connection

Cricket Another ultrasound-based IPS is Cricket[6]. Cricket is an indoor location system for pervasive and sensor-based computing environments developed at the MIT Computer Science and Artificial Intelligence Laboratory, which is able to provide fine-grained location information (space identifiers, position coordinates, orientation, etc.) to applications running on handhelds, laptops, sensor nodes or portable computing devices using both ultrasound and, occasionally, RF signals. Like Active Bat, Cricket system uses TOF measuring method and triangulation location techniques to locate a target. Even in this case, ultrasound emitters are placed on walls or ceilings at known positions. This system requires a receiver mounted on each target object (See Figure 2.8). A peculiar feature of this approach is related to the fact that it provides a privacy livel for the user by performing all the position triangulation calculation locally, in the located object. This implies that the target holds its location information and can decide how and where to publish it. Moreover, emitters also transmit RF messages for time synchronization of the TOF measurements and forwarding their location information in a decentralized fashion. Thus when not enough emitters are available for the triangulation location calculation, the receiver can use the additional RF messages to get proximity location information [14].

The Cricket system addresses the issues of fault tolerance by using RF signals as a second method of proximity positioning in the case of not enough emitters being available. Unlike the Active Bat system which uses a grid of receivers connected to a central station, the Cricket system uses a reduced number of emitters fixed on

[6] Cricket Website - http://cricket.csail.mit.edu/

the ceiling, because the target object receives and processes the ultrasound signals to locate itself.

Commercial Products Very few commercial products use ultrasound signals for positioning purposes. Accordingly to a market research [15], one of the most emerging companies in this area is Sonitor[7], a Norway-based company, which uses USID (Ultrasound Identification) in hospitals or medical centers.

6.2 Infrared

Infrared (IR) light is electromagnetic radiation with longer wavelengths than those of visible light, extending from the nominal red edge of the visible spectrum at 700 nanometers (nm) to 1 mm. This range of wavelengths corresponds to a frequency range of approximately 430 THz down to 300 GHz. Most of the thermal radiation emitted by objects near room temperature is infrared. IR-based positioning system, which offers absolute position estimations, needs line-of-sight (LoS) communication between transmitters and receivers without interference from bright light sources [16]. Thus orientation of IR Tag to the IR reader can cause problems if, for instance, the tracked asset itself is blocking the line of sight view from the IR Tag to the reader. With respect to ultrasound-based positioning systems, IR based systems have higher measurement accuracy (several millimeters) compared from the accuracy achievable in that systems (several centimeters). Infrared light is invisible to the human eye under most conditions, so people can not see placed beacons. [17] Specialized IR receivers placed throughout the facility detect the beacons and determine the approximated position of the object because of the known location of the IR receivers.

Active Badge Active Badge[8] is one of the first IR-based IPS; it was designed at AT&T Cambridge in 1990s, to cover the area inside a building and provide symbolic location information of each active badge such as the room where the active badge is. The Active Badge system uses commonly available IR technology to realize location sensing. By estimating the location of the active badges taken along with the persons, the Active Badge system can locate persons in its coverage area. An active badge transmits a globally unique IR signal every 15 seconds [18]. In each room, one or more sensors are fixed and detect the IR signal sent by an active badge. The position of an active badge can be specified by the information from these sensors, which are connected with wires and forwards the location information of the tracked active badges to a central server.

[7] Sonitor Website - http://sonitor.com
[8] Active Badge Website - http://www.cl.cam.ac.uk/research/dtg/attarchive/ab.html

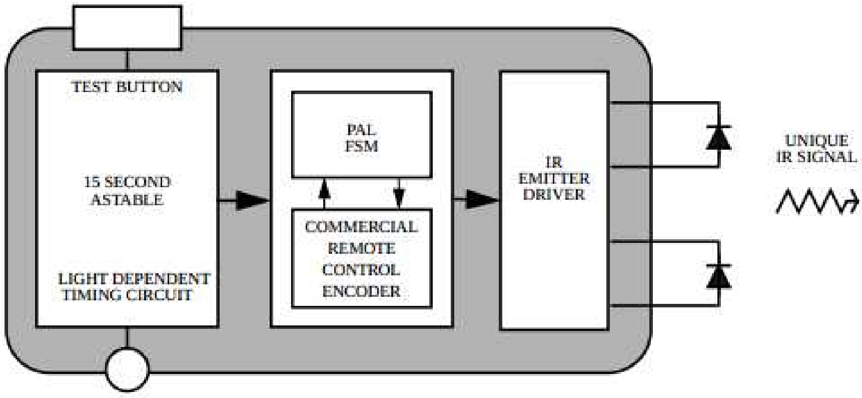

Figure 2.9: Active Badge architecture

The master station, also connected to the network, polls the sensors for badge sightings, processes the data, and then makes it available to clients that may display it in a useful visual form. The badge was designed in a package roughly 55x55x7mm and weighs a comfortable 40g. Although the price of active badges and networked sensors are cheap, the cables connecting sensors raise the cost of the Active Badge system. The active badges taken by persons to locate themselves are light weight and have acceptable size (See Figure 2.9).

Commercial Products Some commercial products that use infrared signals for positioning purposes are, for instance, CenTrak products[9]. Some well known commercial applications are based on Firefly[10] IPS, designed by Cybernet System Corporation, which is an IR-based motion tracking system providing a good accuracy using small tags emitting IR light and mounted on target object to analyse complex virual reality motions. This system consists of a factory calibrated camera array that tracks the position of active tags. The tags are infrared light emitting diodes (LEDs) that are wired to a small controller that can be worn by the user. The controller itself does not need to be tethered to the camera array allowing the user to feel unencubmered and free. Each tag controller is capable of hosting up to 32 tags, and multiple controllers can be slaved to handle up to 256 tags [19]. Another widely adopted IR-based IPS is Optotrack[11], designed by Northern Digital Inc. It also uses IR capable cameras in linear array to track 3D positions of various markers on an object. Triangulation technique helps with calculating the position of IR light emitters. The system can offer a high accuracy of 0.1 mm to 0.5 mm with 95% success probability. However, IR-based-only IPSs are not so common; most

[9] CenTrack Website - http://centrak.com
[10] Firefly Website - http://www.cybernet.com/interactive/firefly
[11] Optotrak Website - http://www.ndigital.com/products/

available products merge the advantage of IR signals with those provided by other sources, mainly used for communication purposes as, for instance, ultrawideband (UWB) or RFID tags (Versus[12] or Vizzia[13] products).

6.3 Optical

Optical (or Vision-based) IPSs are based on the positioning of objects using a system organized on anchors installed in the building. In particular, mobile sensors (i.e. a camera) can be carried by the user (first-person-view) or, from a third-person-perspective, these systems can not require the tracked person to carry or wearing any device. This systems can easily provide, using some image processing techniques, some location-based information such as detecting if a person is sitting on his/her sofa. However, these systems still have some drawbacks. Position estimates are based on saved visual information, which needs to be updated in the case of changes in the environment, such as moving desks in offices. The vision-based positioning is influenced by many interference sources such as weather, light, etc. For example, the turning on and off a light in a room reduces the accuracy of tracking a person's motion. Moreover, the privacy of people is not provided by the vision-based positioning.

CLIPS CLIPS, short for Camera and Laser-based Indoor Positioning System, has its main objective in position estimation of a mobile camera with respect to a static projector on a tripod. The camera acts as the mobile device for positioning objects. The laser device is oriented towards the ceiling and laser beams are on the ceiling. The camera tracks the laser beams and adjusts its orientation with regards to the laser beams location. This king of system is mostly used for robots' localization [24].

Easy Living Easy Living, developed by Microsoft, uses many vision-based location techniques that can capture the motion of the targets with data from a single perspective or multiple perspectives. Easy Living systems use the multiple-perspective vision-based location technique with two cameras covering the whole measuring area. The location estimation in Easy Living system combines color and depth from the two cameras to provide position sensing and target identification services [23].

Commercial Products Thanks to the technologies available on most of modern portable devices, the implementation of Vision-based IPS is more and more extensive. Among these, for instance, BiteLight[14], a start-up Based in Cambridge,

[12]Versus Website - http://versustech.com
[13]Vizzia Website - http://vizziatech.com
[14]BiteLight Website - http://bytelight.com

MA, turns common LED light sources (commonly available in every location) into positioning beacons. Once beacons' signals are detected by a smartphone camera, the device then calculates its position, without the need for any active network connection. As claimed by the company, this IPS is accurate to less than one meter and takes less than a second to compute [64].

6.4 Radio Frequency

After describing positioning technologies not based on RF signals and highlighted their advantages (i.e. an higher accuracy) and drawbacks (i.e. hardware not easily available on modern devices, not able to deal with obstacles and higher number of sensors required), in this section RF based IPSs are described. Radio waves can travel through walls and human bodies easier, thus the positioning system has a larger coverage area and needs less hardware comparing to other systems.

But, probably the most interesting aspect, is that RF-based positioning systems can reuse some of the existing RF technology systems already present in most of indoor venues, such as APs in WLAN [26].

Radio Frequency Identification

Radio Frequency Identification (RFID) is a means of storing and retrieving data through electromagnetic transmission to an RF compatible integrated circuit. RFID is an automatic identification method. A RFID system consists of a tag, a reader and an antenna (see Figure 2.10). The tag is a transponder that can be attached to or incorporated into a product, animal, or person for the purpose of identification using radiowaves. The reader (i.e., a transceiver) is able to read the stored information of the tag in close proximity. RFID tags contain antennas to enable them to receive and respond to radiofrequency queries from an RFID transceiver. There are various types of tags; i.e., passive, active and semipassive tags. Passive RFID tags do not have their own power supply and the read range is less than for active tags, i.e., in the range of about a few millimeters up to several meters. Active RFID tags, on the other hand, must have a power source, and may have longer ranges and larger memories than passive tags. Many active tags have practical ranges of tens of meters, and a battery life of up to several years. Another advantage of the active tags compared to the passive tags is that they have larger memories and the ability to store additional information (apart from the tags' ID) sent by transceiver [27].

The RFID technology can not only adopted for the indoor positioning applications, but also provides many potential services for the demands of users. One of the main advantage of an RFID positioning system consists in the adoption of light and small tags. RFID systems can uniquely identify equipment and persons tracked, however, the proximity and absolute positioning techniques need several

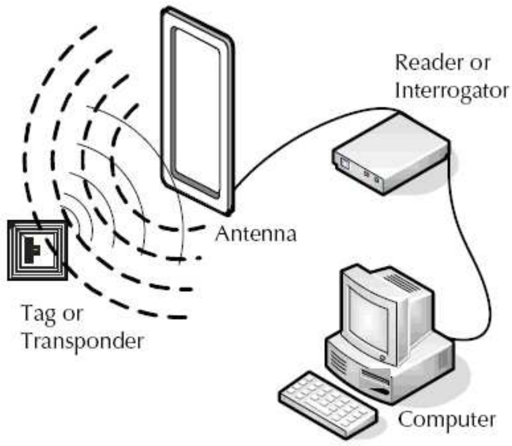

Figure 2.10: RFID Architecture

infrastructure components installed and maintained in the working area.

LANDMARC An example of RFID-based IPS is the LANDMARC system, which is based on the deployment of a group of active RFID readers over the smart environment with partial overlap between the coverage area of different readers, governed by the power levels associated with each reader. The LANDMARC system uses a set of RT reference tags (called landmarks) in a similar manner to RADAR's use of reference locations. The LANDMARC readers receive updates not only from the tag being tracked, but also from the set of static reference tags, whose location is well known. The actual estimated location is computed as a weighted sum of the location of the k-nearest landmark tags. Experimental results demonstrate that the minimum location estimation error using this technique is around 1-2 m.

Ultrawideband

Ultrawideband (UWB) is a radio technology for transmitting information spread over a large bandwidth (>500 MHz), which may be used at a very low energy level for short-range, high-bandwidth communications using a large portion of the radio spectrum. In particular, most recent applications exploit UWB for target sensor data collection, precision locating and tracking applications. UWB signals have a short duration (less than 1 ns) with respect to other technologies and make it possible to filter the reflected signals (caused by obstacles or walls) from the original signal; These properties result in a higher accuracy. Using UWB technology as a support technology in positioning systems has been a popular way of improving the positioning the overall accuracy [20]. UWB signal passes easily through walls, equipment and clothing. However metallic and liquid materials cause UWB signal interference. The use of more UWB readers and strategic placement of UWB readers could overcome this disadvantage. Short-pulse waveforms permit an accurate determination of the precise TOF of a burst transmission from a short-pulse transmitter to a corresponding receiver [21].

Ubisense Being the market leader in this field, offering high accuracy and an extensive software platform, Ubisense[15] provides a state-of-the-art system ready for out of the box deployment. The system hardware consists of Ubisensors and active Ubitags. Pulses of short duration and high energy over a bandwidth between 6-8 GHz are emitted by the Ubitags and received by the Ubisensors. In addition to the unidirectional UWB signals for location computation, control information is exchanged bi-directionally in the 2.4 GHz band between tags and sensors. Location computation is conducted either by the angle of arrival principle (AOA), TOF principle, or a combination of both. As a result of the utilization of these two distinct location principles and the characteristics of the UWB technology to locate objects with an accuracy of about 0.15 m [22].

Wi-Fi

The midrange wireless local area network (WLAN) standard, operating in the 2.4GHz Industrial, Scientific and Medical (ISM) band, has become very popular in public hotspots and enterprise locations during the last few years. With a typical gross bit rate of 11, 54, or 108 Mbps and a range of 50-100 m, IEEE 802.11 is currently the dominant local wireless networking standard. It is, therefore, appealing to use an existing WLAN infrastructure for indoor location as well, by adding a location server. The accuracy of typical WLAN positioning systems using RSS is approximatly 3 to 30 m, with an update rate in the range of few seconds.

RADAR RADAR, is a device-oriented RF-based system for locating and tracking users inside buildings. The system requires each mobile wireless device to physically measure the received signal strength of beacons emitted by multiple 802.11 access points at receiver location to estimate the user's coordinates. The RADAR system employs signal strength and signal-to-noise ratio (SNR) with the triangulation location technique. The multiple nearest neighbors in signal space (NNSS) location algorithm was proposed, which needs a location searching space constructed by a radio propagation model. The RADAR system can provide 2D absolute position information and thereby it can enable location-based applications for users. In some experiments of the RADAR system (conducted by Microsoft and described in [28]), 3 PCs are used as APs and one laptop is tracked as the target object. The system was tested on a floor inside a building, which is a typical indoor environment. The

[15] Ubisense Website - http://ubisense.net

three APs measure the signal strength of the RF signals from the target. These measurements are used to calculate a 2D position of the object. The system achieves an accuracy of about 4 m with about 50% probability. The major advantages of the RADAR system are that the existing indoor WLAN infrastructures are reused and that it requires few base stations to perform location sensing. Thus the RADAR system is easy to be set up. However, the limitation is that the located object needs to be equipped with WLAN technology, which is difficult for some lightweight and energy-limited devices [28].

Bluetooth

Nowadays, various mobile devices (most of commercially available phones, personal digital assistants, etc.) are equipped with Bluetooth radio transceivers. Due to its broad adoption, Bluetooth can be considered a highly ubiquitous standard. Bluetooth was originally a codename for a project lead by a Special Interest Group (SIG) consisting of major companies, like Ericsson, Intel and Nokia.

The Bluetooth bit rate is lower (1 Mbps), and the range is shorter (typically 10-15 m) with respect to Wi-Fi. Moreover, Bluetooth is a lighter standard and supports several other networking services in addition to IP.

Because of their working range of about 15 m, Bluetooth based systems are not precise enough to consider just the reachability of the sensor nodes as in the RFID-based approach. Thus, for positioning, it is suggested to employ received signal strength indications (RSSI) [29], since RSSI decreases with distance between sender and receiver.

Since Bluetooth is a low-cost and low-power technology (Bluetooth tags are small size transceivers), it can be intended as an efficient solution to design IPSs. The Bluetooth positioning systems will suffer from the same drawbacks of RF positioning technique in complex and full of obstacles indoor situations.

7 Bluetooth Low Energy

Bluetooth Low Energy (BLE), also known as *Bluetooth Smart*, is a wireless personal area network (WPAN) technology designed by the Bluetooth Special Interest Group (SIG)[16] to support new applications in the healthcare, fitness, security, and home entertainment fields. Compared to Classic Bluetooth [6.4], BLE is intended to provide considerably reduced power consumption and cost, while maintaining a similar communication range operating in the unlicensed industrial, scientific and medical (ISM) band at 2.4 to 2.485 GHz. BLE uses a spread spectrum, full-duplex signal at a nominal rate of 1600 hops/sec. The widespread use of Bluetooth technol-

[16] Bluetooth SIG Website - https://www.bluetooth.org/en-us

ogy (e.g., in mobile phones, laptops, automobiles, etc.) may fuel adoption of BLE. According to some published forecasts [47], BLE is expected to be used in billions of devices in the near future. The importance of BLE for the Internet of Things, has already been recognized. In particular, consistent with what is described in this thesis, BLE is also adeguate for indoor enviroments positioning techniques, which are considered challenging due to multipath fading. In fact, inherited from classic Bluetooth, BLE accounts with adaptive frequency hopping, which offers a robust solution to indoor signal propagation (described further in Section 3.2).

7.1 BLE Architecture Overview

This subsection presents an overview of the BLE protocol stack and describes the main mechanisms and features of each layer. Similar to Classic Bluetooth, the BLE protocol stack is structured on two main levels: the *Controller* and the *Host*.

- The Controller comprises the *Physical Layer* and the *Link Layer*, and it is typically implemented as a System-on-Chip (SOC), which includes an integrated antenna;
- The Host runs on an application processor and includes high-level layer functionalities as the *Logical Link Control* and *Adaptation Protocol* (L2CAP), the *Attribute Protocol* (ATT), the *Generic Attribute Profile* (GATT), the *Security Manager Protocol* (SMP) and the *Generic Access Profile* (GAP)

Communication between the Host and the Controller takes place through the *Host Controller Interface* (HCI). Finally, non-core profiles (i.e., application layer functionality not defined by the Bluetooth specification) can be used on top of the Host. Although some of the BLE Controller features are inherited from the classic Bluetooth Controller, both types of Controller are currently incompatible. Hence, a device that only implements BLE (which is referred to as a *single-mode* device) cannot communicate with a device that only implements classic Bluetooth. It is expected that many devices will implement both the classic Bluetooth and the BLE protocol stacks. These devices are called *dual-mode* devices. Small power-sensitive devices such as tokens, watches and sports sensors based on single-mode BLE implementation benefit from the low-power consumption advantages enabled for highly integrated and compact devices such as ultra-low power idle mode operation, simple device discovery, and reliable point-to-multipoint data transfer with advance power-save and encryption functionality.

In the case of dual-mode implementation, Bluetooth LE functionality is integrated into Classic Bluetooth circuitry. Subsequently, Bluetooth LE's architecture shares Classic Bluetooth technology radio and antenna, enhancing the development of Classic Bluetooth devices with new capabilities.

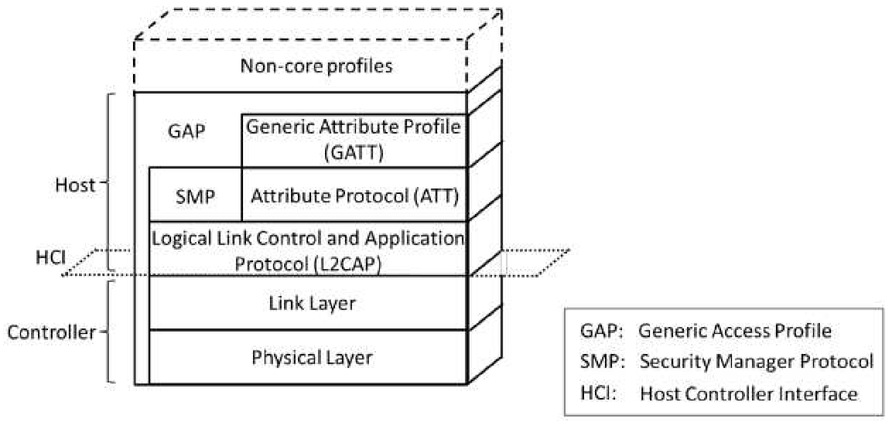

Figure 2.11: Schema of the BLE Architecture

7.2 Ranges

The range for BLE devices may vary depending on the class of the radios used in the implementation:

- **Class 1** radios, which are used in industrial use cases have a range of 100 meters; Their maximum power is 100mW.
- **Class 2** radios, the most commonly found in mobile devices have a range of 10 meters; Their maximum power is 2.5mW.
- **Class 3** radios, which have a range of up to 1 meter; Their maximum power is 1mW.

However, this range can potentially be affected by the surrounding environment, as the signals are susceptible to propagation effects.

7.3 Profiles, Services and Characteristics

Bluetooth LE, like classic Bluetooth, holds the concept of *profiles*, and there are specific profiles for Low Energy devices detailing how a device should behave in a particular application. Manufacturers are expected to implement the appropriate specifications for their device in order to ensure compatibility. The GATT profile, on which BLE is based, is a way of define the transmission of data, known as *attributes*, over a BLE link. All BLE profiles are based on GATT profiles. In particular, with the term *attribute* we could refer both to *services* and *characteristics*. Each attribute is identified by an UUID. For instance, there are profiles for Bluetooth LE devices which are used in healthcare applications. As a remark of this, the Continua Health Alliance consortium[17], in cooperation with the Bluetooth SIG, proposes

[17] Continua Health Alliance Consortium Website - http://www.continuaalliance.org/

some profiles in this field, which are HTP (for medical temperature measurement devices), GLP (for blood glucose monitors), BLP (for blood pressure measurement). More in general, a BLE profile, on the top of GATT one, defines the used services, whether it is the sensor or collector side, the GATT role (server/client) and the GAP role (peripheral/central).

In BLE, GATT defines a framework that uses the ATT for the services discovering and the transfer of *characteristics* from one device to another. A characteristic is a collection of data that includes a value and some related properties (known as Characteristic Presentation Format, CDF, which includes data type (uint16, utf8 string, float64, etc.) and unit (Temperature, Mass, Length, Hertz, etc.)). A *service*, more generally, is a collection of related characteristics, which operate together to expose a particular function. In other words, services describe characteristics (and their UUID), their contents and the format they have, how they can be accessed (read/write) and what security levels are required to manipulate them. For example, a server that works as a temperature sensor service may provide a temperature characteristic for describing the sensor, another characteristic for storing temperature measurement values and a further characteristic for specifying the measurement interval.

7.4 Advertising and Central Modes

One of the main features for which BLE could be adopted in various products is its possibility of switching into an *advertising* mode, i.e., pushing information to enabled devices when they are in the range of a fixed transmitter. Although several technologies already embodied this feature (e.g., RFID), this was not possible in Classic Bluetooth; Classic Bluetooth can not broadcast messages to unknown (i.e. not previously connected) nodes and needs to identify the presence of each individual device in order to send a one-to-one message to keep track of their communication.

BLE's *broadcast advertising modes* are used for the discovery and pairing process, in order to provide a much better and lighter user experience, when pairing and connecting. However, they can also be used for general, unacknowledged advertisements that can be detected by any BLE enabled device. This last aspect is the one which makes low cost beacons possible.

The BLE standard considers two types of devices: a *peripheral* device, which is assumed to be a low-power device that exposes information, and a *central* device. The central is usually a powered device, including a rechargeable battery and with a greater processing power with respect to peripheral ones (e.g., a smartphone or a tablet). Differently from classic Bluetooth or other solutions, peripheral and central devices are very asymmetric in their resource requirements. This technology has been projected having in mind to minimize complexity, power requirements and costs mainly on the peripheral side. This results in the fact that a peripheral device spends the majority of its life asleep, limiting its consumptions, only waking when it needs to send data or interact with central devices.

A peripheral uses advertising packets to broadcast information that any other BLE device within range can hear. To listen to these, central devices implement a *scanner modality*, in which they listen for these advertisements. In particular, over time, both devices switch from an idle state to that of either an advertiser or a scanner. The BLE standard splits the 2.4GHz spectrum into thirty-nine 2.0 MHz wide channels. Thirty-six of these are reserved for data, only used by devices that have paired with each other. The remaining three channels are used for advertisements. These three channels were specifically chosen to avoid the main channels used by Wi-Fi access points, to minimize interferences. When a peripheral wants to broadcast, it starts an advertising event, where the same packet of information is transmitted sequentially on each of the three advertising channels. Devices operating as scanners will detect one of these, and pass the information it contains to the higher level protocol stack and application. This is where we get to the value of the specification, at least as far as location and advertising is concerned. Although the primary aim of advertising packets within the specification is to allow for the discovery of devices and make a secure connection, they also permit small amounts of data to be transmitted for any other device to hear. In particular beacons uses a *non-connectable advertising mode*, where a device transmits a string of data, but will not respond to any request and cannot make a connection. This can be implemented using only a transmitter, with no receiver [5].
Advertising packets consist of a header and a maximum of 27 bytes of advertising data. This can contain multiple items, each grouped as a triplet of an identifying byte defining the data format, the length of the contents, and the content. Defined formats include the signal strength (RSSI), a local name, the Bluetooth service, configuration flags and manufacturer specific information.

8 Conclusions

This chapter provided a suitable background for the understanding of the methods and of results described in the following part of this thesis. In Section 2.2, we provided a complete description of the indoor positioning problem and its formal definition; it is based on a mapping function from a tern $<T, O, C>$ rispectively representing the chosen target, a set of collected observations and a set of calibration parameters, to the estimated target position, $\hat{P}$. In Section 2.3, some theoretical aspects of radio propagation were discussed. Then, in Section 2.4, an overview of signal-based positioning methods and RSSI measurements is added. Moreover, RSSI-based approaches are compared to other signal-based methods. RSSI-based techniques are preferred since they exploit sensors which are, nowadays, widespread in mobile terminals (e.g., smartphones or tablets). Then, the positioning process and their steps are compared in the case of different localization algorithms. We introduced range-free and range-based models. According to the requirements of this project, range-based solutions are the preferred ones. In Section 2.5, we described the metrics adopted to evaluate performance in these systems. The most relevant are *accuracy* and *precision*. They will be used to compare our designed system with respect to other methods and approaches commonly used in literature. Finally, Section 2.6 and Section 2.7 are oriented to the explanation of the underlying technologies used for positioning purposes. Both RF and non-RF solutions are described and a comparison between them is outlined. The latter section describes the Bluetooth Low Energy architecture and how beacons work, on the basis of its structure.

Chapter 3

Channel Characterization and Position Estimate

1 Introduction

The study of signal propagation is an important task when designing a wireless indoor positioning system (IPS). Indeed, in indoor environments, the radio propagation of electromagnetic waves between the transmitter (TX) and the receiver (RX) is characterized by the presence of *multipath* effects caused by various phenomena such as reflection, refraction, scattering, and diffraction. In fact, performance of communication systems is mainly dependent on the propagation environment and on the structure (gain and polarization) and orientation of antennas. In this context, an accurate characterization of the spatial and temporal properties (*space-time* relation) of the channel is necessary for the design of such systems and for the choice of the network topology and complexity. Moreover, moving people within the channel might cause a severe shadowing effect making the propagation channel not accessible during the positioning attempt. Usually, when a path is shadowed, another one, coming from another direction, can keep the radio link alive [48]. In addition, channel characterization should be designed to be auto-adaptive with respect to notable changes in the focus environment. To conclude, estimated calibration parameters are then passed, as an input, to positioning routine (See Definition (2.1)). Positioning algorithm's final results should be as accurate as possible. Methods like *Kalman Filtering*, based on multiple noisy observations, should be adopted for location refinement to reduce output's final error.

In this Chapter, we present a detailed and complete description of our proposals to overcome some of the problems, explained before, that arise during the process of channel characterization and target position estimation. In the following sections, an initial focus is posed on RSSI filtering and on the extraction of meaningful values for the intended application. Then the focus is shifted towards the definition of a real-time calibration model based on *Recursive Bayesian Filtering* (i.e. *particle filter*) and a in-depth treatise on how this approach can lead to a more accurate parameters' evaluation with respect to other methods in the literature. In the last part, an advanced lateration-based algorithm is clarified, founded on an iterative error reduction within a positioning request.

2 Signal Analysis, Feasibility Study and RSSI Filtering

In order to design an accurate IPS, a robust and valid RSSI measurement model should be deployed. In the BLE-based positioning algorithm the only measured input for the system are RSSI measurements, received on the three different channels in its band. Therefore understanding how the RSSI measurements behave is fundamental. In practice, radio signals (BLE included) experience additional attenuation when traveling in mediums such as air or solid materials (e.g., wood) and, therefore, it causes RSSI dynamics being influenced by the structure and layout of the environment in which the considered system operates.

Signal's waves are influenced by the objects they encounter along their paths, in some ways. Indeed, the trajectory of a wave could not just be intended as a straight line: once it hits an object it may, for example, be reflected. This can lead to so called *multipath propagation*. This means that there might be multiple paths from a signal transmitter to the receiver. RSSI values, measured by the receiver, are indeed influenced by multipath propagation since waves, arriving from multiple directions, could either amplify or fade the received signal.

Multipath depends on many phenomena, which will be described soon, that are: *reflection*, *refraction*, *diffraction* and *scattering*. Radio waves can also lose part of their energy when they hit or pass through objects or when passing through a specific medium. In general, this effect, caused by obstacle traversal or by multipath is called *fading*. In other words, fading influences RSSI values measured by a sensor. Both multipath propagation (*fast fading*) and obstacles (*slow fading*) influence the propagation of radio signals in the environment. The exact influence of these effects is a complex function of environment structure and layout. Also the physical properties, like material type and surface structure affect signal propagation. It is practically infeasible to construct a model that can predict signal propagation with exact precision for an indoor environment. The reason for that is the huge number of input parameters required for such a model. This model would also need to be updated for each change in the environment, for example a door being opened or closed. All these phenomena aspects combined with unideal components used in the transmitter and receiver may result in errors into the RSSI measurement, that makes indoor positioning a very challenging field. In this section, some tests were carried to better comprehend RSSI dynamics, then our proposal for RSSI filtering is described.

2.1 Multipath Propagation and Fading

In this subsection, a detailed description on multipath propagation is provided together with an analysis of how it can be intended as a combined resultant of different aspects. This aims at understanding how RSSI varies over time from a physical point of view and how each effect could affect our positioning application. The huge possible and unpredictable combinations of obstacles, room layouts and materials which can be found even in similar scenarios (e.g. domestic environments) results in the impossibility to define an always-valid model for radio wave propagation in indoor spaces [56]. Based on this evidence, our work focuses on defining a probabilistic model which may abstract on these unwieldy aspects. In particular they can be categorized as follows.

- **Multipath components**

  As previously mentioned, multipath propagation is caused by reflection, diffraction and scattering. Multipath propagation becomes more relevant when there is no line of sight (NLoS) between transmitter and receiver. For instance, reflections in a corridor can actually cause the corridor to act as a wave guide making the path loss less than it would be in open spaces. Direct and reflected waves are normally the most influent factors on indoor signal's propagation. On the other hand, diffraction and scattering have typically very high losses.

  Reflection

  As just introduced, while obstacles, and consequent fadings, affect the radio wave amplitude, they can cause additional side effects on how the same wave is moving. When a wave reaches the interface with a second medium (most commonly a wall, for indoor venues), it will typically split into two separate waves. The first one continues to travel into the new medium whereas the second one is reflected from the interface between them, back to the first medium. The reflected wave has the same exit angle as the original wave's entry angle to the second medium's surface. The energy of the reflected ray depends on the collision angle with the obstacle, but also on the electrical and magnetic properties of the reflecting material. In real life, the walls of a normal building are not made of just one single material, but, more likely, by combining several materials. Therefore it seems very unlikely that a reflection from a wall could be predicted without some sort of calibration or measurements.

Scattering

Reflection happens when radio wave collides with particles in the medium where it travels. Scattering can also happen when the wave collides into a surface which is not completely flat. The wavefronts that have been formed due scattering are typically very low power density when compared to the original wave and therefore can be removed from model.

Diffraction

When radio wave reaches a sharp corner it curves around the corner and go over. The modelling of diffraction for different types of real life objects is difficult to do using the exact theoretical model. In order to have a model which approximate most of the real-life cases, Knife Edge diffraction model is usually adopted. According to the model, a well-defined obstruction to an electromagnetic wave acts as a secondary source, and creates a new wavefront. This new wavefront propagates into the geometric shadow area of the obstacle.

- **Fading components**

The type of fading experienced by a signal propagating through a mobile radio channel depends on the nature of the transmitted signal with respect to the characteristics of the channel. Depending on the relation between the signal parameters (such as bandwidth, etc.), different signals undergo different types of fading.

Medium Attenuation

When a wave travels in a medium, some of the energy it contains is absorbed by the atoms passes through. The level of attenuation depends on both the type of material composing the medium and the frequency of the travelling wave. Absorption causes an exponential attenuation and, in the case of indoor environments, it is mainly determined by the presence of walls or hard partitions. The exponential factor, i.e., attenuation rate, is directly affected by the material's conductivity, σ[1], the relative permittivity, ε_r[2], and the material's permeability, μ[3]. The thickness of the obstacle also affects how much the original electric field's amplitude is attenuated. In an indoor environment

[1] σ quantifies how strongly a given material permits the flow of electric current. It is the reciprocal of electrical resistivity and is measured in Siemens per meter (S/m).

[2] In a material, ε_r it is the ratio of the amount of electrical energy stored in a material by an applied voltage, relative to that stored in a vacuum. Relative permittivity is a dimensionless number that is in general complex-valued.

[3] μ is the measure of the ability of a material to support the formation of a magnetic field within itself. In other words, it is the degree of magnetization that a material obtains in response to an applied magnetic field. It is measured in Newtons per Ampere squared ($N{\cdot}A^{-2}$).

absorption happens mainly when the wave is travelling in the air or it goes through a wall.

Slow Fading

In indoor environments, in many cases, there is no line of sight between the transmitter and the receiver. Obstacles blocking the direct path are causing additional attenuation on top of medium attenuation. This additional path loss is called *shadowing* or slow fading. Slow fading causes attenuations that happens at larger distances than the wave length of the signal. Such large-scale fading is explained by the slow loss of the received signal power. Consider, for example, a radio wave following a linear path to a receiving sensor. If an object which absorbs part of the energy contained in the signal is interposed, then the signal received is less strong than when it was emitted. As a result the measured RSSI values will also be lower than before. Usually this is modeled using a lognormal distribution.

Fast Fading

Fast fading is primarly determined by multipath propagation and subsumes the contribution of multipath in the overall fading. Differently from slow fading, it causes additional signal's attenuation variation in areas smaller than the wave length (that, in the case of 2.4GHz signals, as BLE, is around 12.5cm). Small-scale fading is used to describe the rapid fluctuation of the received power over a short period of time. It is caused by the interference between multiple versions of the transmitted signal which arrive at the receiver at slightly different times, with randomly varying amplitudes and phases, and by relative motion of objects. Fast fading typically varies about a mean value and often fast fading is superimposed on slow fading. Depending on whether or not there is a direct path between transmitter and receiver, fast fading can be modeled using a Ricean or Reyleigh distribution. These fast changes are difficult and practically impossible to predict in real life environments, therefore, a simple filters can allow us to handle this quick fluctuation problem.

In order to better comprehend what has been exposed in this subsection, an initial test was performed to get a first idea about how some of the previously described effects in indoor environments can influence our measurements. In particular a transmitter (beacon) and a receiver were placed at a fixed distance of 3.5 meters. Results are in Figure 3.1. Data were collected for a period of one minute. After 30 seconds and obstacle was interposed between the two devices to study what happens when passing from a LoS condition to a NLoS condition. An immediate increase in signal's scattering is observed when obstacle's obstruction happens and RSSI mean value decreases in a matter of seconds, according to slow fading rules.

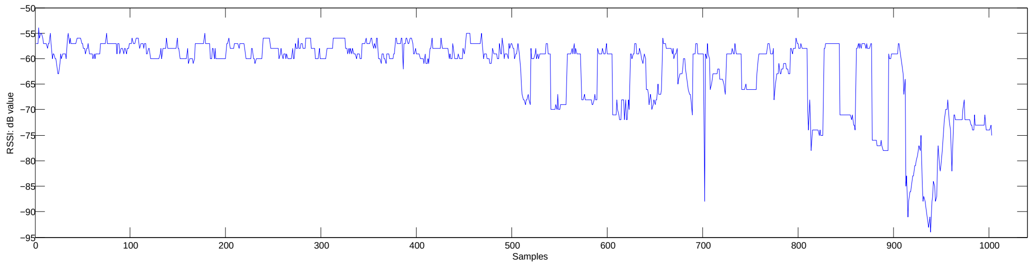

Figure 3.1: RSSI dynamics passing from LoS conditions to NLos conditions

A constant fast fading component was alway present on the signal. It happears as fast signal's variations even in LoS conditions.

2.2 RSSI Stability

In real scenarios a study about RSSI measurements' accuracy and stability is useful to understand what happens to signals that travel over the air, between two antennas (beacons). To analyse the RSSI measurements' stability in an indoor venue where air is the transport medium, a test has been made in the case of a static environment. In our assumptions, transmitter and receiver are fixed. In this tests there are no moving sources of interference, i.e., people in the venue. The goal in these experiments is to see if the statistical distribution of RSSI is changing over a period of time. Since the environment is considered stationary, fading contributions should also be accounted as static. Our expectation for experiment results is a single peaked RSSI probability distribution function. If being so, this would be a very desired outcome allowing positions estimates (extracted considering RSSI values) not vary so much, in time.

Some tests were carried out considering two beacons, one in advertising mode, emitting RSSI signals, and one in central mode, scanning for surrounding BLE devices (See Subsection 2.7.4), at fixed positions, with a separating distance of 5 and 12 meters (medium and far area), placed in front of each other. RSSI were collected for a period of 60 minutes at regular time intervals each 3 minutes (in each interval 150-200 samples are collected). Raw plotting of considered signals are illustrated in Figure 3.2 and Figure 3.3. Both RSSI signals showed a constant scattering within an interval which is, on average, 10dB wide, with a standard deviation of 2.08dB at 5 meters and a standard deviation of 3.52dB at 12 meters. From measurement histograms in Figure 3.4, it is possible to see that RSSI distributions show values spreading around a single peak (which is nearly -85dB for 12 meters and -73dB for 5 meters) for over the 40% of collected values.

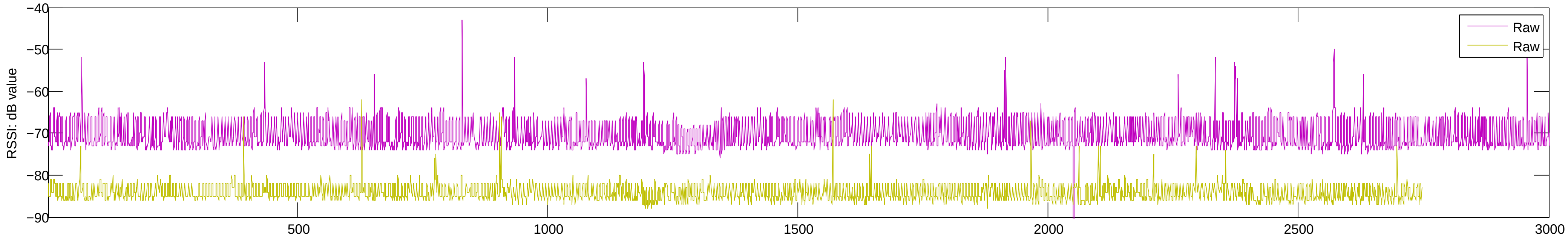

Figure 3.2: RSSI test in static environment at 5 (magenta) and 12 (dark yellow) meters

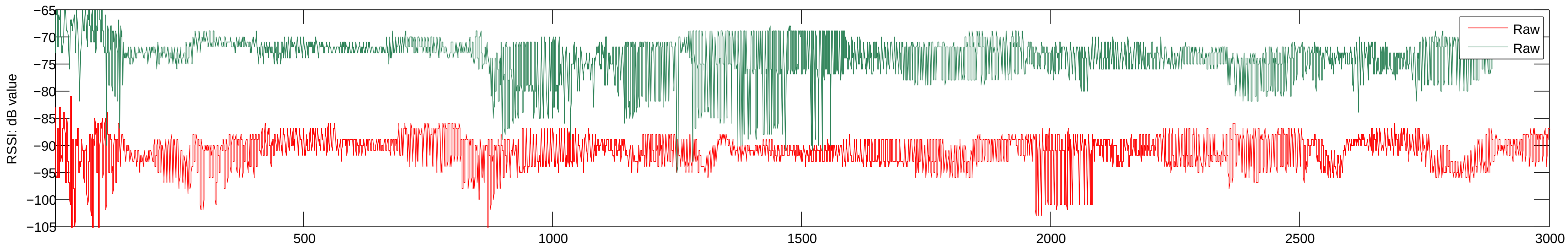

Figure 3.3: RSSI test in harsh environment at 5 (green) and 12 (red) meters

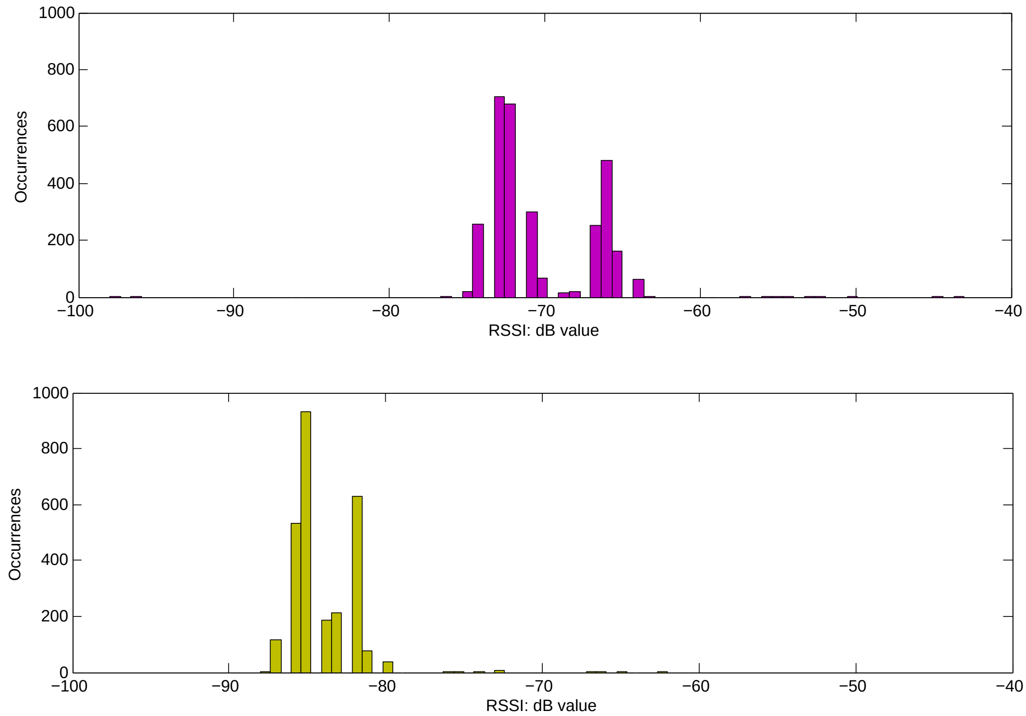

Figure 3.4: RSSI values distribution in static environment at 5 meters and 12 meters

In particular, in the 5 meters scenario, another domination peak is around -66dB. However RSSI evolution in such static scenario is pretty static (i.e., signal dynamics is not changing that much). In this situation, a clear characterization of RSSI signal is possible.

Repeating the same test for 60 minutes, to understand how RSSI varies over time, led to highlight how signal's average can be considered as not changing in focused time interval, at the same distance. Moreover also variability range has the same width during the experiment with a comparable standard deviation at the beginning and at the end of the test, for each set of measures. Results show a positive adoptability of RSSI to measurement in static cases. Although, in a bit more realistic scenario, environment's complexity (e.g., furniture or intermediate walls) and moving people may influence our results.

Different results were obtained when considering the same environment, at the same distance but with moving people, activated Wi-Fi, other BLE devices turned on and PCs. Also the adopted beacons were the same as in previous tests. In this new test, presented in Figure 3.5, a single strongly dominating peak is not present as happened in static case. Analyzing histograms, more minor peaks describe most of the listened RSSI values.

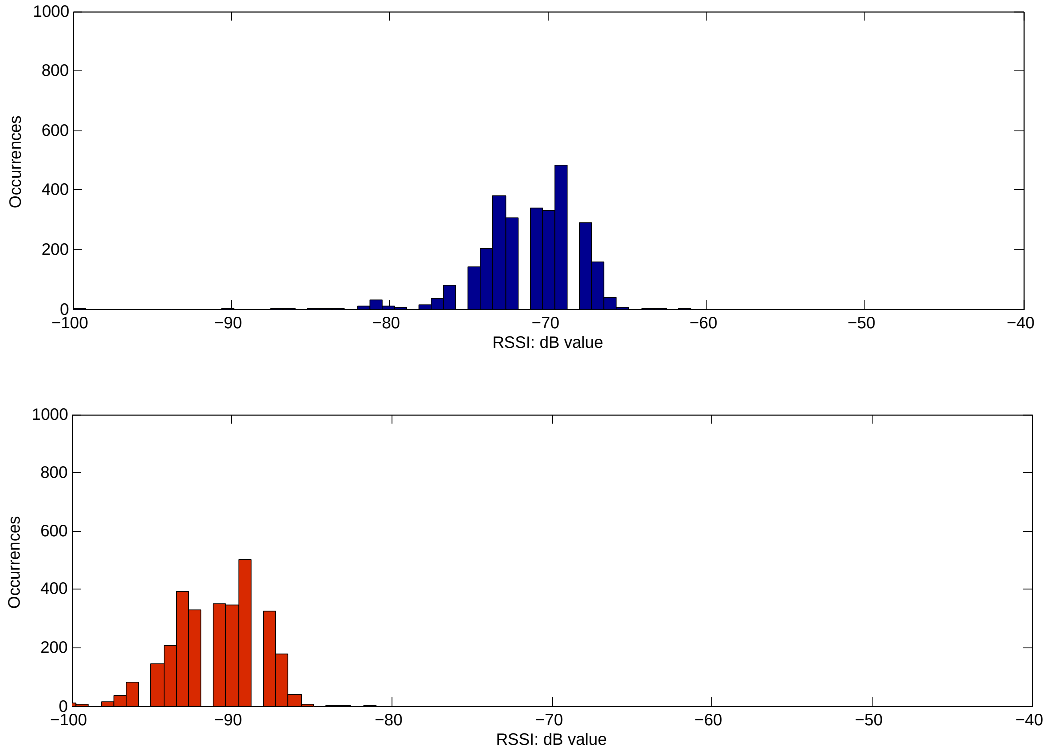

Figure 3.5: RSSI values distribution in harsh environment at 5 and 12 meters

There are no more values concentrated around a single peak. Moreover, signal's average varies in time. For instance, for measurements at 5 meters, average RSSI varies from a value of -69dB to a value of -76dB in an hour without a constant trend, related to the unpredictability of human movements and changing objects' disposition. The same happens for measurements at 12 meters. This could cause sensible variation into the position estimate.

The most obvious reasons for these results is multipath propagation (since noise is mostly visible as a rapid and fast-changing overlapping effect). The fact that the advertised message which is transmitted by the reference point starts as a single wave front but then splits into several when colliding with obstacles, causes the receiver see multiple overlapping signals which have different phases and amplitudes. Having the same signal arriving in different phases causes interference which adds variation to the sum signal amplitude. Using BLE (in which advertising channels are only three) will result in a reduced error with respect to other technologies (e.g. classic Bluetooth with 16 to 32 channels for communication).

Looking again at histograms, it can be shown that standard deviation for 5 meters measurements is 4.02dB, while standard deviation for 12 meters measurements is 3.07dB. In this case near observations show a greater dispersion than RSSI values collected in a distant area.

According to what just illustrated, a note should be added about variability in measures taken at smaller distance. As expected, but this happens only in a static scenario, measurements from 5 m are more reliable if compared to long-range ones as they appear to be more stable and less affected by fluctuations. Being more reliable the short-range measurements offer the possibility to accurately estimate the distances between beacons deployed in the area, but, this is only true if measurements are sufficiently stable or not corrupted.

2.3 Antenna orientation

The relative orientation between the antennas of a sender and receiver has a direct influence on the signal strength measured by the receiver. To see how RSSI measurements were influenced by orientation of the BLE beacons used in the data collection setups, RSSI measurements were performed for a number of different orientations. The reason for doing so was twofold. First it gave an indication of the extent to which orientation had an influence. More importantly, it provided data for finding the optimal orientation of the antennas for localization. In general, since our system is designed in order to minimize installation steps, also beacon's orientation should be taken into account and no human intervention to adjust antenna orientation should be contemplated [49].

In particular, it should be observed that - in indoor environment - also omnidirectional antennas (widespread in commercial devices) may have a preferred transmitting direction (caused by reflections and propagation direction changes due to the venue configuration).

More formally, the relative orientation, O, both for transmitter and receiver, at fixed positions (P_T and P_R), can be denoted by:

$$O = [\phi, \theta]^T \tag{3.1}$$

Bring the horizontal ϕ (*pan angle*) and vertical θ (*tilt angle*) be the offset angles from the origin of the antenna (i.e. where $O_{origin} = [0°, 0°]$).

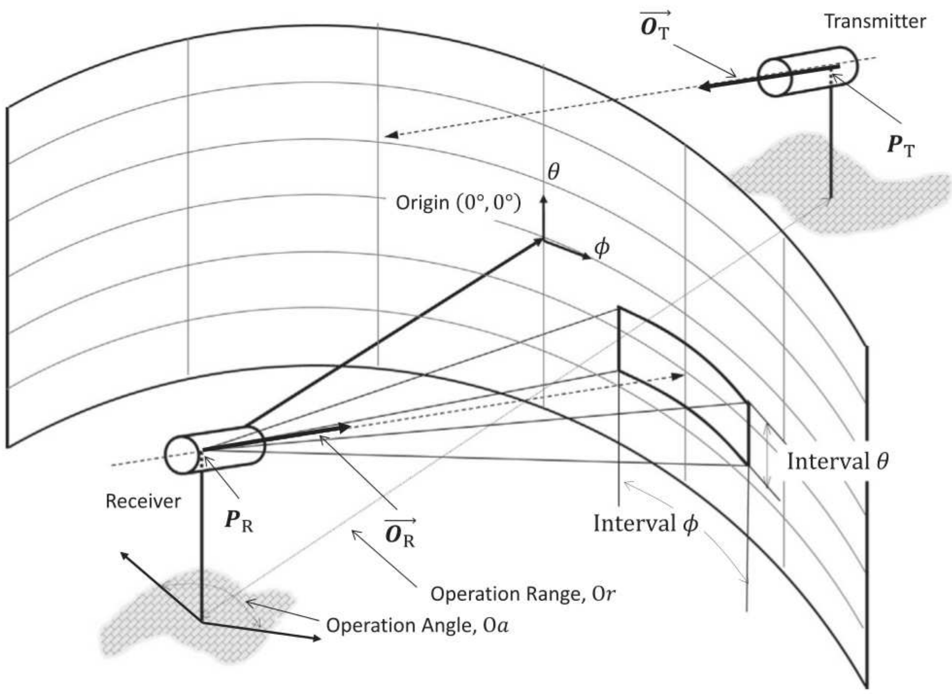

Figure 3.6: Orientation Model

This is shown in Figure 3.6. The ideal scenario is when the two beacons' antennas are facing each other, so that the received power will be maximized. Now, we can assume that this orientation model would be applied to three cases. They are:

- Direct path (LoS) is present between two antennas in a clear environment. In this case, it would not be difficult to determine the necessary orientations for the best connection as it is usually when the two antennas are pointing at each other;
- Antennas are located in a dense space with LoS conditions (strong multipath fading component);
- Antennas are experiencing NLoS conditions (strong obstacle fading component).

In the last two cases, the best antenna orientation is unpredictable, since there could be not trivial orientations that can provide the best. Actually, this results from the likelihood of a multipath effect due to signal reflection from surrounding objects as well as interferences from other electronics devices or shadowing, as explained in Section 3.2.1. For our scenario, the first two cases are the most interesting ones since our positioning range is limited to a room. Moreover, we are not involved in asking the installer to place differently or move BLE beacons in an environment; we are interested in finding how RSSI signal worsens at different relative orientations. In particular, in this thesis tilt angle's variations are not considered (since beacons are placed on a wall, $\theta = 0°$ and the modeled context is intended to be 2D), while the attention is put toward pan angle, which may be location dependent. To deal with directions, we divide a circle's portion (included within ϕ_{start} and ϕ_{end} angulation) to a set L sectors with an equal central angle (in degree), and each sector represents a direction. Considered a reference angle β, there are:

$$L = \lceil \frac{|\phi_{start} - \phi_{end}|}{\beta} \rceil \tag{3.2}$$

sectors around a beacon. The relative direction of a node (i.e. beacon or smartphone) with respect to a beacon is specified by the sector in which the device is located. Each antenna has a coverage range Φ which is measured in the unit of sectors. In other words, if an antenna has a coverage range Φ, it can cover contiguous Φ sectors [50]. Our task in the following test is to define a model in order to cope with beacon's orientation during the calibration steps. Moreover, other authors have shown that a human body may significantly corrupt the RSSI, and a strong correlation between the measured RSSI and the direction that the user is facing. Indeed it is observed that omnidirectional signals are given directional properties because of the presence of the user's body, where usually the statistical distribution of the RSSI varies more than the mean. These aspects will be considered in Section 3.2.4.

According to what explained, our experiment tries to measure the received signal emitted from a fixed beacon, by rotating receiver device from ϕ_{start} to ϕ_{end} with respect to antenna's main propagation axis and producing a set of RSSIs for each listening direction. In particular, in this experiment we used $\phi_{start} = -90°$, $\phi_{end} = 90°$ (see Figure 3.7. Red arrow indicates beacon orientation)
Considering a reference angle of $L = 45°$, we tested received RSSI from a fixed beacon at five orientations. Since beacons are mostly put on a wall their coverage angle can be considered of 180°. Distance between the receiver and the beacon was 2 meters and data were collected for 20 seconds at each orientation. Results are illustrated in Figure 3.8. In particular radiation pattern in clockwise or counterclockwise sense is strongly comparable (it was omitted from plot for sake of simplicity). With respect to no orientation case ($\phi = 0°$), either a 45 degrees orientation and a 90 degrees orientation induce an greater scattering in RSSI values. This is related to not having a face to face orientation between the beacon and a receiver. Formally, this results in an increasing variance which is directly related to devices' relative orientation. Moreover, also a change in the mean is visible when considering greater orientations.

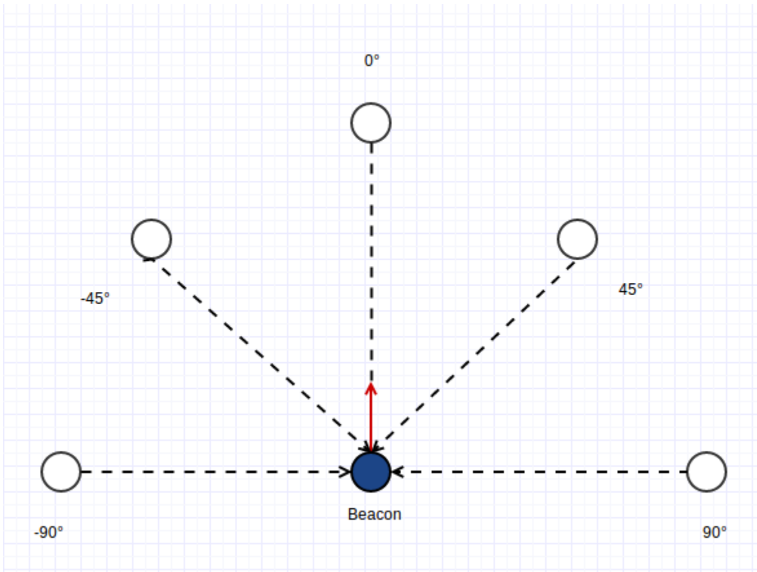

Figure 3.7: Orientation Experiment Setup

ϕ (Degrees)	Mean	Standard Deviation	Min	Max	Max - Min
0	-53.87	1.904	-47.82	-60.677	12.857
45	-54.02	2.335	-48	-58.5	10.5
90	-55.123	2.964	-50	-61.155	11.155
-45	-53.94	2.288	-48.349	-58.112	9.763
-90	-54.7637	2.945	-49.63	-60.849	11.219

Table 3.1: Different orientation effects for RSSI signal

When considering calibration steps, beacons positioning gains a fundamental role since varying their relative orientation can result in a wrong channel characterization. Since their position in a venue is considered to be known, a correction factor should be contemplated to deal with this aspect. According to other tests performed at different distances, the loss related to an orthogonal beacons' positioning is, on average, 3dB. And it has a linear relation with devices' orientations. Our proposed correction metric to estimate the power loss (in dB) related to orientation is explained.

Definition 7 *Let* B_1 *and* B_2 *denote two beacons placed in the same indoor environment, at fixed positions* P_1 *and* P_2*. Expressed as* ϕ *the relative angle between them. The power loss, in dB, related to their orientations can be astimated as:*

$$PL_{dB}(\phi) = -5(sen\phi) \tag{3.3}$$

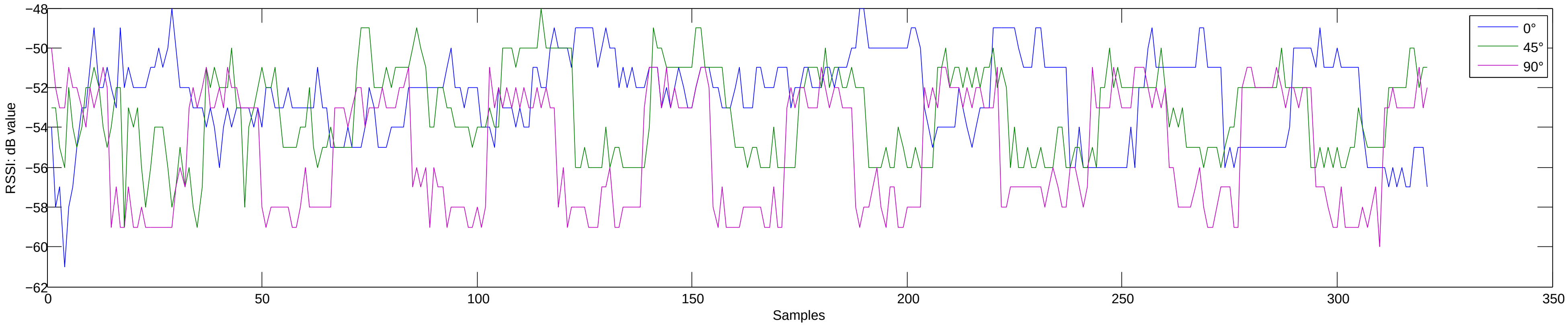

Figure 3.8: Signal's dynamics at different orientations

2.4 Human Presence

From a general point of view, human presence should be considered. In particular, human body represents an additional source of inaccuracies causing unpredictable fluctuations in the RSSI. As already outlined, human body contains around 70% of water, which absorbs part of the 2.4 GHz radio signal, causing a significant decay in the signal's amplitude. It is important to observe that, in the case of indoor communication between a mobile terminal (e.g. a smartphone) and a beacon, there could be two possible different propagation paths between them: One happens when mobile terminal, held by user, has a LoS propagation toward the beacon. The second occur when, in the opposite orientation, the user's body is obstructing the path in line-of-sight (LOS). For instance, experimental results showed that RSSI at a given location might vary by up to 5dB depending on the direction that the user is facing (see Section 3.2.3). Hence, the body of the user creates a systematic source of error and introduces a constant bias in the estimated locations that, if correctly accounted, can offer a beneficial impact on the positioning accuracy. As a consequence, the operating environment of wireless communications in proximity with the user's body is quite different from more traditional wireless networks, as one end of the link is affected by the fact that the body is in the very near field of the device, dictating the non-stationary behavior of the channel. In addition, most of the well-known propagation phenomena happen away from the body in the surrounding space.

To sum up, the reliability of a wireless link operating in such an environment is strongly conditioned by the user's body influence, whose impact on propagation demands a precise analysis. There are a series of time dependent aspects (e.g. user movement or orientation) which must be taken into account. Adopting a very simplistic approach, human body can be modeled electromagnetically as a *homogeneous dielectric cylinder*, where colliding waves generate reflection and diffraction phenomena [53]. The scope of these effects depends on various factors such as the signal's frequency, body dimensions with respect to the wavelength and structure of human tissues. Thus, not all the body parts respond in the same way to the exposition to electromagnetic waves, as if one particular body part is not particularly large with respect to the wavelength, it will have a negligible effect on the propagation mechanism and will yield small fluctuations.

Moreover, antennas in common devices are usually linear omni-directional, in order to cope with a rich multipath environment. The benefit of the adoption of a directional antenna (i.e., stronger propagation beam in a specific direction) would be immediately lost by the effect of the user's head and hand. When a standard wireless device rotates around a blocking object such as the user's body, its radiation pattern is affected in such a way to emulate the behavior of a directional antenna.

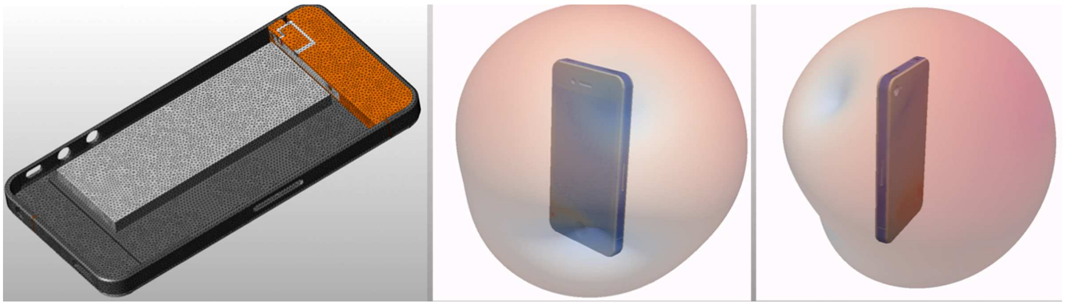

Figure 3.9: Wi-Fi/BLE Antenna Propagation Pattern in Apple's Iphone4S®

By using the RSSI measured at different distances, it is possible to make basic assumptions on the propagation model. Propagation model evaluation might appear inaccurate in reflecting the user-induced anomalies in a practical environment. In fact, the idealized simple assumption that RSSI decreases as the receiver moves away from the transmitter often breaks down in practice. An important matter is also the choice of the maximum physical radius within which human-induced disturbances may be considered to be an integral part of the antenna.

However, as depicted in past publications [54], the contribution in fading related to hand is typically more significant than the rest of the body. This adds more sources of randomness in the link budget determination [55].

In order to evaluate the effects of human presence on RSSI values, we performed some tests in order to understand how a person in the near field of a mobile terminal can influence the RSSI evolution. In particular, the test environment was the same as in Figure 3.1 where, at a distance of 3.5dB, an evaluation on how an obstacle can influence RSSI propagation is illustrated. Here, within an interval of 60 minutes, we tried how a man holding the target device can modify listened signal. In particular, user orientation is changed during the test, at an interval of 25 seconds. This was performed in order to understand how a body can induce NLoS situations during measurements.

According to results in Figure 3.10, when the user is directly facing the beacon, a reduced path loss was identified. In particular, it is important to observe that, while - in the initial tests - a RSSI of 58dB was recorded without human presence and having transmitter and receiver one on the front of the other, here mean value for RSSI is 60dB. Moreover, depending on the room configurations, human presence can accentuate multipath effects, thus signal can appear stronger in not trivial orientation (e.g. at 90°) than with respect to most obvious one (face-to-face). As expected, the greater signal obfuscation was recorded when user held the transmitter in the opposite direction with respect to the beacon antenna.

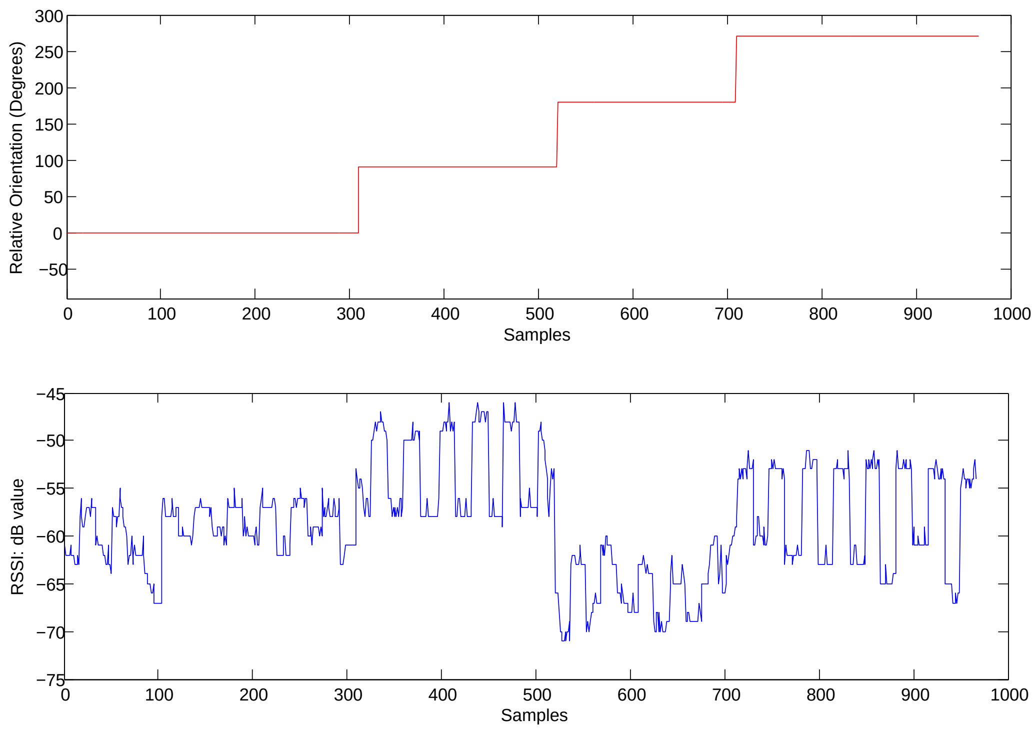

Figure 3.10: Effects of human presence in the near fields of a mobile terminal

2.5 Small Scale Movements

Since our goal is to define a smart positioning algorithm, it is necessary to take into account narrow movements that might happen in the frame while positioning (and related RSSI collection) is done. The received signal strength can vary considerably over small distances (in the order of the signal's wavelength) and small time scales, due to multipath fading. As a result, RSSI can exhibit wide variations even when receiver position changes by as little as a few centimeters. As previously note, in small scale movements the dominating factor that affects the RSSI reading is fast fading. For the accuracy of the positioning system it is very important to make RSSI changes as predictable as possible.

Some previous works state that using multiple antennas will smooth out the effects of small-scale variations in signal strength (i.e. changes in RSSI does not vary much with a change in location). A possible solution could be adopting RSSI readings as an indication regarding if user is still or moving [51]. For instance, it is possible to detect user movement considering beacons' visibility or by an analysis of standard deviation.

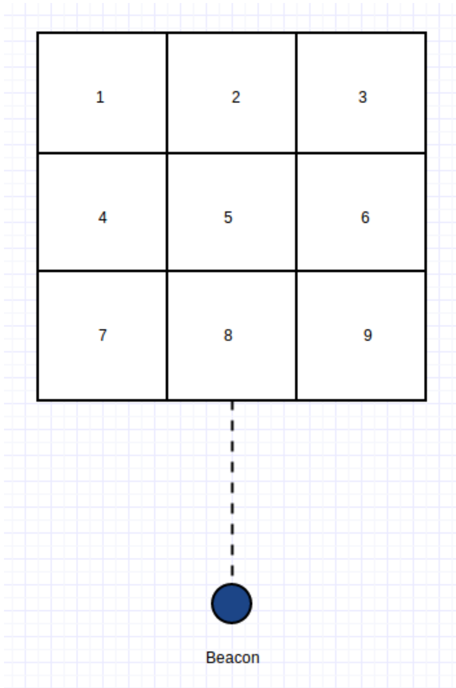

Figure 3.11: Small scale Movements Experiment Setup

In the first case, detection methods use the proportion of the time that the RSSI of a particular beacon is observed within the observation frame: if a beacon becomes unreachable for the receiver this can be a symptom of user movements. In the second case, we consider a mean standard deviation of the RSSI over all the heard access points, as a metric to distinguish between still and moving states. Within the observation frame it is possible measure the standard deviation between the measurements for each detected beacon, and use the average standard deviation over all heard beacons for inferring the motion status.

To comprehend the effects of small scale movements a test was carried. In particular, for our application, a small scale movement is represented by a movement in the near field (1-1.5 meters at most). Our experiment (see Figure 3.11) was based on dividing a squared 2.2mq^2 area in 9 sub-squares and evaluate how RSSI varies with respect to a fixed beacon placed 2 meters far. Results (see Figure 3.12) showed that, even in this case, RSSI may have an extended range of dispersion. In particular, a band of 10dB can be identified. The following figure represents the trend for the values of RSSI with respect to the number of samples. It can be noted as for small user movements sever RSSI variations can be observed, but that always fall in the range of 10 dB. A filtering process is then required.

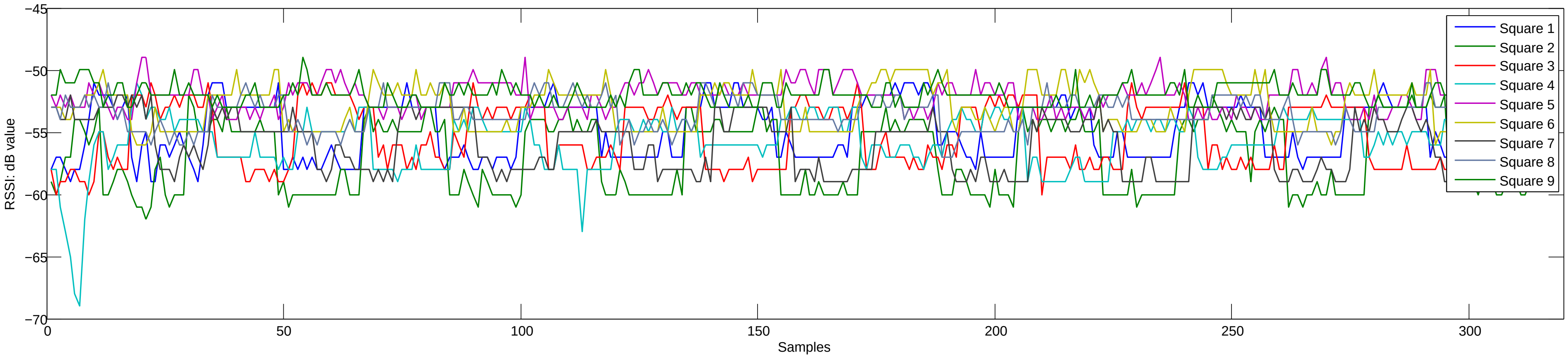

Figure 3.12: Effects of small scale movements on RSSI values

2.6 RSSI Filtering

As noted in the previous sections, there is a not negligible variance in the RSSI measurements when considering real life scenarios. Even though the variance of the RSSI is small when the system is static, the RSSI varies a lot when the devices change position and it is very sensitive to the environment. This means, that the relationship between the signal strength and the distance might not be very clear, and there could be a lot of dispersion of RSSI in a specific venue. Non line of sight (NLoS) conditions and multipath effects can have RSSI showing a lot of dispersion. Hence, filtering of RSSI is necessary to obtain a group of highly credible RSSI values.

RSSI measurements are very noisy, thus the signal amplitude representations are not smooth. The aim of smoothing the recorded data is to obtain a signal which can clearly show the variance of the signal when an obstacle is present or a person is walking or standing, causing interference in the node-to-node communication. For instance, having data with a lower noise level can be helpful for setting up some thresholds in order to trigger some assumptions on the target position [52]. It is very important to state that, by taking a look at the whole set of reported performance results in some past papers, there is not a single filtering technique which always outperforms the others. Filtering adoption has demonstrated to be crucial for increasing stability, however, the decision on which filter to exploit depends on the specific goals of the provisioned mobile service.

Before testing the filters it is important to analyze that RSSI distribution matches the distribution of the measurements which have been previously evaluated in tests described in Sections 3.2.2, 3.2.3, 3.2.4 and 3.2.5. Moreover, if the measurements arrive in random order, the distribution shape should remain the same. According to the literature and according to what we have verified in our tests, RSSIs distribution have a normal distribution model. Its mean is μ, and standard deviation is σ. Hence, for a specific set of RSSI values, collected from a beacon i in n time slots, it may be expressed as:

$$R = [r_i(1), r_i(2), ..., r_i(n)]. \tag{3.4}$$

If x is a RSSI reading and $x \in R$, we use $f(x)$ to denote its Probability Density Function (PDF). In this case:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \tag{3.5}$$

Considering the collected samples, it is possible to characterize the parameters of this distribution. More in details:

$$\begin{aligned} \mu &= \frac{1}{n}\sum_{t=1}^{n} r_i(t)\ ; \\ \sigma &= \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_i(t)-\mu)^2}\ . \end{aligned} \tag{3.6}$$

According to past works, the adoption of some filtering techniques on RSSI was already documented. Here we try to experience how filtering behaves on BLE signals. Previously adopted filters were:

- **Median Filter**: Median filtering method is, probably, the most intuitive filter to apply. It is based on aggregating a set of RSSI collected values and replacing a set of neighboring in time entries (called *window*) with their median value. For one-dimensional signals, the chosen window is composed by the first few preceding and following entries. Formally, after n time slots:

  $$RSSI(n) = \underset{t=n-w,\dots n+w}{median}(r_i(t)) \tag{3.7}$$

  Having w representing the window size. Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically.

- **Feedback Filter**

  This type of filter is a *moving average* filter of the first order. To exclude the noise components in radio-frequency signal, we might filter the interpolated data for each beacon with this low pass filter. Its governing equation is:

  $$RSSI(n) = \upsilon RSSI(n-1) + (1-\upsilon)RSSI(n) \tag{3.8}$$

  Having $0 < \upsilon < 1$.

  The current RSSI depends on the previous evaluated RSSI value. According to some previous works, υ can be comprised between 0.65 and 0.8. In particular, the median and feedback filtering methods well perform in outdoor environments when the LoS is guaranteed. On the contrary, both have comparable issues in indoor environments where LoS conditions usually lack.

- **Maximum Filter**

  This filter is based on the assumption that the indoor fading always makes the RSSI value decreasing and, in any case, it increases its value. Therefore, we can compute the maximum RSSI among collected values in n time steps, in order to filter the lower RSSI which is usually interfered by noise. Formally, after n time slots:

$$RSSI(n) = \max_{t=1,\ldots n} r_i(t) \tag{3.9}$$

- **Gaussian Filter**: Results obtained by the average statistical model had a poor effect in the case of large disturbance. Higher probability areas in the RSSI distribution can be selected by adopting a Gaussian filtering to improve the overall estimated position accuracy. Mathematically, Gaussian filter modifies the input signal by convolution with a Gaussian function. The principle of processing data with Gaussian model is that the unknown node may receive n RSSI value. It will select the RSSI value through the probability area of most frequent occurrences, and then get the average. This approach reduces the probability of a number of small and large disturbance events influencing on the overall measure to enhance the positioning accuracy of the information.

- **Kalman Filter**: Kalman filtering module tries to estimate RSSI values by representing the RSSI time evolution as a combination of signal noise (measurement noise) and signal dynamics laws (process noise). A linear stochastic equation models the RSSI evolution, with signal/process noise assumed to be independent of each other, white, and with normal probability distribution. Our filter works by minimizing process/measurement noise through a two phase algorithm: first, a predictor performs next RSSI estimation; then, a corrector improves RSSI estimation by exploiting current RSSI measurement. A more detailed description about Kalman Filtering is provided in Subsection 3.4.1.

Other works [52] showed the adoption of other types of filtering (e.g. *Savitzky-Golay*, etc); according to them, results obtained after using a Kalman filter better take into account rapid changes or shadowing if compared with other studied algorithms.

Our tests on filtering are aimed at evaluating the best filter to adopt in RSSI measurements. In order to evaluate the better filtering solution, signal's dynamics has been examined by applying some of the filters from those presented above.

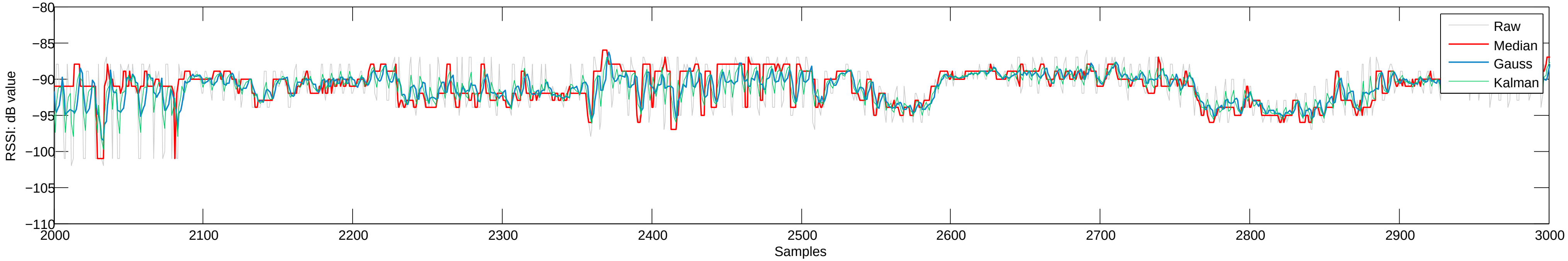

Figure 3.13: Filter comparison at 12 meters in harsh environment

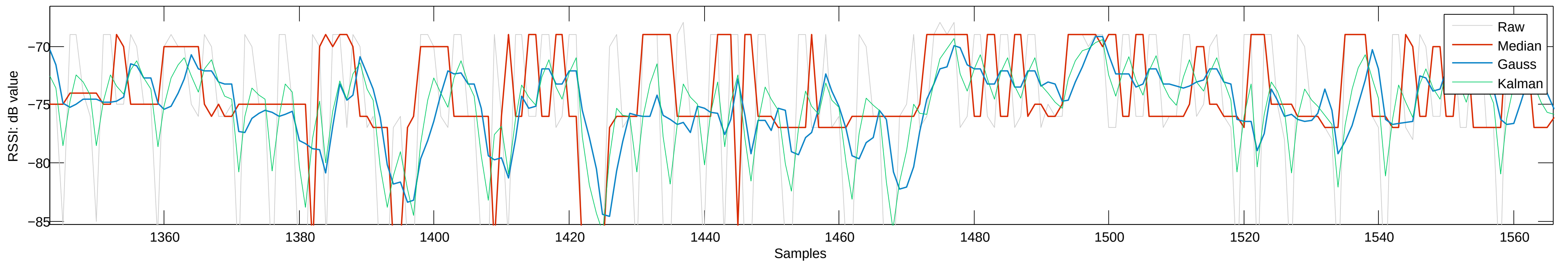

Figure 3.14: Details of Filter comparison at 5 meters in harsh environment

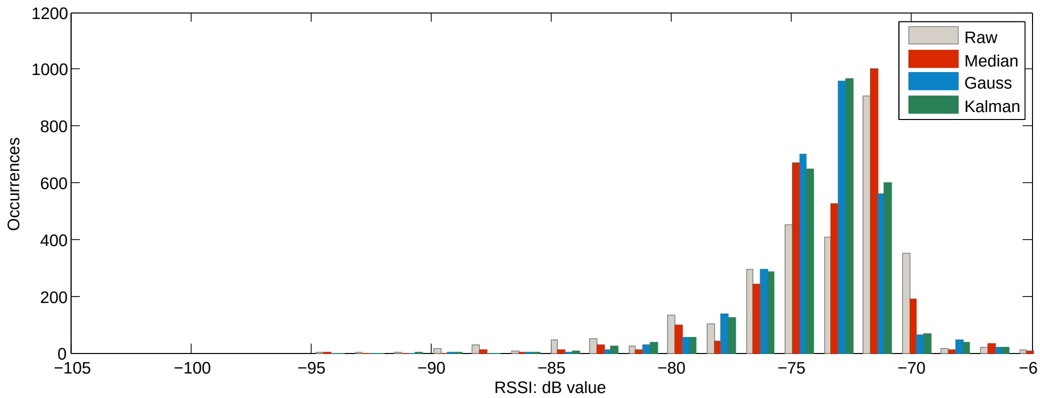

Figure 3.15: Histograms of RSSI distribution after filtering - 5 meters in harsh environment

Filter	Mean	Standard Deviation	Min	Max
Raw	-73.7634	4.0205	-95	-62
Median	-73.3429	2.8555	-94	-65
Gaussian	-73.7783	2.3901	-90	-64.9566
Kalman	-73.7637	2.588	-91.3776	-64.8515

Table 3.2: Filtering results for 5 meters RSSI observations in harsh environment

Filter	Mean	Standard Deviation	Min	Max
Raw	-91.1398	3.07	-120	-81
Median	-90.8655	2.224	-103	-83
Gaussian	-91.1406	1.7606	-99	-85.744
Kalman	-91.1398	1.9302	-103	-83

Table 3.3: Filtering results for 12 meters RSSI observations in harsh environment

Datasets were extracted from a noisy venue, in order to comprehend how filtering could better described RSSI evolution versus time. In particular, obtained results are presented in Figure 3.13 and Figure 3.14.

As it could be seen considering the presented histogram (Figure 3.15), all filters try to reduce noise in RSSI signal. Some comparison tables to evaluate how each one treats the manipulated data (at different distances) are introduced (see Tables 3.2 and 3.3).

When considering which filter to adopt, we must remark that fast-fading is the main problem in RSSI analysis. Filtered signal should be as smooth as possible, reflecting in a sensible way the changes in the signal mainly related to slow fading and *shadowing*. Another additional metric, to be evaluated when the previous requirement is satisfied, is to reduce standard deviation in filtered data to have a minor dispersion and a clearer dynamics. Even the correct choice of filtering paramters is a primary aspect. An extended test was performed to find them. Moreover, according to Bluetooth Low Energy specifications, standard deviation (considered as a parameter in gaussian filtering) has a value of 6dB. In addition, window's size (for Gaussian filter and for median filter) works on five samples at a time.

Having a closer look to filtered RSSIs, the most suitable are the one resulting from Kalman Filtering and the one resulting from Gaussian Filtering, since Median filtering has a coarse evolution and a high standard deviation. Kalman Filter and Gaussian Filter, in the one-dimensional case, require a small amount of memory for their execution and are not computational expensive. Their performance is comparable, but due to its greater immediacy and a reduced standard deviation, later in this work, the adopted filter for the RSSI analysis is the Gaussian one.

This section has tried to highlight the fundamental role of RSSI filtering in the current project. Indeed, it must be observed that, since we are considering a probabilistic approach for propagation parameters estimations (these aspects will be described in the following section), our focus is concerned with obtaining a more reliable RSSI sample collection instead of retrieving a more accurate and stable RSSI signal from each beacon. In this sense, filtering aims at supporting a better characterization of the BLE signal dynamics.

3 Particle Filter for Channel Characterization

Comprehending physics of indoor radio propagation is a key point for this thesis. As introduced in Section 2.3, in *free space* (ideal environment) a radio signal attenuates because the wave-front expands while it moves further from the source. With an isotropic, i.e. perfectly omni-directional, antenna this attenuation is related to the area of a sphere which center lies in the source of the wave, in the beacon. This ideal behaviour is called *free space path loss*. In real conditions, the attenuation produced by indoor signal propagation makes the above law not valid anymore. In particular, in these cases, path loss depends on some environment related *propagation parameters*. Then our proposal for estimating propagation parameters for each beacon is described. As stated in the Summary and recalled in the previous section, the biggest difference between Particle Filtering based methods and the traditional positioning methods, in Wireless Sensor Networks, lies in the fact that the first do not focus on obtaining a more accurate RSSI values from each beacon (which seems complex, for the high variability of RSSI values), but on obtaining a more reliable sample collection, and through the continuous adaptation of a probability distribution, eventually, it will converge to the most probable propagation model parameters. The parameters are modeled as independent variables, with possible values in suitable sets. Dealing with probability distributions rather than point-wise estimates of the parameters makes the algorithm more robust. In particular, Particle Filter algorithm is focused on using a weighted set of samples to indicate the posterior distribution of the model parameters. Parameters' probabilities are updated at every new measurement, for all particles. Each step of calibration, as will be introduced, is divided into prediction and particles' updating section.

3.1 Free space path loss

Under ideal free space conditions and assuming lossless antenna feeders the received, P_r, and transmitted, P_t, powers are related according to the *Friis transmission formula*, which describes path loss (PL) (See Formula (2.5)) in free-space:

$$PL = \frac{P_r}{P_t} = G_t(O_t)\ G_r(O_r)\ (\ \frac{\lambda}{4\pi d}\ )^2 \tag{3.10}$$

where $G_t(O_t)$ and $G_r(O_r)$ are, respectively, the antenna gains for the transmitter and the receiver; λ is the wavelength (in BLE, 2.4GHz results in 12.5 cm of wavelength), d is the distance between the antennas.

In particular, gains depend on antenna's efficiency, $E_{antenna}$[4] and Directivity Gain, D[5], which is influenced, among other factors, on antenna orientation, O (see Formula (3.1)). Since antenna (i.e., beacon) orientations, beyond their placements, are the only parameters that can be managed in our positioning scenario, it was explicitly introduced in the formula. Intuitively, signal can be visualized as a power spreading over the surface of a sphere of radius r, centred at the antenna. Therefore the available power at the receiver antenna is proportional to $\frac{1}{r^2}$. From a logarithmic point of view, it means that received power decays with distance by 20 dB/decade.

More precisely, expressing the ratio between powers in a logarithmic fashion (converting powers in dBm), Formula (3.10) becomes:

[4] $E_{antenna}$ is a measure of the efficiency with which a radio antenna converts the radio-frequency power accepted at its terminals into radiated power.

[5] D, Directivity measures how much more intensely the antenna radiates in its preferred direction with respect to an ideal isotropic antenna.

$$PL_{dB} = P_{r,dBm} - P_{t,dBm} = 10\ log_{10}(\ \frac{P_r}{P_t}\ ) = \\ G_t(O_t)_{dB} + G_r(O_r)_{dB} + 20\ log_{10}\ (\ \frac{\lambda}{4\pi d}\ ) \tag{3.11}$$

It is important to state that the previous formula applies only under some ideal conditions. These are:

- d should be >> with respect to λ. The fields of an antenna can broadly be classified in two regions, the *far field* and the *near field*. It is in the far field that the propagating waves act as plane waves and the power decays inversely with distance. The far field region is also termed as Fraunhofer region and the Friis equation holds in this region. If the opposite happens, then the equation would give the physically impossible result that the receive power is greater than the transmit power. This is not a restrictive requirement for our system, since our signal has a short wavelength;
- Antennas are in unobstructed free space, with no multipath happening. This requirement is pretty impossible to be fulfilled in indoor venues. Since our positioning models, like others in literature, are based on these propagation rules, a positioning error can not be totally absent from our system;
- Antennas should be correctly aligned and polarized. This aspect has been discussed and evaluated by a concrete test in Section 3.2.3. It is relevant to observe that, since our goal is to design a positioning system which should have, as a primary feature, an easy deployment (i.e. no restricting limits or rigid rules to be followed during room setting), our system must deal with different antennas' orientations;
- P_r and P_t are related from the transmitter's and receiver's antenna structures and components.

To summarize, these exposed ideal conditions are almost never achieved in ordinary indoor communications, due to obstructions, reflections and multipath effects, that have been already described in details. The effects of misalignment of the antennas can be included by additional factors.

Location	PLE
Store	1.8 - 2.2
Factory	1.6 - 3.3
Home	1.3 - 3
Office	1.3 - 3.5

Table 3.4: Common values for Path Loss Exponent

An alternative formulation [65] of the Path Loss expression (extension of the Friis formula) at a certain distance d, can be evaluated in relation to a reference point, having a distance d_0 from the considered antenna. This distance should be appropriate for the propagation environment, and usually it indicates the minimal granularity for the positioning system. In indoor environment, $d_0 = 1$. This alternative expression, for $d > d_0$ is:

$$P_r(d) = P_t\ K\ (\frac{d}{d_0})^2 \tag{3.12}$$

In this formula, K is a constant value representing free-space path loss up to distance d_0, that depends on the antenna characteristics and its orientation.

Empirically, in indoor fields, it was experienced that received power decreases with an order that is greater than 2, as expressed in the Friis formula related Path Loss expression. The relation between the average received power and the distance is determined by the expression where α is called *the path loss exponent* (PLE). In this, sense Formula (3.12) may be expressed as:

$$P_r(d) = P_t\ K\ (\frac{d}{d_0})^\alpha. \tag{3.13}$$

According to other works [56], the α and PL_{d_0} values strongly depend on the environment. A list of some common accepted PLEs is presented in Table 3.4. The value of α depends on the environment and it is affected by multipath propagation and shadowing. In a vacuum and unbounded space the value of α is equal to 2, because there are no fading effects. For a typical office building α is expected to be $\neq 2$; this can be caused by walls absorbing the signals energy, making signal strength decay faster compared to the vacuum and unbounded space, or reflecting the waves, letting them arrive at the receiver with different amplitudes and phases. Accurately predicating the value of α is almost impossible for all but simplest environments; its value is usually estimated using empirical measurements. More in general, α values are comprised between 1 and 4.

In particular, it is possible to define the *Path Loss* in Formula (3.13), expressed in dB, as:

$$PL_{dB}(d) = P_{r,dBm}(d) - P_{t,dBm} = K_{dB} - 10\ \alpha\ log_{10}(\ \frac{d}{d_0}\ ); \tag{3.14}$$

K_{dB} represents the Path Loss evaluated at distance d_0 and can be alternatively expressed as PL_{d0}.

More in general, Path Loss depends on various factor:

- The distance between transmitting and receiving antennas;
- Line of sight clearance between the receiving and transmitting antennas;
- Antenna height;

By reversing Formula (3.14), givem a listened $RSSI$ value, it is possible to evaluate the distance d. Hence:

$$d = 10^{\frac{PL_{d0} - RSSI}{10\alpha}}. \tag{3.15}$$

3.2 Lognormal Shadowing modeling

Shadowing, as described in Subsection 3.2.1, is the effect that makes the received signal power fluctuate due to artifacts or people, obstructing the propagation path between transmitter and receiver.

The log distance path loss model does not consider the fact that the surrounding environment may be vastly different at two different locations having the same distance between transmitter and receiver. According to experimental measurements at any value of d, the path loss $PL(d)$ at a particular location is random and distributed log-normally (normal in dB) around the mean distance. In other words, a practical case of noise in a mobile radio channel of such type, when Path Loss at distance d is expressed in dB, is an additive Gaussian Noise. This means that, when the signal is transmitted over such channels, the signal is perturbed only by the addition of this kind of noise and path loss parameters, while fast fading is implicitly removed using pre-processing filters. This noise channel applies in a mobile system, where the mobile and surrounding objects are not in motion.

Formally, this means that:

$$\overline{PL}_{dB}(d) = PL_{db}(d) + X_\sigma = PL(d_0)_{dB} - 10\ \alpha\ log_{10}(\ \frac{d}{d_0}\ ) + X_\sigma \tag{3.16}$$

If, as commonly happens, $d_0 = 1$ the Formula (3.16) can be expressed as:

$$\overline{PL}_{dB}(d) = PL_{db}(d) + X_\sigma = PL(d_0)_{dB} - 10\ \alpha\ log_{10}(d) + X_\sigma \tag{3.17}$$

where, X_σ is a zero-mean Gaussian distributed random variable (in dB) having σ as standard deviation. Empirical studies show that σ ranges from 4 dB to 13dB (See Figure 3.16).

In order to adequately characterize the above formula for a specific environment, it is fundamental to observe that parameters $PL(d_0)$, α and σ statistically describe the path loss model for an arbitrary location having a specific separation between transmitter and receiver. Widespreadly in past works and literature, these parameters were estimated, in practice, from measured data, at known distance from the transmitter, using linear regression (in Least Square Sense, LSQ) such that the difference between the measured and estimated path losses is minimized in a mean square error sense over a wide range of measurement locations and transmitter-receiver distances.

Finding the best fit for the cited parameters, using LSQ, depends on the minimization criterion being used. A criterion which is often used is minimizing σ^2 (error variance). Minimizing σ^2, means finding the values for $PL(d_0)$ and α which result in the minimal variance in error between measured RSSI and expected RSSI values. Finding the best fit for parameters $PL(d_0)$ and α for this minimization criterion is expressed by the following equation:

$$(\hat{PL}(d_0), \hat{\alpha}) = \underset{PL(d_0),\alpha}{argmin} \sum_{i=1}^{N} (RSSI_i - PL(d_0) + 10\ \alpha\ log_{10}(d_i))^2; \tag{3.18}$$

here N is the number of sampled RSSI measurements, $RSSI_i$ is the value for measurement i and d_i is the distance between access point and transmitter for measurement i. The values of d_i are assumed to be known, since during calibration access point and measurement locations are also known. The estimation of the propagation model parameters is a main issue in IPSs. As explained, distance estimations are obtained from received signal strength information, which is extracted from received RSSI packets. The precision of these systems mainly depends on the proper propagation model selection. An issue that might be experienced using *mostly adopted* models is that environment parameters are considered to be static.

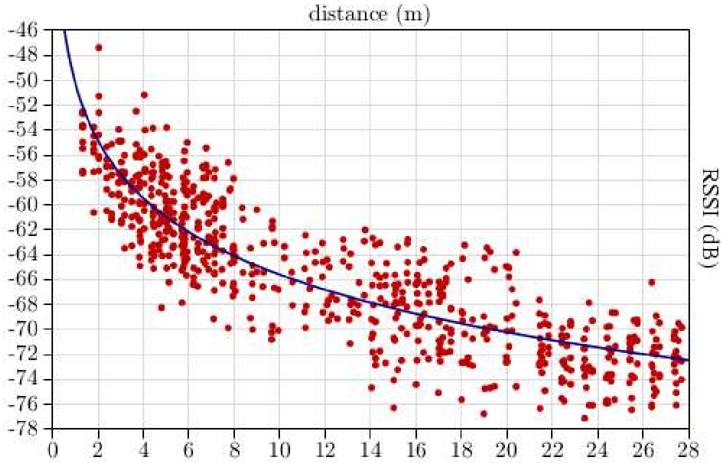

Figure 3.16: Path Loss Model fitting [66]

In a more realistic scenario, model parameters should be intended as continuosly evolving, according to modifications in the target environment. This is the goal of our work. This estimation is made dynamically and in real time. Therefore, it can track propagation model changes due to environmental changes. To reach this goal a Bayesian filtering is adopted.

3.3 Particle Filter

Our work can be categorized as a probabilistic approach. The main tool adopted for real time channel modeling throughout this thesis will be Bayesian filtering using Monte Carlo sampling, where the probability distribution of the characterizing channel parameters is captured, followed, and calculated by RSSI sampling. This method can use an arbitrary a-priori distribution converging (or *collapsing*) to a sampled distribution. The particle filter is designed for a hidden *Markov Model* (HMM), where the system consists of hidden and observable variables. The observable variables (observation process) are related to the hidden variables (state-process) by some functional form that is known. Similarly the dynamical system describing the evolution of the state variables is also known probabilistically (see Figure 3.17).

A generic particle filter estimates the posterior distribution of the hidden states using the observation measurement process. In particular, a generic $S(t)$ represents the model's state at a specific time. $R(t)$ indicates the observations obtained at time t. Particle Filter aims at estimating the sequence of hidden parameters that are represented by states, $S(t)$, based only on the observed data $R(t)$.

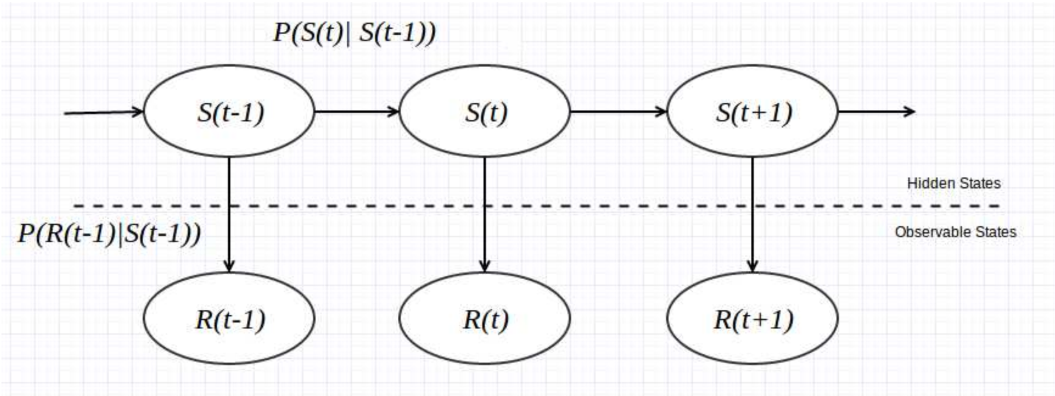

Figure 3.17: Hidden Markov Model for Particle Filter

The HMM underlying model assume $S(t)$ and the observations $R(t)$ can be modeled in this form:

- $S(t)$ is a first order Markov process such that $S_t|S_{t-1} \sim P(S(t)|S(t-1))$, having a starting distribution $P(S(0))$. This is also called *transition prior probability*;

- $R(t)$, observations, are conditionally indipendent given the state. In particular they depend on S, according to $R_t|S_t \sim P(R(t)|S(t))$.

In the specific scenario which has been be adopted in our study, state and observations evolutions are analitically described accordingly to the following structure:

$$\begin{aligned} S(t) &= g(S(t-1)) + u(t), \\ R(t) &= h(S(t)) + v(t); \end{aligned} \tag{3.19}$$

having g and h known functions, $u(t)$ and $v(t)$ are noises. If $u(t)$ and $v(t)$ are Gaussian and g and h linear, an alternative solution for solving this problem can be interely based on Kalman filtering.

Particle methods generate a set of samples that approximate the a-posteriori distribution, known also as *target distribution*, $P(S(t)|R(0), ...R(t))$ which practically means characterizing state evolution starting from observations. This is exactly the goal we are trying to achieve in channel characterization too, starting from RSSI readings. So, considering N samples collected, expectations with respect to the target distribution are approximated by:

$$E[f(S(t))]_{P(S(t))} = \int f(S(t))P(S(t)|R(0), ...R(t))dS(t) \approx \frac{1}{N}\sum_{i=1}^{N} f(S(t)_i) \tag{3.20}$$

having f able to describe distribution's features, as - for example - its moments.

Sequential Importance Resampling

In particular, in this work, the adopted Particle Filter is the *Sequential Importance Resampling* (SIR) [67]. Its implementation is based on approximating the target distribution $P(S(t)|R(0),...R(t))$ by a weighted set of M particles. The set of particles can be formally represented as:

$$[\ (w_k(t), S_k(t))\ ]; \tag{3.21}$$

having $k = 1...M$. The weights $w_k(t)$ are approximations of the relative posterior probabilities (densities) of the particles such that, at a specific time t:

$$\sum_{k=1}^{M} w_k(t) = 1. \tag{3.22}$$

According to the Formula (3.20) and considering M particles, expectations with respect to the target distribution are approximated by:

$$E[f(S(t))]_{P(S(t))} = \int f(S(t))P(S(t)|R(0),...R(t))dS(t) \approx \frac{1}{M}\sum_{i=1}^{M} w(t)_i f(S(t)_i) \tag{3.23}$$

SIR performance is dependent on the adopted *proposal distribution*, $Q(S(t)|R(0),...R(t))$. It is a distribution from which we can easily draw samples. If we choose a good proposal distribution similar to the posterior distribution, the imbalance of weights among the particles can be reduced, and therefore we could achieve high accuracy and high computational efficiency. A dependence in P and Q on the past filter states, $S(0),...,S(t-1)$, is left as implicit.

Algorithm Overview

At the beginning, given M particles, all their weights are set to $w_k(t) = 1/M$, for $k = 1,...M$. Particles can be initially sampled from a starting Uniform distribution over the set of possible values.

Given N observations, a single step (among N) of SIR is structured as it follows:

- **Prediction**: For $k = 1,\ldots,M$ extract samples from the proposal distribution, Q. In other words, in this step, a new set of states are generated according to Q. Formally $S(t) \sim Q(S(t)|S(0),...S(t-1))$. A possible generating approach can be, for example, based on *Metropolis-Hastings algorithm* [68]). In our work prediction step has been performed by perturbing the particles according to a variation factor drawn from a Gaussian distribution.

- **Weight Updating**: Update the weights, considering the last observation $R(t)$. In particular:

$$w_k(t) = w_k(t-1)\frac{P(R(t)|S(t))\ P(S(t)|S(t-1))}{Q(S(t)|S(0),...S(t-1))} \tag{3.24}$$

Note that the optimal proposal distribution is given as the target distribution. When this happens, recalling the Markov Chains properties, $Q(S(t)|S(0),...S(t-1)) = P(S(t)|S(t-1))$. Hence, Formula (3.24) can be represented as:

$$\hat{w_k}(t) = w_k(t-1)P(R(t)|S(t)) \tag{3.25}$$

- **Weight Normalization**: Normalize the weights. Formally:

$$w_k(t) = \frac{\hat{w_k}(t)}{\sum_{j=1}^{M} \hat{w_j}(t)} \tag{3.26}$$

- **Resampling**: This algorithm suffers a serious drawback: the variance of the importance weights might only increase over time. Practically, this means that after a few iteration steps all but one of the normalized weights are very close to zero. Hence it is impossible to avoid a loss of the quality of the estimated density and ultimately the filter will diverge. The solution to this problem is a *resampling* step. The performance of the algorithm can be also affected by proper choice of resampling method. According to some works on this topic [58], the most adopted resampling scheme is the *systematic* one. It is favourable, both in resampling quality and computational complexity. To decide if apply a resampling step or not, an evaluation of the effective number of particles, N_{eff} is done. N_{eff} is expressed as:

$$N_{eff} = \frac{1}{\sum_{j=1}^{M}(w_j(t))^2} \tag{3.27}$$

In particular if $N_{eff} < N_{threshold}$, resampling is performed.
Systematic resampling, which is adopted in this work, as all the other resampling methods, aims at drawing M particles from the current particle set with

probabilities proportional to their weights. In particular, resampling steps are:

– Generates M ordered numbers, according to the following criterion:

$$u_k = \frac{(k-1) + \tilde{u}_k}{M} \tag{3.28}$$

Having $\tilde{u}_k = \mathcal{U}[0, 1)$, for $k = 1, ...M$.

– Allocate m_i copies of the particle $S(t)_i$ to the new particle set, where:

$$m_i = \text{the number of } u_k \in \big(\sum_{j=1}^{i-1} w_j(t), \sum_{j=1}^{i} w_j(t)\big] \tag{3.29}$$

After resampling step, if done, all particle weights are set to $w_k(t) = 1/M$, for $k = 1, ...M$.

3.4 Path Loss Model Parameters Estimation

Usually, the values of path loss model parameters are commonly assumed to be constant. However, this consideration is not valid for real environments when parameters can suddenly change, due to the loss of LOS conditions. These parameters should only be considered constant for a certain period of time, and a reliable location algorithm needs to optimally accommodate and adapt to changing or unknown channel conditions. A possible solution to this problem could be the adoption of a Particle Filtering for tracking path loss parameters. The main advantage of this new approach is the possibility to let the value adapt in a real-valued range between two fixed limits, that is, without forcing the values to a fixed set of discrete values, possibly extracted from off-line measurements.

Our approach defines a particle filter for each beacon, to describe the propagation dynamics for the signal emitted. This is related to the fact that it is not guaranteed that all beacons radiate in the same manner. Even with the same underlying hardware from the same manufacturer, depending on their antenna orientation, radiation could be different, and this results in obtaining path loss parameters. In particular, for a beacon i we can describe its propagation pattern in terms of particle filter. In particular:

- A state, $S_i(t)$, is a pair composed by $(\alpha(t), PL_{d0}(t))$ to characterize the path loss model for the i-th beacon.
- An observation, *R(t)*, is a pair composed by $(d, RSSI)$. In particular, d is the distance from the transmitting beacon, where $RSSI$ is the indication received at that distance.

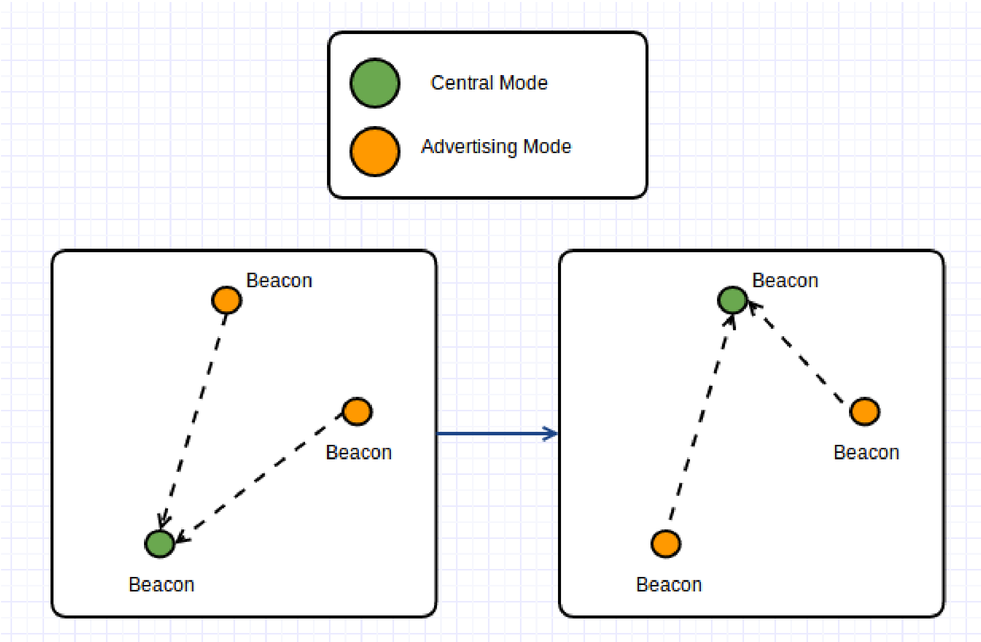

Figure 3.18: Particle Filter Test Setup

Supporting Infrastructure

Channel characterization is at the basis of system calibration. In order to adequately perform calibration steps, a complementary architecture should be deployed. In particular, the main focus of calibrating process is extracting a series of $R(t)$ observations, useful for system training. This means that, considering a fixed number of beacons in a room, each beacon propagation model should be trained with respect to a set of pairs (distance, received RSSI) obtained from other beacons listening to it. Since one of the goals of our work is reducing the number of beacons in a room and recalling BLE communication roles (see Section 2.7), we can not consider beacons covering fixed and specific roles (i.e., only advertising or only central mode enabled nodes) in a room. For this reason anchors should switch between advertising and central mode; they should emit RSSI packets while in advertising mode and make beacons in central mode collect them; on the contrary while beacons are in central mode they should collect data about listened RSSI packets from surrounding advertising anchors and save them on a central node for further processing (see Figure 3.18). Switching between central and advertising modes is done periodically at regular interval based a minimum time interval plus a randomizing time factor. More details on this are provided in Section 4.2. This provides data for calibration step.

Collected data are then used for calibrating propagation models for a venue. In particular, at regular time instants, *R(t)* data are loaded from the central node's database and used to evaluate propagation parameters according to Particle Filter model. This is a continuous process. Data describing signal propagation from each emitting beacon are used for characterizing the related path loss law. As noted above, a particle filter is defined for each beacon in the room.

In the positioning process, which is triggered by the final user and logically disjoint from calibration process, particle filter data are requested by targets for reversing the path loss law starting from listened RSSIs from surrounding beacons and transform them in the estimations of relative distances. These distances are then used as inputs for the positioning algorithm (trilateration based, see Section 3.4.2) which is usually performed locally, on the target to be located.

Path Loss parameters estimation using Particle Filter

From a statistical point of view, $PL(d)$, in RSSI, can be seen as distributed according a Gaussian distribution having a mean of $(PL_{d0} - 10\ \alpha\ log_{10}(d))$ and a variance of σ_{PL}^2. In particular, σ_{PL} can be considered as constant and represents an upper bound based on the worst deviation value observed from measurements. According to experimental tests, to guarantee the convergence of our algorithm, an upper bound value for σ_{PL} is chosen and it must be greater than any real value this parameter could take in real scenarios.

Thus, formulating the problem in terms of analitical distributions, the goal for the particle filter is to estimate the target distribution:

$$P((\alpha(t), PL_{d0}(t))|R(t)) \tag{3.30}$$

The particle filter steps described in the previous section are now adapted to our channel characterization problem.

Given a fixed number of particles, M, the algorithm is composed by a limited number of steps. In addition, an upper and lower limit for each of the path loss parameters is defined. This can be formally represented by:

$$\begin{cases} \alpha_{min} \leq \alpha(t) \leq \alpha_{max} \\ PL_{d0,min} \leq PL_{d0}(t) \leq PL_{d0,max}. \end{cases} \tag{3.31}$$

In details, for each step (i.e., when a new observation is available):

- **Initialization**: At the beginning particles are initialized from a bivariate Uniform distribution, $\mathcal{U}((\alpha_{min}, PL_{d0,min}), (\alpha_{max}, PL_{d0,max}))$. All their weights are set to $w_k(t) = 1/M$, for $k = 1, ...M$.

- **Prediction**: Particles updating is done considering perturbating noises for the path loss parameters. In particular, their evolution is expressed in the following format:

$$\begin{aligned} \alpha(t) &= \alpha(t-1) + \eta \\ PL_{d0}(t) &= PL_{d0}(t-1) + \nu \end{aligned} \tag{3.32}$$

  Having η and ν a Normal distribution and holding the variations in the dynamic model for the M particles. Particles predictions happens following a random approach. Hence:

$$\begin{aligned} \eta &= \mathcal{N}(0, \sigma_\alpha^2) \\ \nu &= \mathcal{N}(0, \sigma_{PL_{d0}}^2) \end{aligned} \tag{3.33}$$

  Designing a correct filter, in this case, requires to choose the best values for σ_α^2 and $\sigma_{PL_{d0}}^2$.

- **Weight Updating**: In order to update the weight related to a specific particle, $P(R(t)|(\alpha(t), PL_{d0}(t)))$ is evaluated and multiplied for the previous weight value, $w_k(t-1)$. Recalling that:

$$\begin{aligned} R(t) &= (RSSI(t), d) \\ PL(d,t) &\sim \mathcal{N}((PL_{d0}(t) - 10\ \alpha(t)\ log_{10}(d)), \sigma_{PL}^2) \end{aligned} \tag{3.34}$$

  Consequently:

$$P(R(t)|(\alpha(t), PL_{d0}(t))) = \frac{1}{\sqrt{2\pi\sigma_{PL}^2}}\ e^{(-\frac{RSSI(t) - PL(d,t)}{2\sigma_{PL}^2})} \tag{3.35}$$

  In particular, $PL(d,t)$ is evaluated, using Formula (3.18), with respect to the state of updating particle, $(\alpha(t), PL_{d0}(t))$ at a specific distance d.

- **Resampling**: This step was done accordingly to what explained in the previous section. In particular it is necessary to choose an adequate threshold value to trigger resampling procedure, $N_{threshold}$.

- **Parameters estimation**: Path loss exponent, $\alpha(t)$ and Path Loss at reference distance, PL_{d0} are estimated considering:

$$(\hat{\alpha}(t), \hat{PL}_{d0}(t)) = \sum_{i=1}^{M} w_i(t) S_i(t) \tag{3.36}$$

Particle Filter setup

Specifically, in order to set up each filter it is important to configure its parameters. What needs to be chosen is:

- The minimum and maximum accettable values for the parameters;
- A fixed value for σ_{PL} which describe the RSSI dispersion around its mean value;
- Fixed state transition evolution parameters, σ_α and $\sigma_{PL_{d0}}$. They describe the noise perturbating the states in the prediction step;
- The threshold value, $N_{threshold}$, to trigger resampling.

Particle Filter evaluation

Some tests were carried in order to understand how the filter behaves in real positioning scenarios and choose the best configurations. Some parameters, for example, are considered fixed. They are:

- M, particles number. Since particle filter algorithm will be executed at each calibration step (which in our work has a frequency of 3 minutes), particles number will be reduced to limit complexity. We choosed M = 10;
- Fixed maximum and minumum values acceptable for parameters. In particular:

$$\begin{aligned} \alpha_{min} &= 1, \\ \alpha_{max} &= 4, \\ PL_{d0,min} &= -65dB, \\ PL_{d0,max} &= -55dB \end{aligned}$$

- We considered small scale perturbation in model parameters. Since number of observations for RSSI is high we can leave this value low; In our case σ_α and $\sigma_{PL_{d0}}$ are both equal to 0.1. This low standard deviation is not a problem for our algorithm.
- Threshold value to trigger resampling is put to $0.7 \times P$. This is a common value in literature.

For instance, considering an office room, with personal computers and people moving, we studied how particle filter performed with respect to a more classical approach based on least squares fitting (LSQ) for path loss model parameters estimation (these methods were discussed in Section 2.4.4). In particular, we did some test to understand how to better configure Particle Filter parameters. We studied how characterize standard deviation for RSSI signal under these conditions; some tests were carried out to better define σ_{PL}.

As introduced, beacons has been placed in a harsh environment. They were activated in order to start estimation of propagation parameters for each beacon, through a Particle Filter based characterization. In particular, α and PL_{d0} have been calculated for each installed anchor and evaluated during our experiment time-frame (25 min). Then, according to posed propagation parameters, distances were estimated between a target and each beacon. In our test real distances between target and each beacons are 2m from Beacon C, 3m from Beacon A and 4m from Beacon B. People movements and other BLE enabled active devices were detected meanwhile (see Figure 3.19). Our goal is to quantify how well distances are estimated starting from collected RSSI. In particular, considering a fixed dataset of collected RSSI from a receiver, we used them as an input to evaluate which σ_{PL} gave the best result.

Figure 3.19: Particle Filter Test Setup

Obtained results are described in the Tables 3.5, 3.6 and 3.7. Each row represents the calibration error for a single beacon i (see Section 2.5):

$$\varepsilon_{calibration,i} = \hat{d}_j - d_j; \tag{3.37}$$

last column includes the overall calibration error (see Definition (2.21)).

In particular, σ_{PL} shows a better evolution for values $\sigma_{PL} = 3dB$ and $\sigma_{PL} = 5dB$. We chose the latter. This is consistent to what explained in Section 3.2. In particular we obtained an average $\varepsilon_{calibration}$ for $\sigma_{PL} = 3dB$ which was 1.055m, while for $\sigma_{PL} = 5dB$ was 0.986m and for $\sigma_{PL} = 10dB$ was 1.10m.

Moreover, it could be noted as Beacon A experiences the highest Path Loss Exponent (PLE). This can be related to the fact that human obstacles are obstructing the direct LoS between beacons and this necessarily involves a greater PLE.

In addition, comparing obtained Particle Filter performance with that obtained using a LSQ based one, we obtained the results for error in distance evaluations presented in Table 3.8. $\varepsilon_{calibration}$ applying LSQ method is significantly higher with respect to Particle Filter. Concretely, we obtained a $\varepsilon_{calibration} = 2.885$m.

This outcome highlights how Particle Filter based solution can be considered more robust with respect to LSQ solutions. Moreover, we provided a basic proof about how PF method enhance the precision level obtained by LSQ method, which is a commonly used approach for this problem. We also reported the evolution of the PLE for the described test and how the Path Loss curve fit varied over time (see Figure 3.20). The evolution of the path loss exponent in time was strongly correlated to the dynamics within the room and to obstacles in the near range. This results in significantly different values for PLE in the three beacons and, consequently, in different path loss describing curves.

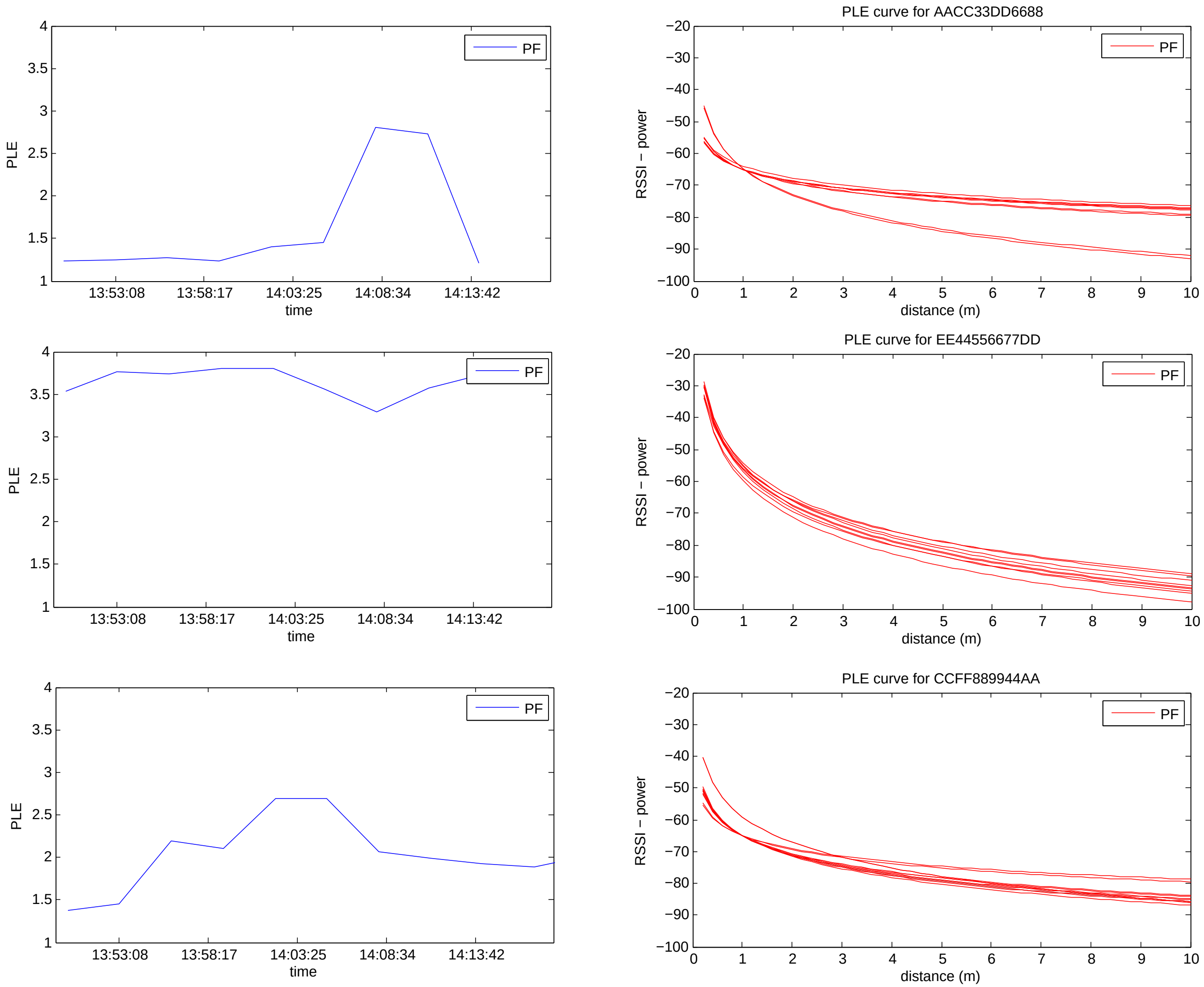

Figure 3.20: Path Loss Exponent Evolution in Particle Filter

ε Beacon A (m)	ε Beacon B (m)	ε Beacon C (m)	$\varepsilon_{calibration}$ (m)
2.5949	0.0835	0.5045	1.06
1.0872	1.4593	3.4712	2.00
1.0981	0.2128	0.4092	0.57
1.1535	0.4198	0.0668	0.54
2.9565	0.3660	0.2987	1.20
2.2436	0.2660	0.2555	0.92
1.3975	0.8102	0.4930	0.90
1.6708	1.0009	0.8363	1.16
1.4953	0.9893	0.0475	0.84
2.9107	0.1336	0.6274	1.22
2.7958	0.0835	0.7244	1.20

Table 3.5: Calibration errors from beacons for $\sigma_{PL} = 3dB$

ε Beacon A (m)	ε Beacon B (m)	ε Beacon C (m)	$\varepsilon_{calibration}$ (m)
1.9110	0.0835	0.5238	1.20
0.6715	1.4847	3.6162	1.92
0.6775	0.2128	0.4183	0.43
0.7148	0.3341	0.3875	0.47
2.6422	0.2740	0.8099	1.24
2.2209	0.1568	0.0024	0.79
1.3301	0.7784	0.3972	0.83
1.6250	0.9608	0.7350	1.10
1.4325	0.9589	0.0381	0.80
2.4673	0.1336	0.5758	1.05
2.3282	0.0835	0.6676	1.02

Table 3.6: Calibration errors from beacons for $\sigma_{PL} = 5dB$

ε Beacon A (m)	ε Beacon B (m)	ε Beacon C (m)	$\varepsilon_{calibration}$ (m)
2.7737	0.0835	0.5004	1.11
1.2872	1.4847	3.4598	2.07
1.3015	0.2128	0.4084	0.64
1.5032	0.3341	0.1555	0.66
3.3559	0.2740	0.5248	1.38
2.2656	0.1568	0.1428	0.85
1.5571	0.7784	0.4277	0.92
1.7196	0.9608	0.7670	1.14
1.6427	0.9589	0.0106	0.87
3.1848	0.1336	0.5829	1.30
3.0903	0.0835	0.6751	1.28

Table 3.7: Calibration errors from beacons for $\sigma_{PL} = 10dB$

ε Beacon A (m)	ε Beacon B (m)	ε Beacon C (m)	$\varepsilon_{calibration}$ (m)
2.3820	8.6398	2.3628	4.46
1.1485	7.6142	3.4735	4.07
1.1623	4.1150	2.8171	2.69
1.1460	0.4497	0.2336	0.60
3.4796	0.3922	0.1608	1.34
9.7888	0.1193	0.4874	3.46
1.4283	0.6597	0.6885	0.92
2.7761	1.0513	1.0374	1.62
4.0693	0.4751	0.2287	1.59
2.8776	9.6686	2.5898	5.04
2.9178	12.2189	2.7148	5.95

Table 3.8: Calibration errors from beacons for LSQ method

4 Positioning based on Kalman Filtering

In this section, a description of the adopted trilateration algorithm is presented. It is a lateration-based algorithm. In particular, we use the RSSI variance, extracted from measurements from a single beacon in a venue, as an indicator of the distance error in the positioning process. Then, positioning final estimate is obtained through a refinement step, based on a Kalman Filter.

4.1 Kalman Filter

If the process and measurement noises are assumed to be Gaussian and the positioning model can be considered only influenced by very short range movements, a Kalman Filter (KF) approach can be used to estimate user's final position. The Kalman filter is an efficient recursive filter that statistically estimates the internal state of a system from a series of measures which are subject to noise. It can also be adopted to characterize disturbance agents on system, that have a Gaussian distribution with zero mean.

The Kalman filter, in practice, averages a prediction of a system's state with a new measurement using a weighted average. The purpose of the weights is that values with better estimated uncertainty are considered more trusted. The weights are calculated from the covariance, a measure of the estimated uncertainty of the prediction of the system's state. The result of the weighted average is a new state estimate that lies between the predicted and measured state, and has a better estimated uncertainty than either alone. This process is repeated every time step, with the new estimate and its covariance informing the prediction used in the following iteration.

The Kalman filter uses a dynamical model system, known control inputs (if available) to that system, and multiple sequential measurements to form an estimate of the system's varying quantities that is better than the estimate obtained by using any one measurement alone.

The state of the filter, is represented by two variables: p, which is the state estimate at current time and C, the error covariance matrix. The Kalman Filter evolution is most often conceptualized as two distinct phases: *prediction* and *updating*. In details, they are organized as follows:

- *Prediction step*: It uses the state estimate from $(k-1)$ to produce an estimate of the state at the current time k, considering a linear stationary dynamic system subject to process noise;

$$\begin{aligned} \hat{p}^{-}(k) &= A\hat{p}(k-1) + w(k-1) \text{ (estimate of state)} \\ C^{-}(k) &= AC(k-1)A^{T} + Q_k \text{ (estimate of covariance)} \end{aligned} \tag{3.38}$$

Having:

- **A**: State transition model which is applied to the previous state;
- **w(k)**: Process noise which is assumed to be extracted from a zero mean normal distribution with covariance Q_k. Formally, $w(k) \sim \mathcal{N}(0, Q_k)$.

- *Updating step*: Current observation information is used to refine the state estimate. Governing equations for this step are:

$$\begin{aligned} K(k) &= C^{-}(k)H^{T}(HC^{-}(k)H^{T} + R_k)^{-1} \text{ (Kalman gain)} \\ \hat{p}(k) &= \hat{p}^{-}(k) + K(k)(z(k) - H\hat{p}^{-}(k)) \text{ (estimate of state)} \\ C(k) &= (1 - K(k)H)C^{-}(k) \text{ (estimate of covariance)} \end{aligned} \tag{3.39}$$

Having:

- **H**: Observation model which maps the true state space into the observed space;
- **v(k)**: Measurement noise which is assumed to be extracted from a zero mean normal distribution with covariance R_k. Formally, $v(k) \sim \mathcal{N}(0, R_k)$;
- **z(k)**: New measurement. In particular, $(z(k) - H\hat{p}^{-}(k))$ is the deviation of the current measurement with respect to the estimated value, according H.

4.2 Positioning Approach and Trilateration Algorithm

Our lateration algorithm is based on the Adaptive Lateration (AL), described in Section 2.4.4. In particular, It includes also the reliability factor of the estimates of the radii from beacons. Reliability of a radius is given by the variance of the RSSI that determines that radius. Positioning is then refined with the adoption of a Kalman Filter.

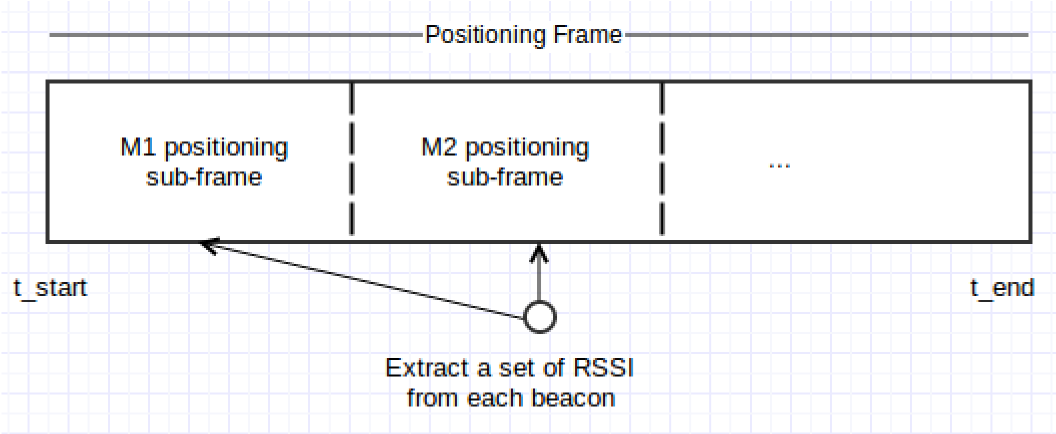

Figure 3.21: Positioning Time Frames

The proposed method splits a positioning time frame in a series of time sub-frames and for each of them a set of RSSI measurements, from every beacon in the venue, is collected. This approach is based on a positioning routine that works knowing positions of the beacons, an estimation of distances between each beacon and the target node and, finally, a reliability index for RSSI measurements. The algorithm, for sake of clarity, will be proposed for the minum number of beacons, but it can be scaled up to any beacons' network dimension.

Definition 8 *Let $N \geq 3$ be the number of available beacons in a venue (for simplicity). Let $B \in \mathbb{R}^{N \times 2}$ describe their positions in a 2D space, according to a reference system relative to the considered room. A single positioning attempt can be based on M sets of RSSI readings, got from each beacon and collected over the positioning time frame. Hence, $D \in \mathbb{R}^{N \times M}$ is an estimation of distances, extracted from each set of measurements, between the target node and each beacon using calibrated Path Loss models. Let $R \in \mathbb{R}^{N \times M}$ be the reliability matrix (which describes the RSSI measurement variability for a set of collected values). In particular:*

$$B = \begin{bmatrix} x_{b1} & y_{b1} \\ x_{b2} & y_{b2} \\ x_{b3} & y_{b3} \\ \cdots & \cdots \end{bmatrix} D = \begin{bmatrix} \hat{d}_{1,1} & \hat{d}_{1,2} & \cdots & \hat{d}_{1,M} \\ \hat{d}_{2,1} & \hat{d}_{2,2} & \cdots & \hat{d}_{2,M} \\ \hat{d}_{3,1} & \hat{d}_{3,2} & \cdots & \hat{d}_{3,M} \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} R = \begin{bmatrix} \delta^2_{1,1} & \delta^2_{1,2} & \cdots & \delta^2_{1,M} \\ \delta^2_{2,1} & \delta^2_{2,2} & \cdots & \delta^2_{2,M} \\ \delta^2_{3,1} & \delta^2_{3,2} & \cdots & \delta^2_{3,M} \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} \quad (3.40)$$

Our approach is based on a positioning routine that knows the positions of the beacons, an estimate of distances between each beacon and the target node and a reliability index for RSSI measurements. The algorithm, for sake of clarity, will be proposed for the minum number of beacons, but it can be scaled up to any beacons' network dimension.

In particular, in each positioning sub-frame, for $i = 1, ...M$, a positioning function is evaluated. This function can be formally expressed as:

$$pos(B, D_i, R_i) \longrightarrow (x_{target}, y_{target}); \tag{3.41}$$

having D_i and R_i as the i-th column of D and R, respectively. Each beacon j, with $j = 1, ...N$, can be intended as the center of a circumference having radius equal to $d_j \in D_i$. Measure reliability can be expressed as the possible error in distance (hence, radius) estimation from a specific beacon. This is graphically shown in Figure 3.22.

A description of the proposed method is now presented. Considering the circumferences having as centers the coordinates of two beacons, for example beacon $j = 1$, (x_{b1}, y_{b1}), and beacon $j = 2$, (x_{b2}, y_{b2}), their radii are the estimated distances between each beacon and the target node. These are $\hat{d}_1$ and $\hat{d}_2 \in D_i$. These circumferences can intersect each other or not. Practically:

- If they intersect (in one or two points), the point having the minimum distance with respect to the third beacon (i.e. center of the third circumference) is picked, P_{min}. The first intermediate estimated target position is given by a weighted mean, using as weight the third beacon's realiability $\sigma_j^2 \in R_i$, between the coordinates of P_{min} and the coordinates of the center of the third beacon, (x_{b3}, y_{b3}). In particular an higher σ_j^2 is traduced to a minor trust in the distance estimation from that beacon (see Figure 3.23).
- In the second case, two distinct situations could happen. They are:

  - A circumference is internal to another. Then we will proceed by increasing the radius of the smaller circumference and decreasing the radius of the largest circumference, according to their reliability, until obtaining two intersections. Among these two points the one closer to the third beacons is taken into account and we will proceed as described in the previous case;

  - Circumferences are disjoint. Therefore we will increase the radii of both circles, in proportion to the reliability of their measurements until getting two points of intersection. Among these two points the one closer to the third beacons is taken into account and we will proceed as described in the previous case.

The proceeding above will be repeated for all the possible combinations of two beacons, present in the venue. The final target estimation is calculated as the mean of the intermediate positions evaluated at each step (see Figure 3.24).

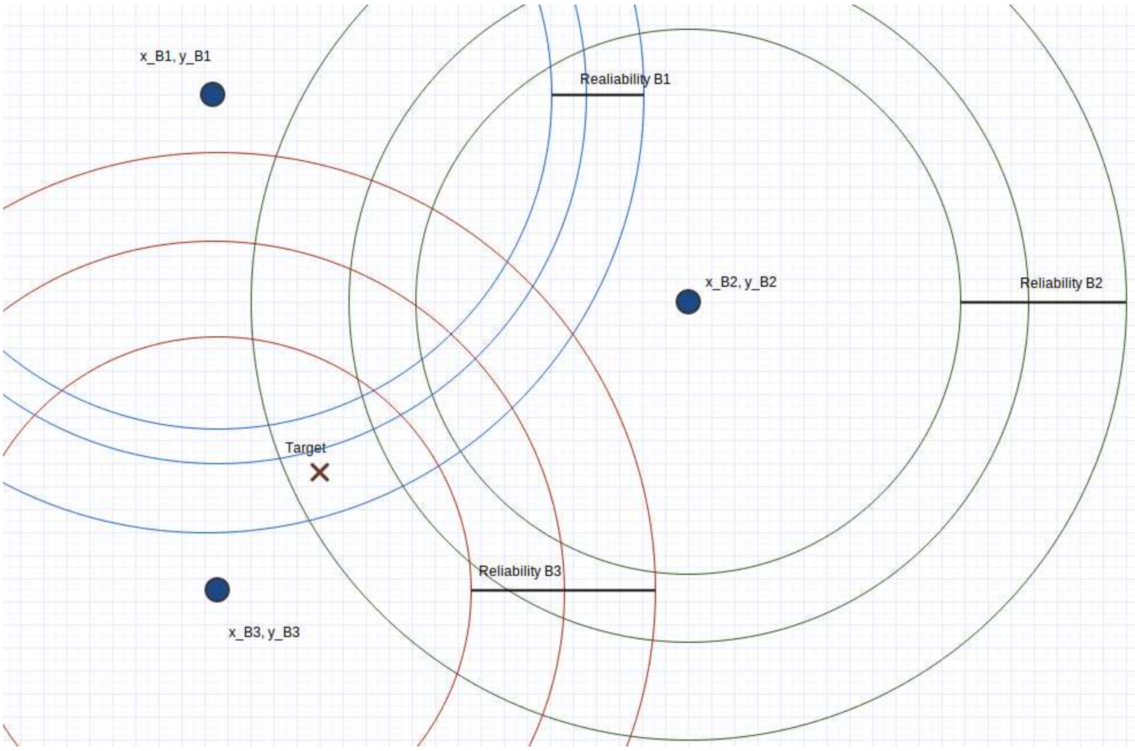

Figure 3.22: Trilateration and Measure Reliability

Proximity Correction

Inspired by proximity algorithms, our proposed approach embodies a proximity feature to better estimate positions were user is very close to a beacon. In particular, when applying the positioning steps describe above, if a beacon is listened with an RSSI value that is lower or equal to a $RSSI_{proximity}$ and its reliability is lower or equal to a $\Psi_{proximity}$, then the estimated intermediate position is set as the exact beacon location.

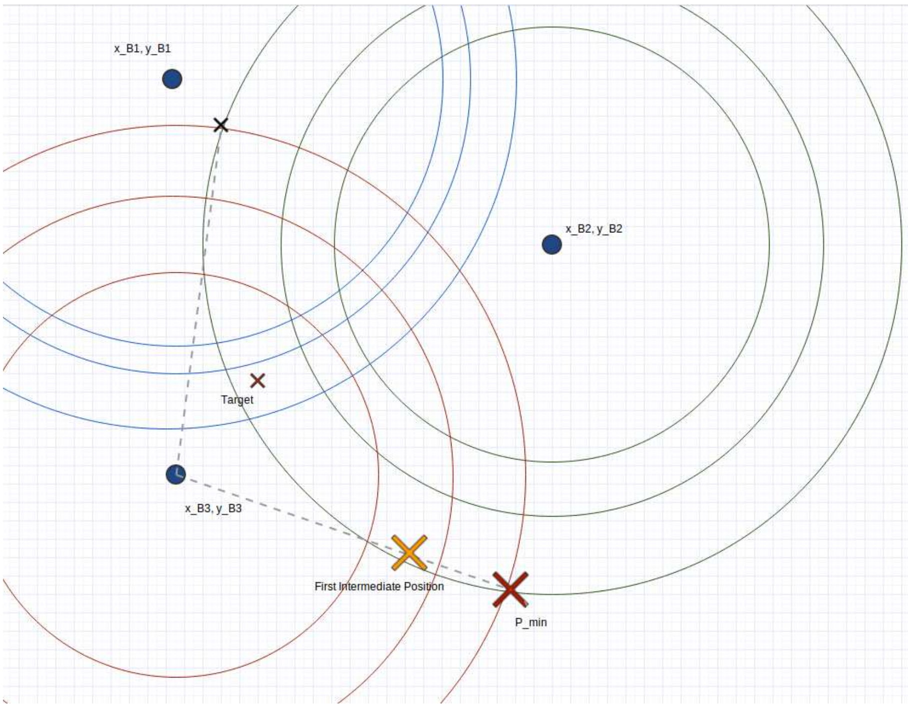

Figure 3.23: Picking one of the intermediate positioning points

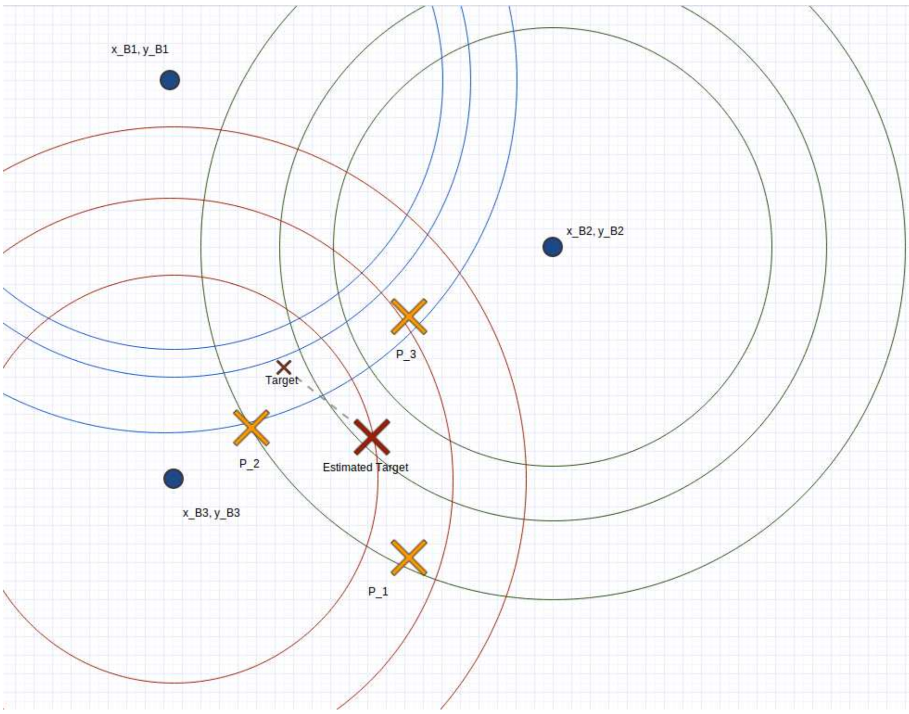

Figure 3.24: Final estimation using adaptive trilateration

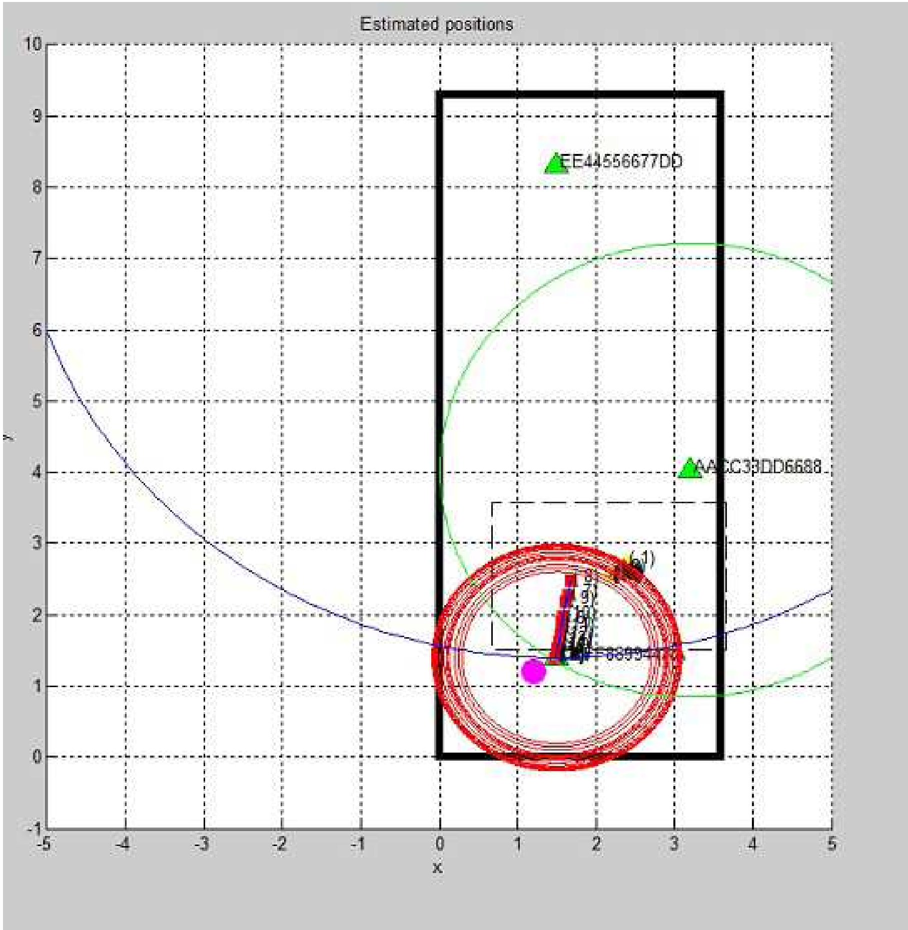

Figure 3.25: Kalman Filter based refinements on positioning. Magenta dot represents the real position for the user, red ones are the outcomes of the Kalman filter. Average positioning error is 1.4m.

4.3 Positioning Refinement using Kalman Filter

The state of the Kalman Filter for our problem, is the user position. In particular the state estimation represents the user position in the indoor venue, $p = [x, y]^T$ according to a local reference system. Observations ($z(k)$) are the new iteratively observed user positions, using the trilateration algorithm described above.

Since we are dealing with a positioning model in which user is not intended to move while performing position, our state evolution is simplified as follows:

$$\hat{p}^-(k) = \hat{p}(k-1) + w(k-1); \tag{3.42}$$

this means that the estimation of a position at step k is dependent by the estimation at step *k-1* (the user is considered to be stationary during positioning). The variation in the position, caused by the process and described by w involves a slight perturbation in the estimated location.

H can be intended as the identity matrix because the measurements are directly related with the system state variables. In particular, the most interesting aspect is related to the fact that $v(k)$, i.e., the measurement error, includes all the effects of RSSI fluctuations that were described in Section 2 of this chapter.

Moreover positioning steps (described before) are performed for each n-tuple of estimated distances, extracted from the set of measurements. Output positions, evaluated in this way, are considered as the $z(k)$ for our Kalman Filter.

5 Conclusion

This chapter described the main proposed advancements in this thesis, that will be practically evaluated in the next Chapter. In Section 3.2, we provided a complete and deep analysis of the signal of interest for this work. An extended description of multipath fading and shadowing is included, trying also to examinate each factor determining these effects from a physical point of view. We deeply studied how RSSI varies in indoor venues and how this is related to some not negligible components, such as *antenna orientation*, *human presence* and *small scale movements*. We outlined that the only factor that can be considered in our system, since one of the requirements is keeping the installation process as simple as possible, is antenna orientation. We propose a correction factor to take into account this aspect while calibration our model.

In the last part of this section, some previously adopted RSSI filter (to remove multipath and fast fading components) are described. We did some comparisons between them in order to choose the best one for our work. In terms of performance and computational complexity, we chosed the Gaussian filter. To sum up, this first section provided a feasibility study of RSSI in BLE-based positioning systems.

In Section 3.3 our Bayesian approach to estimate channel characterization parameters is outlined. In particular an exaustive definition of Particle Filter is provided and of the lognormal path loss model. We, then, formally described how particle filter can be adopted in estimation of the path loss exponent, α and listened value at reference distance, PL_{d0}. Finally, In Section 3.4, we described our positioning approach and how results can be improved using a Kalman Filter. In particular, a definition of the Kalman Filter is given, then our position algorithm is described. Our positioning method exploits the variances of the RSSI measurements and use them as a measure of reliability for estimated distance. Then a proximity correction is depicted in order to have better results when the target is close to each beacon.

Chapter 4

Experimental Results

1 Introduction

After having explained and presented some of our research results, we detail in this chapter some of the experimental tests we performed and compare them with similar results available from literature. Moreover, we illustrate the architecture we built up for this purpose and depict a brief description of adopted technologies and the modular organization of the system. In particular, localization algorithms and methods deeply influence localization performances. A correct setup for this parameters should be found. Some configurations (e.g, particle filter setup) have already been descripted.

2 System Architecture and Technical Implementation

A precise description of the overall system architecture is now presented. In particular our IPS solution is based on three main modules; The *beacons*, a *central processing node*, or *base station*, and *target nodes*. Beacons are displaced into the environment and are the core tools adopted in our work. In particular, the final user is responsible to place beacons into the mapped room. Beacons are usually placed near ceilings or on the top of the furniture in the venue; User has to report their position on the system. Beacons' positions and orientations are needed to calculate their distances and their relative orientations in order to correct some measures. Moreover, beacons are designed to exchange calibrations data to the central processing node, via Wi-Fi.

The Central Processing node could be locally deployed or can be in the cloud. Its goal is to estimate the propagation parameters for each beacon in the venue, starting from the sent calibration data from those beacons. Moreover, the central node exposes an API used to estimate position for a target node. In particular passing a series of collected RSSI, target position can be calculated.

Finally, the target node is a device carried by the user. In this scenario it is represented by a smartphone. Its functionalities are collecting RSSI readings from surronding beacons and open a connection to the server in order to get final position.

2.1 Beacons

Since our work aims at developing an adaptive solution to the positioning problem, we designed a context-aware beacon which is able to switch automatically between advertising and central states. As described in Section 2.7, in Bluetooth Low Energy communication, there are two key players: the central and the peripheral nodes. Each player has a different role in Bluetooth Low Energy communication. A peripheral typically has data that is needed by other devices. A central typically uses the information provided by a peripheral to accomplish some tasks. In particular, while in the advertising state it forwards RSSI signal to the other reachable beacons, while when it is in the central state it tries to collect RSSI from beacons exposing a specific characteristic (to identification purpose) and send this data to the central node.

We developed our beacons as iOS Apps which integrate, by software, the features of status switching, between advertising and central mode. These beacons were built up exploiting the `CBCentralManager` class of the `CoreBluetooth` framework, available in iOS ≥ 5.0. `CBCentralManager` objects are used to manage discovered or connected remote peripheral devices (represented by `CBPeripheral` objects), including scanning for, discovering, and connecting to advertising peripherals.

When a beacon is in central mode and receives RSSI values from a peripheral (BLE device) in advertising mode, the method `didDiscoverPeripheral:advertisementData:RSSI:` in the `centralManager` class is invoked on the Central device, which, according to the Developer Library[1], returns the current received signal strength indicator (RSSI) of the peripheral, in dB.

To enable or switch to advertising mode in a beacon, the first step is to allocate and initialize a peripheral manager instance (represented by a `CBPeripheralManager` object). Then, a set up for services and characteristics and their relative publishing is needed. Finally, it becomes possible to advertise some of created services by calling the `startAdvertising:` method of the `CBPeripheralManager` class (See Figure 4.1).

Beacons were placed in our target environment on walls, in order to simulate real scenarios (See Figure 4.2). The best beacons placement is in LoS conditions between them and at the room's corner, pointing to the center of the venue. This

[1] Apple's Dev Library Website - https://developer.apple.com/library/

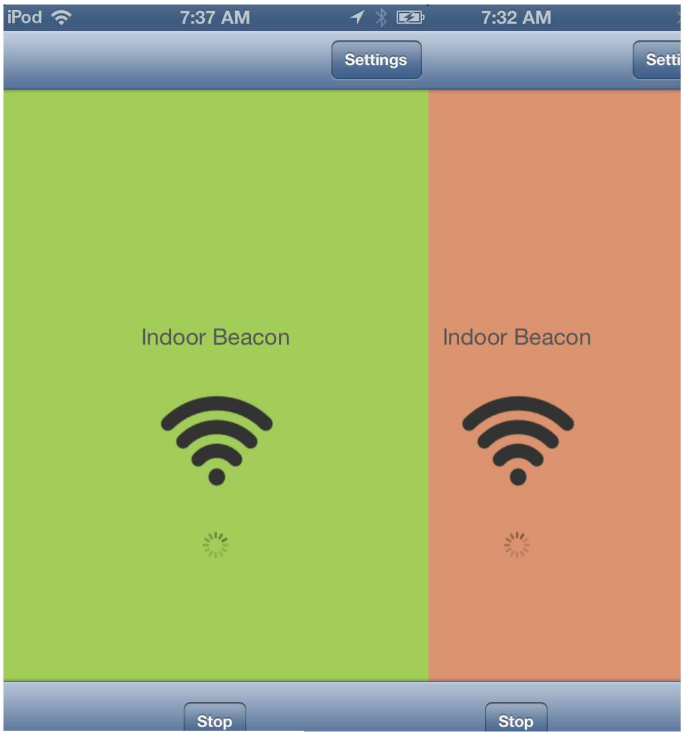

Figure 4.1: Beacon App changing state from central (green) to advertising (orange) one.

will avoid some fixed obstructions that will limit the positioning performance.

Data collected in central mode are passed to *Central Processing Node* via an HTTP POST request to calibrate propagation model for each beacon. This obviously requires a Wi-Fi connection for a single transmitter. In future works (See Chapter 5) a communicating mesh/grid of beacons can be deployed in order to have a single device with network capability within a venue, for example a smartphone connected to the home wireless network, and defining a routing mechanism between them, to have data passing beacon-by-beacon until arriving to the connectivity-enabled device. Beacons, in that case, do not need to integrate Wi-Fi module, which can be expensive in terms of cost and power consumption. To sum up, beacons should be able to exchange RSSI data, so, in any case, a connection between them for data transfer needs to be estabilished.

Off the shelf alternative solutions are also available in the market, like Estimote[2] or Kontact[3] products. However, since we need inter-beacons communications to calibrate our venue we can not adopt these solutions. Connectivity features for beacons are usually not immediatly available via the SDK offered by producers so

[2]Estimote Website - http://www.estimote.com
[3]Kontakt Website - http://kontakt.io/

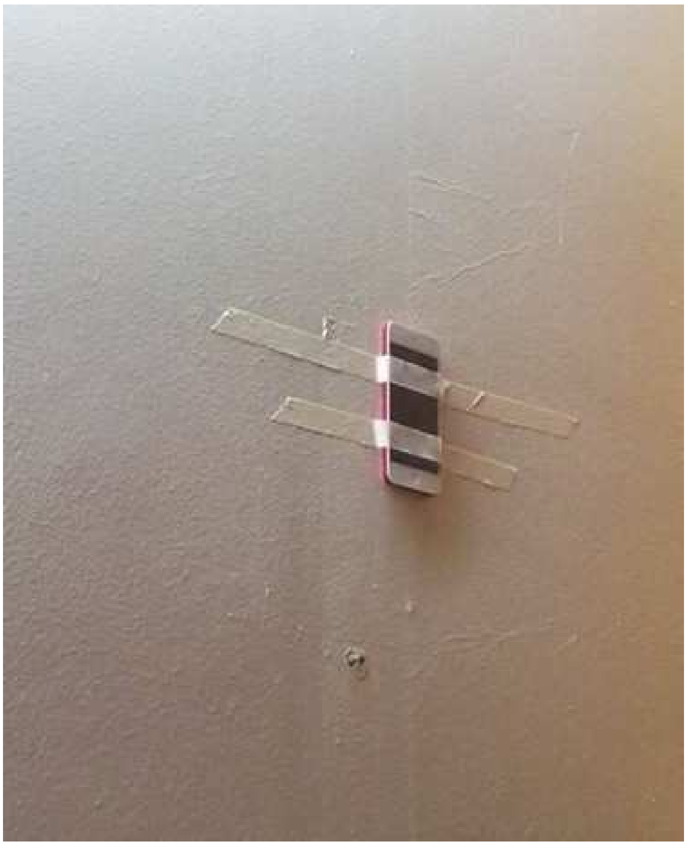

Figure 4.2: Beacon placement on wall during setup

a control of data exchanging can not be done in a straight way. For this reason, we went for a simulated solution using iPhone, iPad or iPod based applications.

2.2 Central Processing Node

The Central Processing node, or base station, is responsible for collecting calibration data from beacons, via HTTP requests. It exposes a REST API, enabling beacons to pass such information to the elaboration node. Moreover, it holds the logic for calibrating steps and leave to target node the final position estimation. Previously obtained parameters are then requested from target node in order to estimate its position. It is possible to have this node locally deployed (e.g. on a local machine) and have communications happening on local network, or to have it accessible from the internet, for instance using an Amazon Web Service[4] (AWS) instance. The last solution is the one adopted in this work. It is important to observe that for an effective and real deployment of this solution, an access control level should be implemented to access to the API, e.g., after having performed a registration step.

[4] Amazon Web Services Website - http://aws.amazon.com/

This can be also useful to control access of users in specific locations or track their movements (e.g., for elderly people monitoring). Moreover, in some scenarios depending on the target node typology (e.g., reduced computational power), also the positioning process could be done on this side, allowing users to POST the set of RSSI received from beacons.

Central Node implementation is based on Python[5] and Node.js[6] programming languages. Node.js is a Javascript based framework and uses an event-driven, non-blocking I/O model. In particular, Restify[7] module is used. It is a Node.js module built with the purpose of creating REST web services.

The Central Processing Node is structured on two components: *Communication* layer and *Logic* layer. In details:

- Communication layer exposes APIs for adding a venue (e.g., Home) and a set of locations (e.g., Living Room) to the system, which will be used in calibration routines. Beacons positions are also highlighted and added to the system through this API. Ordinary operations for beacon position changing, room and location setup are allowed. Calibration procedures for a venue can be turned on and off using APIs.

- Logic layer is responsible for basic calculations in calibration steps. It embodies a Python encoding of particle filter steps, prediction and updating. For the mathematical reasoning some well-known libraries are adopted. In particular, Numpy[8] and Scipy[9].

2.3 Target Node

A target node is a device (in this study, a smartphone) which is capable of:

- Collecting RSSI data from surrounding beacons;
- Retrieve calibration data from Central Processing node, both with listened beacons and related beacons/venue structure.

This node will implement the positioning routines. For our project, both iOS and Android app were developed. In particular, BLE native support on Android phones became available on the 4.3 version of the OS (updates were definitively downloadable starting from December 2013 - January 2014). BLE support on iOS

[5]Python Website - http://www.python.org/
[6]Node.js Website - http://nodejs.org/
[7]Restify Project Website - http://mcavage.me/node-restify/
[8]Numpy Website - http://www.numpy.org/
[9]Scipy Website - http://www.scipy.org/

was integrate since iPhone4S (2011). However the application structure is the same for both the platform. Both apps collect RSSI values turning the BLE central mode on, for a specific time frame. We detected that best times in order to have a reasonable amount of samplings, are between 90s and 120s. On average a packet is received from a beacon every 0.08s, which means about 1000 samples per minute.

2.4 Components Interactions

The previously described components interact in an integrated way in order to reach the final goal. Two separated processes can be considered which could happen also in the same time. In particular, as deeply stated in previous sections, they are *calibration* and *positioning*.

Calibration

In the calibration step, interactions happen between Beacons and Central Node. The scope of this process is to define, accordingly to channel characterization algorithm, described in Section 3.3, propagation parameters for path loss model. In particular, in this work, we analyse signal evolution, at different distances, for each beacon in the room. A Particle Filter calibration model is defined for each anchor in a venue.

As already introduced, each beacon acts in two modalities (Central and Peripheral), switching between them. The goal is to avoid two types of beacons (sending RSSI and collecting RSSI), in the same location, which would result in an higher number of placed nodes. Deploying beacons at different relative distances makes possible, in this way, to have a heterogeneous dataset (i.e., different listened RSSI at different distances). Received RSSI data are collected while a beacon is in Central Mode (Recall Figure 3.18). When Central Mode is active, a beacon listens to RSSI values arriving from other nodes in the room. Since we know the distances between each pair of beacons is possible to build up the data series composed by pairs (received RSSI, distance) which will be passed to the Central Node to perform the proper calibration. Data collected from beacons are passed (opening an HTTP connection) to the Central Node, which stores them in its local database. After sending data to the Central Node, a beacon moves to the Advertising status. Now it start to emit RSSI packets. These packets will be intercepted by any beacon in Central Mode listening for a specific characteristic.

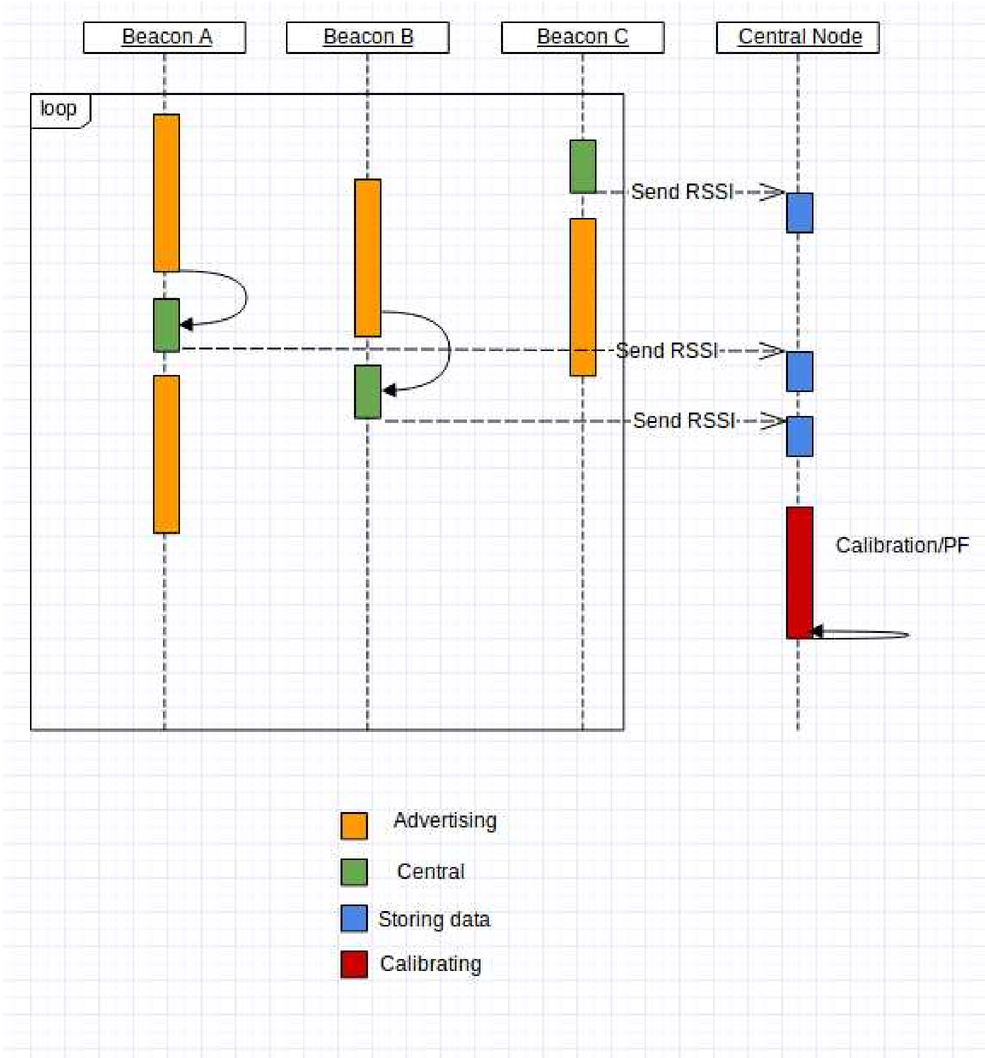

Figure 4.3: Sequence Diagram for Calibration step

The time a beacon spends in Central mode is called *Central Time*, while the time it spends Advertising packets is called *Advertising Time*. Usually a beacon spend much more time avertising than in Central mode. This was done in order to have a high probability of a beacon being visible for a specific target, while performing positioning. In addition, to avoid the case in which two or more beacons are simultaneously in Central mode (which would result in poor calibration setup, since one data series of (distance, received RSSI) will not be available), a *Central Time* and *Advertising Time* are composed by a minimal amount of time plus a randomization time factor, drawn from a Uniform distribution within a specific interval (see Figure 4.3).

In particular:

	Minimal Amount of Time (s)	Additional Random Time (s)
Central Time	15.00	±5.00
Advertising Time	180.00	±30.00

Table 4.1: Central Time and Advertising Time

At regular time instants, Central Node (which in the previous time has collected RSSI data received from different beacons) triggers a new path loss model estimation. In particular, it queries the local database in order to extract the RSSI data series which have not been already examined and processed. Not elaborated RSSI data are passed to the calibration routine in order to perform a new estimation. Newly calculated parameters are then reachable through APIs. In our work, Central Node calculates new parameters estimations every 3 minutes.

Positioning

In the positioning step, interactions happen between all the components of our IPS. In particular, positioning process is not related by any order with respect to calibration one. These processes could also happen simultaneously. When a target needs to be positioned it starts collecting RSSI values from surrounding beacons. Then according to listened beacons, it asks (via an HTTP request through APIs) to the Central Node for their correspondent propagation parameters. The collecting period lasts for 30 seconds. In particular, as described in Section 3.4.2, scanning time is divided in scanning sub-frames. When readings from a specific beacon are missing in a specific sub-frame, this is discarded. Then, within each sub-frame, for each listened beacon, the RSSI is filtered, to remove the fast fading component, and averaged. These RSSI values are used to calculate the distances between each beacon for a single scanning sub-frame using the obtained propagation parameters. Our proposed trilateration method is applied and positioning estimates are refined using Kalman Filtering. Except for parameters request, all the positioning calculations are performed, locally, on the target.

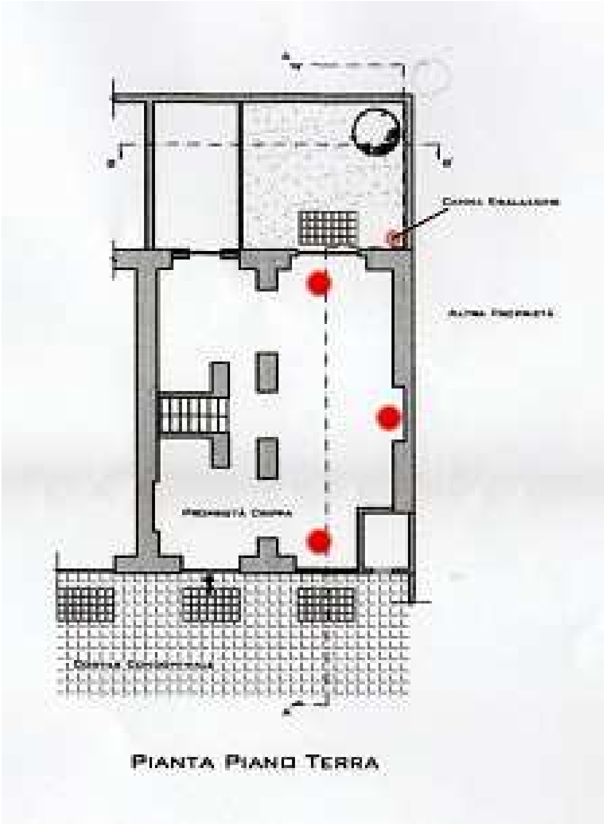

Figure 4.4: Office environment

3 Practical tests

In this section, some tests were done in two specific environments and at different conditions. These settings are explained in the following part, describing also system performance. They reflect some of the most common conditions which can be faced in indoor venues. They are useful to provide a concrete evaluation of how our IPS solution works and relate it with performance which are documented in literature, where errors are mostly limited in a range between 2 and 4 meters [60] [61]. Unfortunately, most of documented comparable systems (range-based) are mainly based on classic Bluetooth technology.

3.1 Office Environment

We tested our system in an office environment time. The room is 3.6m × 9.6m and 3 beacons were placed in the room on walls on different sides (see Figure 4.4).

Beacon ID	x	y
CCFF889944AA	1.5	1.4
AACC33DD6688	3.2	4.1
EE44556677DD	1.3	8.4

Table 4.2: Beacons placement in Office Environment

ε	0.907	0.542	0.485	1.695	1.240	1.933	1.452	2.056	1.352	1.668	1.906

Table 4.3: Positioning Errors, ε_{pos}, in meters, in Office environment after Kalman Filter Refinement

ε	1.230	0.865	0.708	2.018	1.710	2.258	1.920	2.523	1.480	2.138	2.241

Table 4.4: Positioning Errors, ε_{pos}, in meters, in Office environment before Kalman Filter Refinement

We performed our tests with people moving in the room, other BLE devices turned on and Wi-Fi connection up and running. Beacons were placed at specific positions (see Table 4.2). Every beacon has an associated ID and exposes a specific service. Beacons can listen only to other beacons advertising a specific BLE service (identified by a unique UUID), in order to avoid the scan for RSSI from external and non proper devices. After having placed beacons in the room, the calibration routine was started. Beacons turn from advertising to central state every three minutes. Positioning was performed using a smartphone (BLE enabled) and data was then post processed using MATLAB tools. Positioning process lasts 30 seconds and within this period RSSI samples from surrounding anchors are collected. In particular, the scanning period - as previously described - was segmented in sub-frames having an equal extent. As detailed in Section 4.2.4, it can happen that a beacon might be in central mode while user terminal performs scans. So, in that case, data from three beacons are not available. The specific sub-frame having less than three reference nodes are listened is then discarded.

Results

In this part, an analysis of our proposed method is described. In particular, 11 positioning attempts were performed at different points of the room and, accordingly to the definition of accuracy (see Section 2.5), obtained results are presented in Table 4.3 and Table 4.4. The whole test lasted 30 minutes. As could be noted, mean error is 1.385 meters.

Beacon ID	α	PL_{d0}
CCFF889944AA	1.452	-63.667
AACC33DD6688	1.306	-59.181
EE44556677DD	3.21	-53.899

Table 4.5: Office Environment - Particle Filter parameters for Test 1

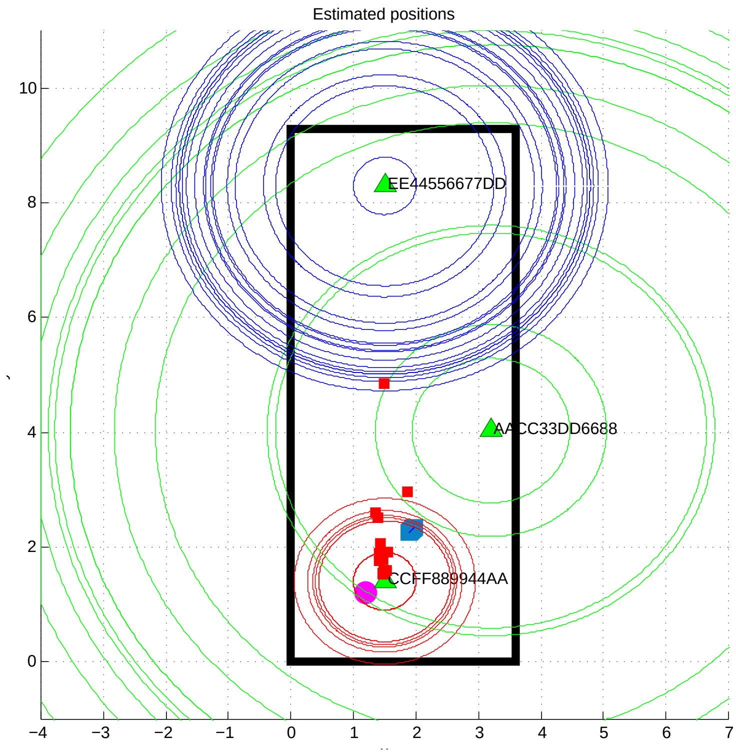

Figure 4.5: Office environment - Positions for Test 1

For what concerns precision, the 55% of the obtained positions we have an error which is below 1.5 meters while, for the 72% it is below 1.7 meters. In this scenario, beacons density is $\frac{3}{34.56mq} = 0.029$ *beacons/mq*. It can be observed that beacons positioning was done without a precise evaluation of the coverage of the anchors in order to simulate real scenario, when final users place them intuitively.

A deep analysis of the obtained positioning results is described, in the remaining part of this section, considering positioning runs number 1, 5, 9 (over 11).

In the first case (Figure 4.5), real user position (magenta dot in plot) is very close to beacon CCFF889944AA. According to the Particle Filter, used for calibration, when positioning happens the evaluated parameters are described in Table 4.5.

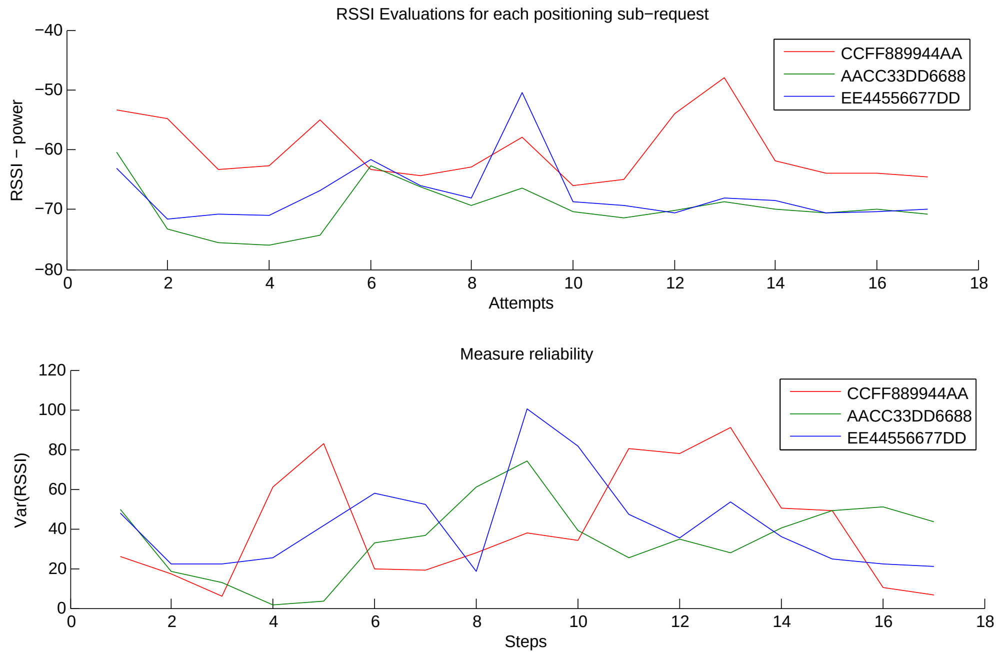

Figure 4.6: Office environment - RSSI mean value and variance for Test 1

Due to close obstacles, PL_{d0} was higher for CCFF889944AA. The same holds for AACC33DD6688. An obstructed link between EE44556677DD and other reference nodes results in a higher value for α. So, it could be noted how closeness to a specific anchor is reflected into a more stable localization near that reference. This clearly results considering received RSSI values (Figure 4.6). Moving obstacles between calibrations influence propagation from beacon EE44556677DD, since it leads to an underestimated distance. This aspect can not be handled in a deterministic way, but it is intrinsic in the positioning problem applied to real life contexts.

According to the calibrated path loss model, RSSI from CCFF889944AA is the highest between the three listened values and this results in a near estimated distance. However, RSSI signal for that beacon has a not negligible dispersion, caused by aforementioned near-field obstacles' interferences. On the other hand, the farthest anchor shows the highest peak in variance with respect to the maximum values for other beacons. This is related to an higher probability of undergoing sever multipath effects in the propagation link.

The Kalman Filter is used to control noisy measurements. In particular this reduces the effect of high RSSI variability through time, in an iterative fashion. This results in a reduced error adopting a Kalman filter in the positioning steps. Indeed, ε_{pos} varies from 1.230 meters to 0.907 meters adopting it.

Beacon ID	α	PL_{d0}
CCFF889944AA	1.352	-63.824
AACC33DD6688	1.243	-59.335
EE44556677DD	3.087	-53.162

Table 4.6: Office Environment - Particle Filter parameters for Test 2

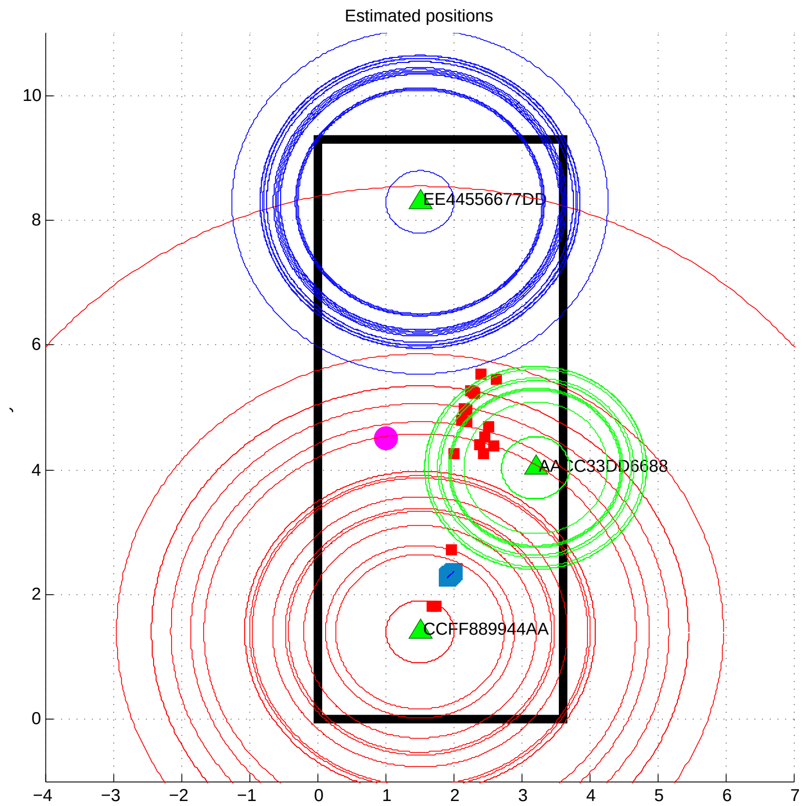

Figure 4.7: Office environment - Positions for Test 2

This results into an higher density of estimated positions near the real position of the user (red squares). In particular, comparing the output of our algorithm with the results provided by a combination of Min-Max positioning algorithm and a LSQ calibration process (see Section 2.4), shown on map as blue squares, it is possible to clearly highlight how the proposed approach outperforms by 30% the MinMax-LSQ approach.

In the second case (Figure 4.7), real user position (magenta dot in plot) is away, on average, from each beacon and it is close to the room center. According to the Particle Filter used for calibration, when positioning happens the evaluated parameters are described in Table 4.6.

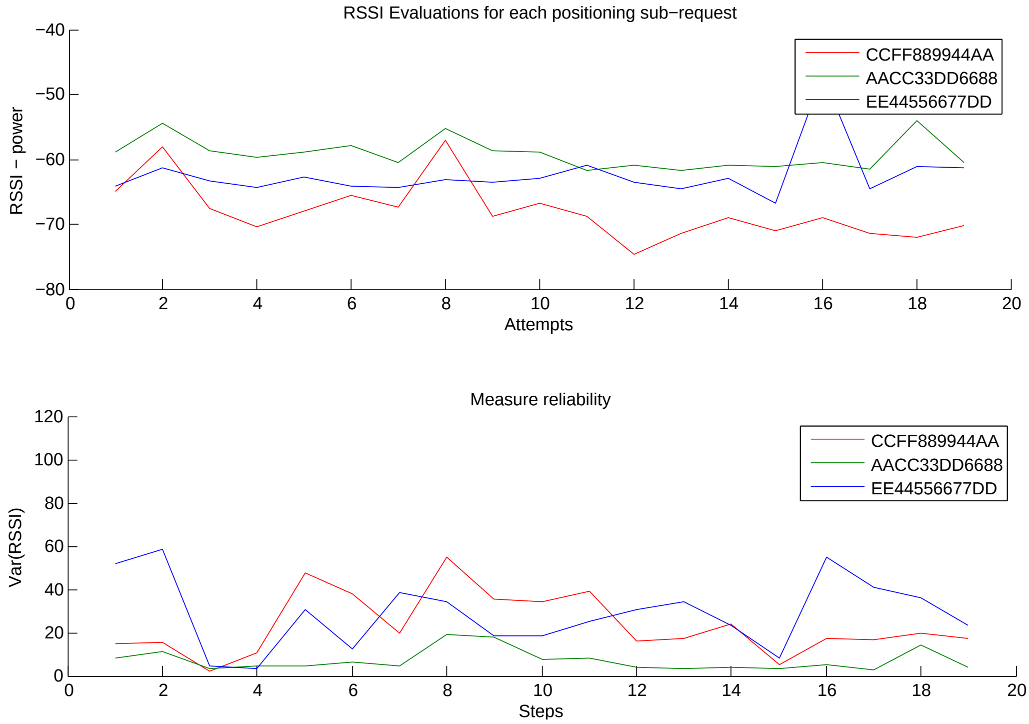

Figure 4.8: Office environment - RSSI mean value and variance for Test 2

It could be observed that Particle Filter parameters do not change so much between the two positioning steps (10 minutes delay). This can be seen comparing Table 4.5 with Table 4.6. The comparison demonstrates how rapid changes over time do not significantly influence the calibration process, which aims at extracting a set of parameters that fit the most commonly observed propagation conditions in the environment.

In this situation, the nearest beacon is AACC33DD6688 at 2.61 meters. Other two beacons have a comparable distance. In particular, near-field obstacles make distance estimates from CCFF889944AA more unstable. This clearly results considering received RSSI values (Figure 4.8).

According to the calibrated path loss model, in this case, there is not a clear, stronger signal, so proximity corrections does not trigger in this case. CCFF889944AA shows the lowest signal power and will result in a farthest positioning. However, RSSI signal for that beacon has a not negligible dispersion, caused by aforementioned near-field obstacles' interferences. The same holds for EE44556677DD. The most stable mesurement, with respect to signal variance, is related to beacon AACC33DD6688. This causes a nearer positioning with respect to this beacon.

Beacon ID	α	PL_{d0}
CCFF889944AA	1.229	-63.923
AACC33DD6688	1.204	-60.426
EE44556677DD	3.001	-52.401

Table 4.7: Office Environment - Particle Filter parameters for Test 3

Final outcomes are characterized by an higher density of estimated positions (red squares) near the real position of the user. In particular, comparing again the output of our algorithm with the results provided by Min-Max/LSQ (blue squares), it has an improved accuracy of 48%. Kalman adoption makes ε_{pos} vary from 1.71 meters to 1.24 meters adopting it.

In the last case (Figure 4.9), real user position (magenta dot in plot) is very close to beacon EE44556677DD. According to the Particle Filter,used for calibration, when positioning happens the evaluated parameters are described in Table 4.7.

In particular, it should be noted that parameters evolution is almost stable compared with Table 4.5 and Table 4.6, since it is not considering temporary variations in the calibration steps. Morever the intended configuration is similar to the first presented in this test, having a smaller distance with respect to a specific beacon. In this case, it is EE44556677DD. Again, it could be observed how closeness to a specific anchor is reflected into a more stable localization, near that reference. This clearly results considering received RSSI values (Figure 4.10).

According to the calibrated path loss model, listened RSSI from EE44556677DD is the highest between the three listened values and this results in a near estimated distance. With respect to the first case, a more remarked difference between collected values can be noted. However, RSSI signal for that beacon has also a reduced dispersion, caused by clearer listened signal. On the other hand, the farthest anchors shows a comparable values for their variance. This reflects real distances.

This results to an higher density of estimated positions (red squares) near the real position of the user. In particular, also in this case, improvements with respect to Min-Max/LSQ have a similar trend compared to the first case. Adoption of Kalman Filter, make also ε_{pos} improve from 1.48 meters to 1.352 meters.

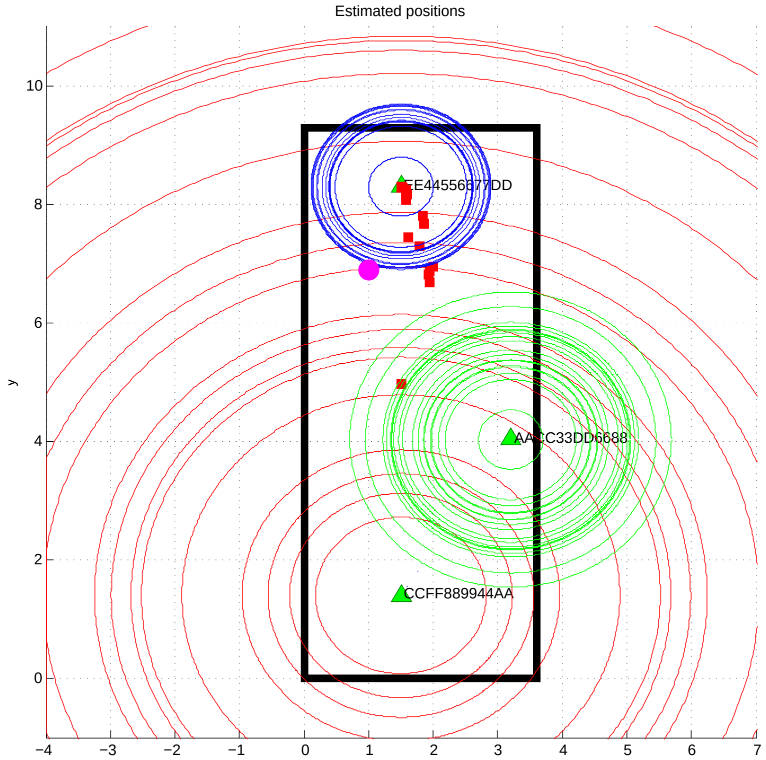

Figure 4.9: Office environment - Positions for Test 3

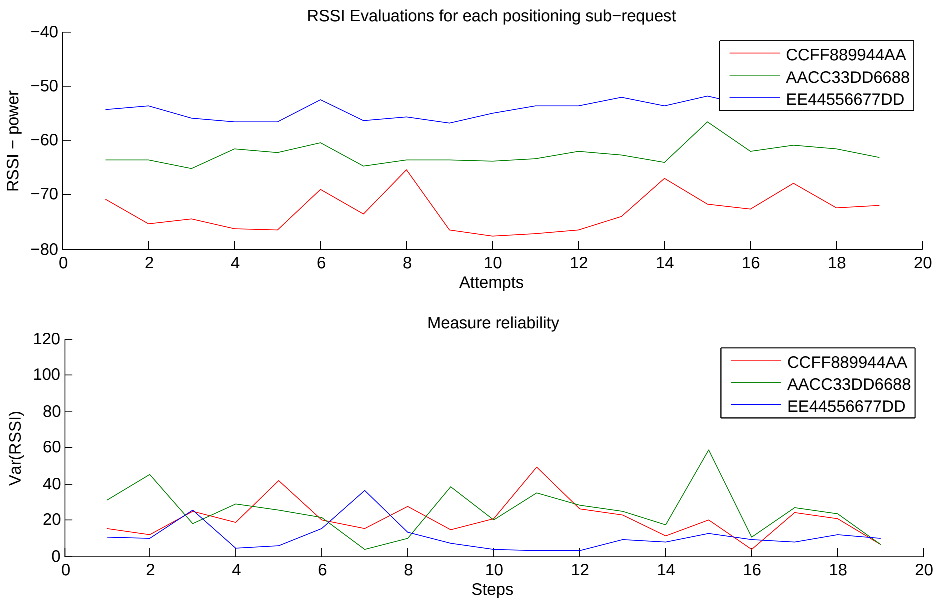

Figure 4.10: Office environment - RSSI mean value and variance for Test 3

Figure 4.11: Home environment

Beacon ID	x	y
CCFF889944AA	3.0	0.0
AACC33DD6688	3.8	12
EE44556677DD	4.3	4.8

Table 4.8: Beacons placement in Home Environment

3.2 Home Environment

We tested our system in an home environment. Room is 8m × 12m and 3 beacons were placed in the room (See Figure 4.11). Two beacons were placed on different side walls, while a beacons was placed on the rooftoop, at the same height of the others and perpendicularly disposed with respect to the floor, with an antenna orientation ortogonal to the other two. In this case, we are considering a mansard (high percentage of wood present).

We performed our tests with no other people moving in the room. We adopted the same beacons as in the Office test and they were placed at specific, fixed positions (see Table 4.8).

ε	0.934	1.270	0.659	0.730	1.917	4.103	1.531	1.014	1.238
	3.593	0.634	1.311	0.898	3.629	3.119	1.470	3.026	-

Table 4.9: Positioning Errors, ε_{pos}, in meters, in Home environment after Kalman Filter refinement

ε	1.154	1.433	0.879	0.950	2.228	4.424	1.880	1.284	1.508
	3.914	0.840	1.591	1.148	3.950	3.430	1.690	3.337	-

Table 4.10: Positioning Errors, ε_{pos}, in meters, in Home environment without Kalman Filter refinement

After having placed beacons in the room, the calibration routine was started. Beacons had been turning from advertising to central state every three minutes. Positioning was performed using a smartphone (BLE enabled) and data was then post processed using MATLAB tools. Positioning process lasted 30 seconds and within this period RSSI samples from surrounding anchors are collected. In particular, scanning period - as previously described - was segmented in sub-frames having an equal extent. Moreover, it can happen that a beacon might be in central mode while user terminal performs scans. So, in that case, data from three beacons are not available. The specific sub-frame having less than three reference nodes are listened is then discarded.

Results

In this part, an analysis of our proposed method is described. In particular, 17 positioning attempts were performed and results are presented in Table 4.9 and Table 4.10. Test lasted 60 minutes. As could be noted, the mean error is 1.83 meters. For what concerns precision, the 58% of the obtained positions we have an error which is below 1.5 meters while, for the 64% is below 1.7 meters. In this scenario, beacons density is $\frac{3}{96mq} = 0.031$ *beacons/mq*. It can be observed, as in previous test, that beacons positioning was done without a precise evaluation of the coverage of the anchors in order to simulate real scenario, when final users place them intuitively.

A deep analysis of the obtained positioning results is described, in the remaining part of this section, considering positioning runs number 2, 7, 11 (over 17).

In the first case (Figure 4.12), real user position (magenta dot in plot) is in the near field of beacon AACC33DD6688. Considering Particle Filter, used for calibration, when positioning happens the evaluated parameters are described in Table 4.11.

Beacon ID	α	PL_{d0}
CCFF889944AA	2.254	-62.991
AACC33DD6688	2.756	-62.987
EE44556677DD	3.87	-62.899

Table 4.11: Home Environment - Particle Filter parameters for Test 1

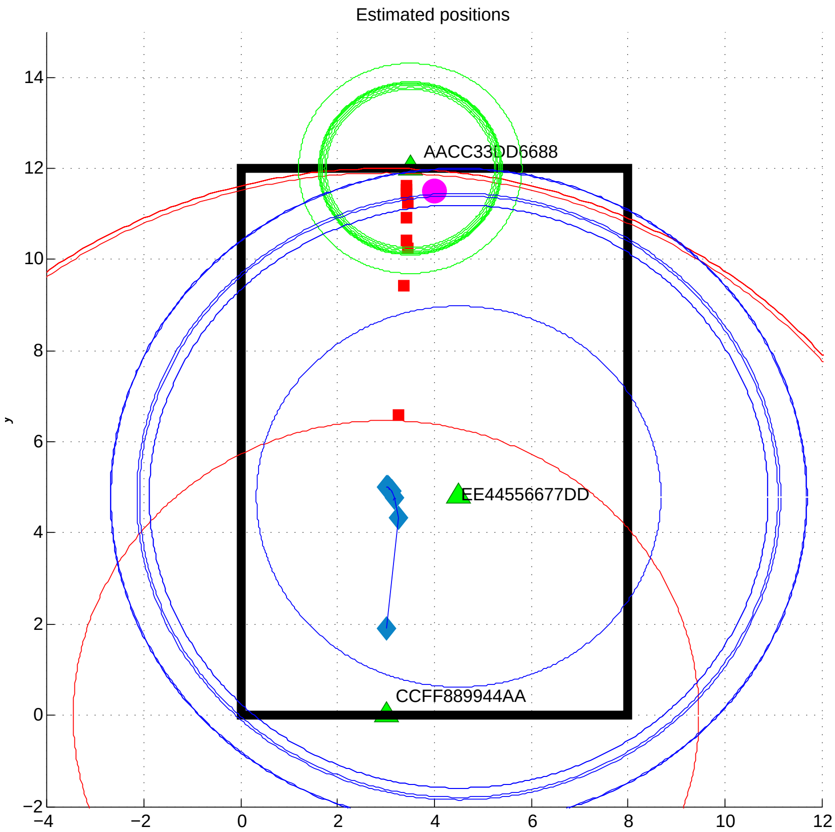

Figure 4.12: Home environment - Positions for Test 1

Since no near obstacles were detected close to the beacons in the room, PL_{d0} was almost constant within the room. Path loss exponent for EE44556677DD was higher with respect to others since it considers its antenna orientation (ortogonal with respect other beacons' antennas and allows to compensate this effect. See Section 3.2.3).

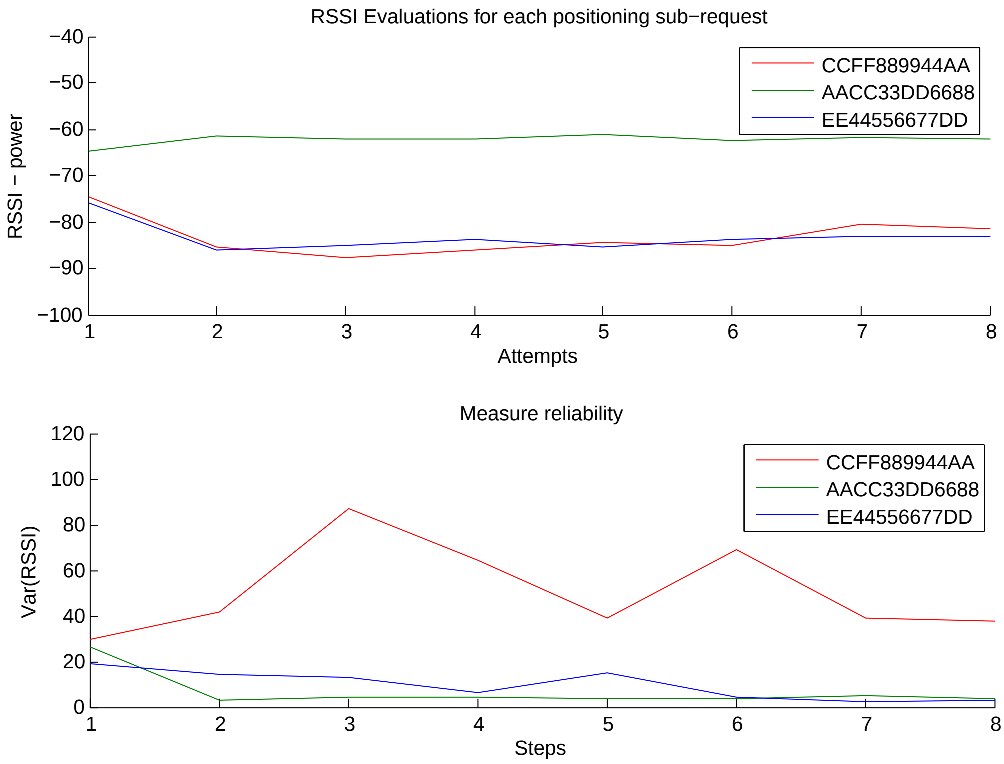

Figure 4.13: Home environment - RSSI mean value and variance for Test 1

So, in a pretty regular way, closeness to a specific anchor is reflected into a more stable localization near that reference. This clearly results considering received RSSI values (figure 4.13). Stronger value is received from nearest beacon, while mid-power received values corresponds to intermediate beacon and weakest listened anchor results in a greater distance. Since no relevant obstacles were found in the environment, this scenario is compliant to standard (ideal) propagation laws.

According to the calibrated path loss model, listened RSSI for AACC33DD6688 is the highest between the three listened values and this will result in a near estimated distance. Moreover, RSSI signal for that beacon has a minimal dispersion, caused by the static configuration for the venue. On the other hand, the farthest anchor shows the highest peak in variance with respect to the others, due to a more probable fading effect. This results to an higher density of estimated positions near the real position of the user (red squares).

Beacon ID	α	PL_{d0}
CCFF889944AA	2.258	-62.993
AACC33DD6688	2.713	-62.815
EE44556677DD	3.99	-62.990

Table 4.12: Home Environment - Particle Filter parameters for Test 2

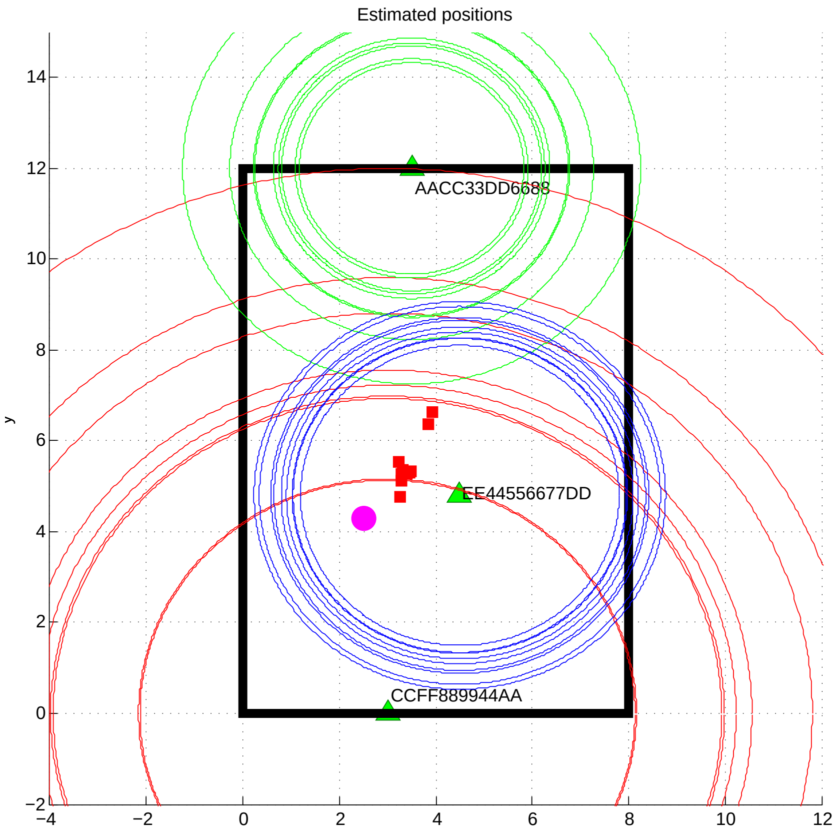

Figure 4.14: Home environment - Positions for Test 2

In particular, comparing the output of our algorithm with the results provided by a Min-Max/LSQ (blue squares), it clearly highlights a 49% improvement in positioning accuracy. In addition, Kalman Filter is used to control noisy measurements. In particular, ε_{pos} varies from 1.433 meters to 1.270 meters adopting it.

In the second case (Figure 4.14), real user position (magenta dot in plot) is in central area of the room. It could be observed that filter parameters are almost the same. This is mostly related to the absence of great obstacles in this scenario, so fading related to the home furniture is averaged and it does not cause rapid changes in the calibration procedure. Evaluated parameters are described in Table 4.12.

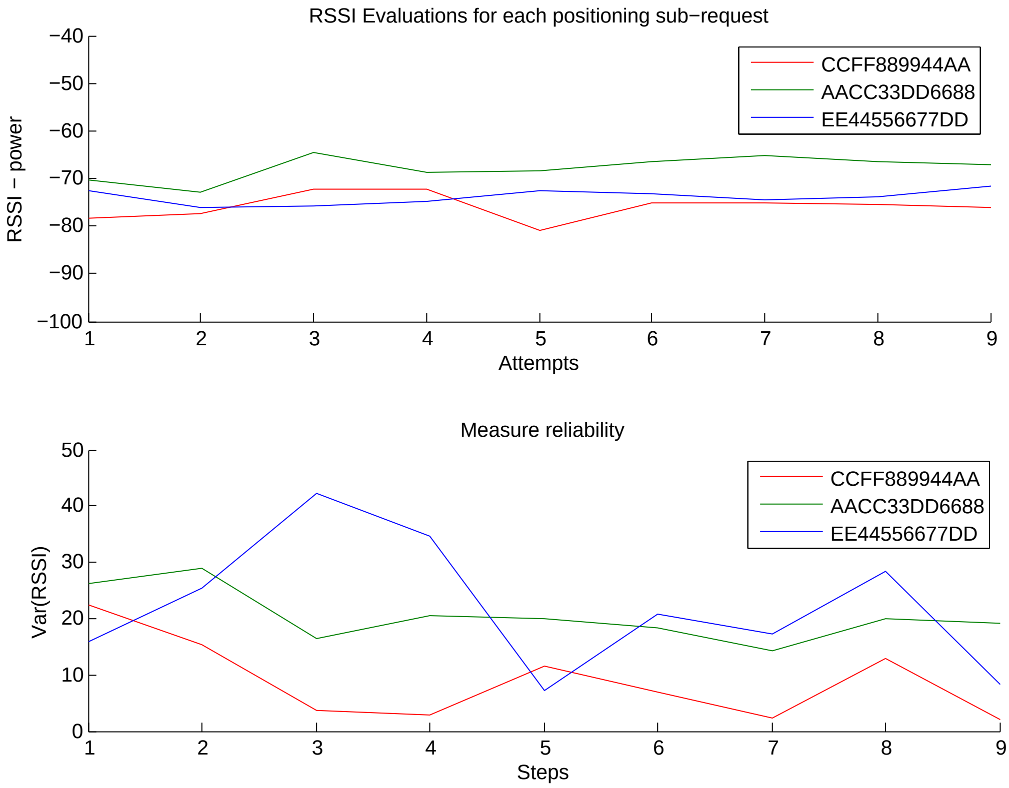

Figure 4.15: Home environment - RSSI mean value and variance for Test 2

In this situation, nearest beacon is EE44556677DD at 1.8 meters. Other two beacons have a comparable distance.

According to the calibrated path loss model, in this case, and comparing with the center point in office venue, there is not a clear, stronger signal, so proximity corrections does not trigger in this case. Signals are comprised in a 10dB band and distance estimations are mainly based on calibration parameters. However, RSSI signal for the nearest beacon has a not negligible dispersion, which can be caused also from the human presence in the direct propagation trajectory. The most stable mesurement, with respect to signal variance, is related to beacon CCFF889944AA. This causes a nearer positioning with respect to this beacon, according to real position. Kalman adoption makes ε_{pos} vary from 1.88 meters to 1.531 meters adopting it.

In the last case (Figure 4.16), real user position is displayed as a magenta dot in plot. Considering Particle Filter, used for calibration, when positioning happens the evaluated parameters are described in Table 4.13.

In particular, it should be noted that parameters evolution is almost stable and

Beacon ID	α	PL_{d0}
CCFF889944AA	2.242	-62.970
AACC33DD6688	2.979	-62.935
EE44556677DD	3.95	-62.987

Table 4.13: Home Environment - Particle Filter parameters for Test 3

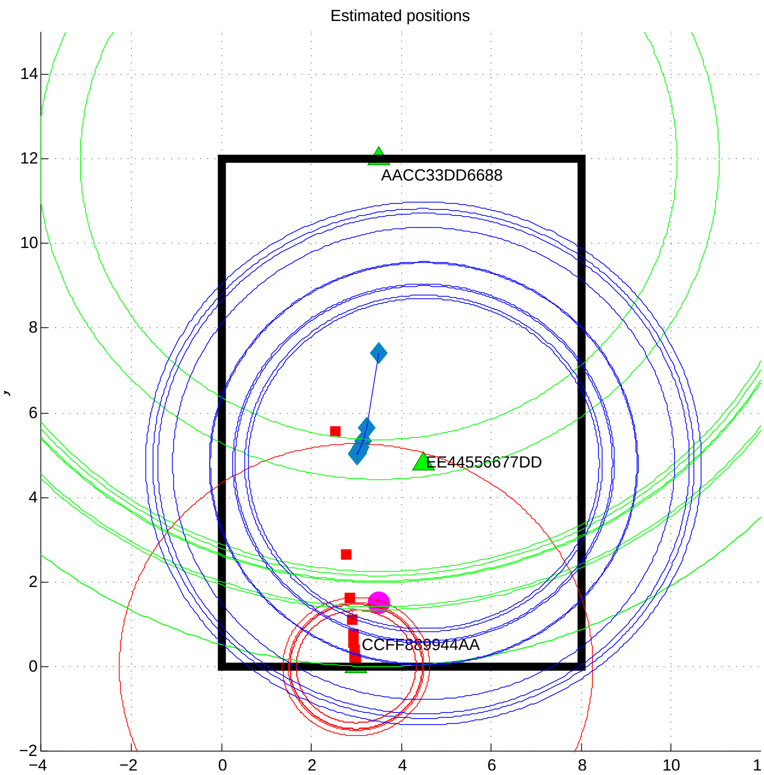

Figure 4.16: Home environment - Positions for Test 3

limited, since it is not considering temporary variations in the calibration steps. Morever the intended configuration is similar to the first presented in this test, having a smaller distance with respect to a specific beacon. Again, it could be observed how closeness to a specific anchor is reflected into a more stable localization, near that reference. This clearly results considering received RSSI values (figure 4.17).

According to the calibrated path loss model, listened RSSI for CCFF889944AA is the highest between the three listened values and this will result in a near estimated distance. However, RSSI signal for that beacon has also a very limited dispersion, caused by clearer listened signal. In particular, also in this case, great improvements are present with respect to Min-Max/LSQ. This have a similar trend compared to the first case (blue squares, more than 70%). Adoption of Kalman Filter, make also ε_{pos} improve from 0.95 meters to 0.634 meters.

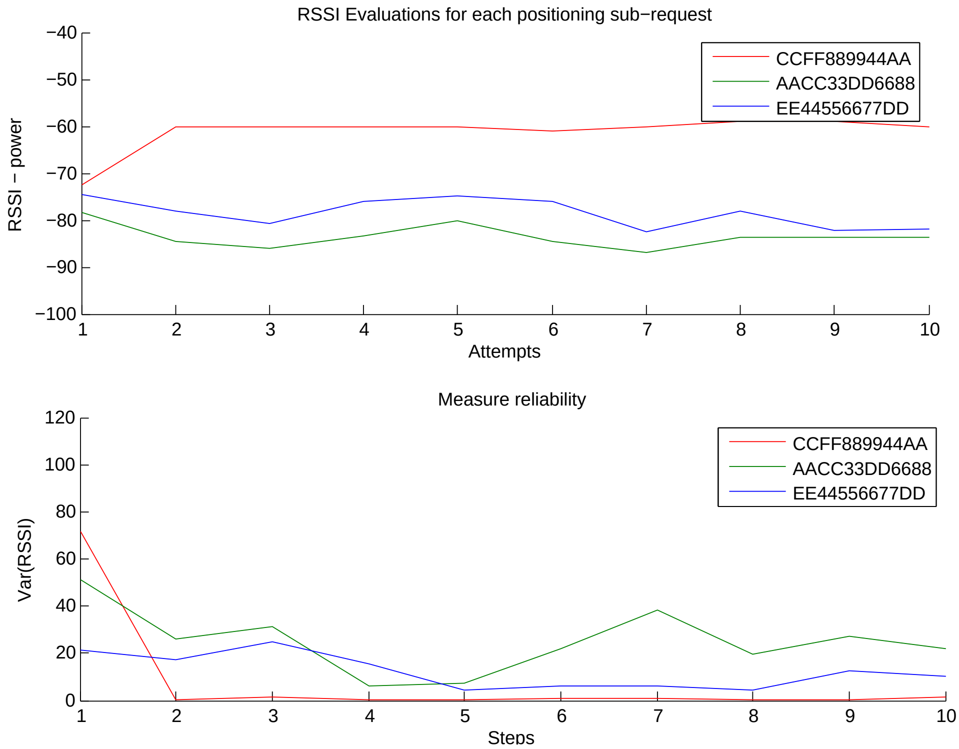

Figure 4.17: Home environment - RSSI mean value and variance for Test 3

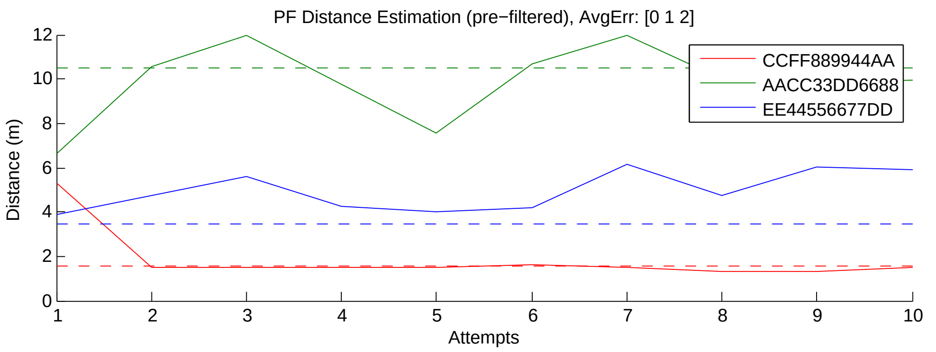

Figure 4.18: Home environment - Distance estimation (Real vs. Particle Filter) for Test 3

4 Conclusions

This chapter provided an overview of the achieved results and system practically built. In particular, in Section 4.2, a detailed description of the main components of our proposed IPS is provided: *beacons*, *base station* and mobile (*target*) node. Accordingly to what formally introduced in Chapter 2, our goal is to practically find the position of a target node in an environment, exploiting transmitting surrounding beacons. A room is continuously undergoing a process of path loss model calibration, which can be done (remotely or locally) by a base station. Base station embodies all the algorithms and methods described in Chapter 3, to treat RSSI values, its high variability and beacons displacement. Some implementation details are also included. In Section 4.3, some tests were presented in different environments. In particular, our system was tested in Office and Home environments. Obtained accuracy in this situations was better (at least, comparable) with respect to other systems in literature having a reduced infrastructure complexity (reduced number of beacons). Moreover, described system outperforms some of the classical methods adopted in literature, like Min-Max for positioning or Least Squares estimators for path loss modeling.

Chapter 5

General Conclusions

This work has aimed to propose an innovative approach to the location of a mobile device in indoor environments exploiting Bluetooth Low Energy (BLE) wireless technology. The possibility of identifying the position of a mobile terminal in a closed space is a research field which gained an increasing interest particularly in the vast scenario of Location Based Services, bringing an added value for both the user and service providers. In the implementation of the positioning mechanism, BLE was used since it is becoming increasingly widespread across commonly available terminals. The approach has shown, in tests, to be efficient in relation to the type of the considered scenarios. The contexts of the localization system are that of indoor venues (home, office) in which the location of people is evaluated. To determine whether Bluetooth Low Energy is a viable localization technology for this application, some minimal requirements for our system properties were set. In particular, requirements for our system are:

- Be auto-adaptive to the environment;
- Require minimal configuration;
- Uses a limited amount of beacons in the room.

Based on these requirements the selected metric for Bluetooth Low Energy that can be used to estimate target locations is the Received Signal Strength Indicator (RSSI), which is an information that can be extracted from most of the BLE-enabled system. In the calibration phase, according to the measured data, the system calculates path loss exponent value and path loss at reference distance. We can use path loss model for comparing the actual distance and estimated distance. On the contrary a set of uncontrollable parameters has been identified that may possibly have a negative impact on localization accuracy. These parameters are:

- Varying levels of transmitting power for different target devices;
- Unknown height of the target devices;
- Human presence when performing positioning.

It is important to point out that solutions described in literature do not usually provide the environmental adaptability required in the real life applications, when dealing with indoor venues. The most probable cause of this discrepancy is that the commonly considered Log-Normal Shadowing (LNS) model does not consider parameters to be location dependent, while this appears to be the case in the test environments. This idea is reinforced by the fact that the estimation of LNS model parameters using linear regression did not result in the best localization accuracy. For instance, better localization results were obtained using Bayesian and statistical methods. In addition, Particle Filter has the ability to incorporate specific types of prior knowledge, which is proved to be useful and greatly reduces some effort in channel characterization. Also relative orientation between target devices and the beacons antennas has commonly been considered as a limitating aspect for the overall accuracy.

This thesis, proposes a path loss model characterization based on the use of a Particle Filter to estimate parameters. It was shown how our approach results in a better positioning accuracy with respect to linear regression and bounding-box positioning. Indeed, an average improvement of 30-40% was found with respect to the aforementioned approaches. Moreover it was also noted that, considering a constant minimal number of beacons, the error increases nearly proportional to the increase of the size of the room. The system has a fairly good precision with 50% probability of being within ∼1.5 meters of the actual position when the mobile terminal, performing positioning does not move.

1 Future Works

In our work, the lognormal path loss model is used to estimate the distance inside an indoor environment. Some issues could arise when considering multi-rooms environment. In particular, wall fading can result in unforeseen results. Some models are known for taking into account indoor partitions. One of these, also known as ITU Model for Indoor Attenuation, is a radio propagation model that estimates the path loss inside a room or a closed area inside a building delimited by walls of any form. Suitable for appliances designed for indoor use, this model approximates the total path loss an indoor link may experience. Another approach can be based on considering a double slope path loss propagation model. In particular, slope varies when radio waves encounter an obstacle. To practically estimate the attenuation induced by partitions, a deep study about wall influence on RSSI should be carried on.

Another relevant aspect is related to the choice of a positioning algorithm which can be less influenced by beacons' placement. A concrete solution can be represented by

MultiDimensional Scaling (MDS). In particular, MDS is a localization method that transforms proximity information into geometric embedding. Practically, MDS is a set of statistical techniques used in information visualization for exploring similarities or dissimilarities in data. An MDS algorithm starts with a matrix of item-item dissimilarities, then assigns a location to each item in d-dimensional space, where d is specified a priori (2D or 3D). It can reduce more the human intervention. MDS has proven to be robust to disturbing factors such as erroneous beacons' positions or missing connectivity data.

Another critical aspect to be considered in order to practically deploy our proposed system is hardware implementation. Our idea is based on an automatic role switching (advertising and central modes) in a beacon while performing calibration actions. We have realized that no other solutions on market are available implementing inter-beacons communication. For instance, Estimote beacons declare that their beacons have the potential to support this feature, but it is not available on their SDK (both for Android or iOS). In particular, this solution will require a routing mechanism between anchors in order to get calibration messages flowing from a beacon to another while performing calibrations and arrive at base station (local or remote) to perform path loss model evaluation. Beacons are intended to last for a long time so no heavy computations or continuous active state should be considered in order to not reduce and overconsume their battery life.

A final proposal could deal with a moving target (and then to a dynamic positioning application) instead of a static positioning process. This could be done by integrating the single positioning step into an interative and repeated positioning process in order to support user movements. Positions refinements, i.e., Kalman filters, should be adapted to this case.

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