Practical Implementation of a Hybrid Indoor Localization System

Leonardo Sestrem de Oliveira

Dissertation presented to the School of Technology and Management of Bragança to obtain the Master Degree in Industrial Engineering. Work developed during the double degree exchange program between the Instituto Politécnico de Bragança (IPB) and the Universidade Tecnológica Federal do Paraná (UTFPR).

Work oriented by:
Professor PhD Paulo Leitão
Assistant Professor D.Sc. Ohara Kerusauskas Rayel

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Dedication

I dedicate this work to everybody that helped me finish this project in one way or another, in special to my parents, Arlete and Valdir, my sister, Estefany, my girlfriend, Laryssa, professors and friends.

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Instituto Politécnico de Bragança (IPB) and Universidade Tecnológica Federal do Paraná (UTFPR) for the opportunity of being part of the exchange program between them.

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To the professors of IPB and UTFPR, and to each employee of IPB and UTFPR that were part of my development as student and researcher.

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Abstract

Indoor localization systems occupy a significant role to track objects during their life cycle, e.g., related to retail, logistics and mobile robotics. These positioning systems use several techniques and technologies to estimate the position of each object, and face several requirements such as position accuracy, security, coverage range, energy consumption and cost. This master thesis describes a real-world scenario implementation, based on Bluetooth Low Energy (BLE) beacons, evaluating a Hybrid Indoor Positioning System (H-IPS) that combines two RSSI-based approaches: Multilateration (MLT) and Fingerprinting (FP). The objective is to track a target node, assuming that the object follows a linear motion model. It was employed Kalman Filter (KF) to decrease the positioning errors of the MLT and FP techniques. Furthermore a Track-to-Track Fusion (TTF) is performed on the two KF outputs in order to maximize the performance. The results show that the accuracy of H-IPS overcomes the standalone FP in 21%, while the original MLT is outperformed in 52%. Finally, the proposed solution demonstrated a probability of error < 2 m of 80%, while the same probability for the FP and MLT are 56% and 20%, respectively.

Keywords: Fingerprinting; Multilateration; Indoor Positioning System; Kalman Filtering; Sensor Fusion.

Resumo

Os sistemas de localização de ambientes internos desempenham um papel importante na localização de objectos durante o seu ciclo de vida, como por exemplo os relacionados com o varejo, a logística e a robótica móvel. Estes sistemas de localização utilizam várias técnicas e tecnologias para estimar a posição de cada objecto, e possuem alguns critérios tais como precisão, segurança, alcance, consumo de energia e custo. Esta dissertação de mestrado descreve uma implementação num cenário real, baseada em Bluetooth Low Energy (BLE) *beacons*, avaliando um Sistema Híbrido de Posicionamento para Ambientes Internos (H-IPS, do inglês *Hybrid Indoor Positioning System*) que combina duas abordagens baseadas no Indicador de Intensidade do Sinal Recebido (RSSI, do inglês *Received Signal Strength Indicator*): Multilateração (MLT) e *Fingerprinting* (FP). O objectivo é localizar um nó alvo, assumindo que o objecto segue um modelo de movimento linear. Foi utilizado Filtro de Kalman (FK) para diminuir os erros de posicionamento do MLT e FP, além de aplicar uma fusão de vetores de estado nas duas saídas FK, a fim de maximizar o desempenho. Os resultados mostram que a precisão do H-IPS supera o FP original em 21%, enquanto que o MLT original tem um desempenho superior a 52%. Finalmente, a solução proposta apresentou uma probabilidade de erro de < 2 m de 80%, enquanto a mesma probabilidade para FP e MLT foi de 56% e 20%, respectivamente.

Palavras-chave:*Fingerprinting*; Multilateração; Sistema de Localização para Ambientes Internos; Filtro de Kalman; Fusão de Sensores.

Contents

List of Tables

List of Figures

Acronyms

AoA Angle of Arrival.

AoI Area of Interest.

AP Access Point.

BLE Bluetooth Low Energy.

CDF Cumulative Distribution Function.

CISCO Cisco Systems, Inc.

CSMA/CA Carrier-Sense Multiple Access/Collision Avoidance.

FP Fingerprinting.

GNSS Global Navigation Satellite System.

GPS Global Positioning System.

H-IPS Hybrid Indoor Positioning System.

IoT Internet of Things.

IPB Instituto Politécnico de Bragança.

IPS Indoor Positioning System.

ISM Industrial, Scientific and Medical.

KF Kalman Filter.

KNN k-Nearest Neighbour.

MLT Multilateration.

NN Nearest Neighbour.

OLS Ordinary Least Squares.

PDF Probability Density Function.

PDU Protocol Data Unit.

RF Radio Frequency.

RFID Radio Frequency Identification.

RP Reference Point.

RPi Raspberry Pi.

RSSI Received Signal Strength Indicator.

TDoA Time Difference of Arrival.

TN Target Node.

ToA Time of Arrival.

ToF Time of Flight.

TTF Track-to-Track Fusion.

Tx Power Transmit Power.

UTFPR Universidade Tecnológica Federal do Paraná.

UWB Ultra Wide Band.

WKNN Weighted k-Nearest Neighbour.

WSN Wireless Sensor Network.

Chapter 1

Introduction

The value of the data plays a crucial role in the digital transition era, being noticed a huge amount of devices connected to Internet, aiming to exchange, share and store data, using Internet of Things (IoT) technologies. In fact, as estimated by Cisco Systems, Inc (CISCO), the number of connected objects to Internet will be 29.3 billion in 2023 [1]. The real interest behind the IoT are the capabilities it offers, promising to create a world where all objects are connected to the Internet and communicate with each other with minimal human intervention [2], [3]. The principal goal is to design a better world for humanity, where the surrounding objects recognize what the users desire, their preferences, and what their needs are, fulfilling all these factors automatically without an explicit instruction [4]. The IoT allows the interconnection between people and objects, anytime, anywhere, interacting with anything and anyone, over any path/network, and any service [5]. Figure 1.1 illustrates this definition more clearly.

The remarkable IoT applications can be divided into three macro categories: industry, environment and society [6]. Moreover, these principal topics can be classified in other subtopics like transportation, healthcare, industrial automation, and emergency situations when the human's decision is difficult. The IoT transforms traditional objects into smart ones, where every specific application (vertical market) interacts with independent services (horizontal market) through information flux gotten from sensors and actuators,

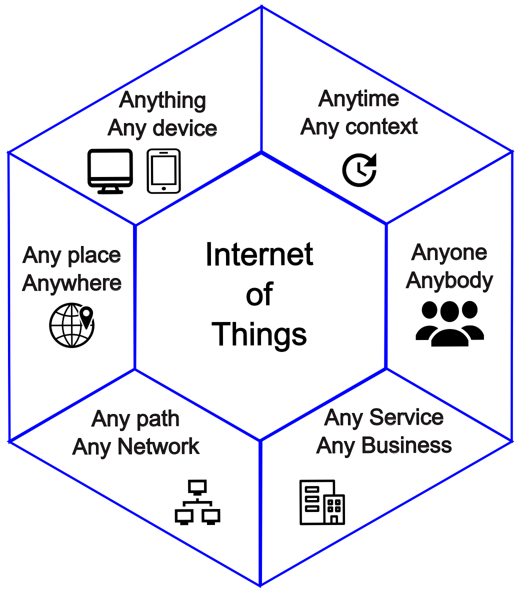


Figure 1.1: Definition of the Internet of Things.

which communicates with each other [7]. This transformation is illustrated in Figure 1.2, highlighting the notable potential of the IoT.

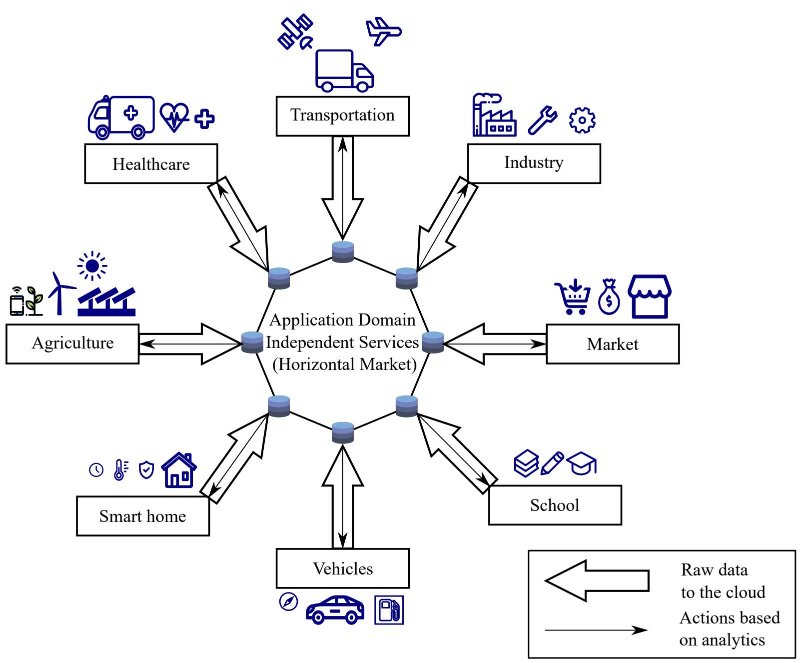


Figure 1.2: The overall picture of IoT emphasizing the vertical markets and the horizontal integration between them.

In this context, the data collection is performed employing a significant plethora of sensors that can make measurements in diverse types of variables, and uses IoT technologies to transmit the acquired information to Internet applications, typically forming a Wireless Sensor Network (WSN) [8]. The collected data may be analysed using Artificial Intelligence algorithms to extract knowledge, e.g., related to monitoring, diagnosis, prediction, optimization and planning, contributing to improve the systems' performance, decision-making tasks and people's life quality.

As presented in Figure 1.3, several applications, e.g., logistics, retail and mobile robotics, require data containing information related to the localization of objects, such as materials products, devices and people, demanding a dynamic association of the item position in the environment [6]. This localization process should consider the use of a variety of sensors to track the position of the objects and IoT technologies to transmit the information flow to other devices and applications.

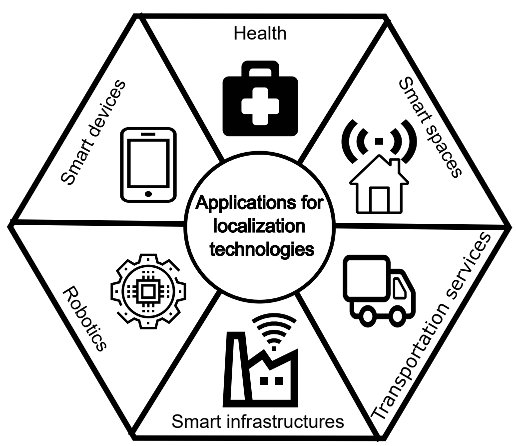


Figure 1.3: Application areas of Localization services.

In localization applications smart devices, such as cell phones, tablets and watches are generally used as source of location data [6]. The accuracy of these systems is dependent on the scenario in which they are implemented, from centimeters in gaming, to meters in indoor geolocation, to tens of meters for broadcasting advertisements in shopping malls or supermarkets [9].

Another possible application is localization for robotic platforms, where a variety of rolling and flying ground robots of different models can be employed in warehouse management, manufacturing, military missions, security, delivery, aerial photography and health [9]. Therefore, the information of robot's location is primordial. The accuracy requirements of moving robots vary according to context, size, and environment and can range from millimeters operating inside the human body, to a few meters for indoor areas and tens of meters for outdoor environments [10].

Hospitals present several possibilities to employ a location system, then providing safety, security, and also improving efficiency in the working environment [11]. Doctors can track their patients, besides it is possible to locate commonly used equipment and specialized tools, such as defibrillators to an emergency situation and surgery apparatus [12], [13].

From the importance of knowing the location of an object or person, combined with the concept of IoT comes the idea of Indoor Positioning System (IPS), which is a particular localization system aiming to locate objects or living beings inside an indoor setting [14].

Across indoor environments, the application of Global Navigation Satellite System (GNSS) is impaired since the satellites signals are subjected to a strong attenuation when crossing obstacles like walls, which are common in indoor settings [15]. Therefore, the popular outdoor solutions such as Global Positioning System (GPS), GLONASS, and COMPASS, do not obtain a good performance in indoor applications [16]. Additionally, these solutions present a high energy consumption and economic cost, besides this type of system usually gets a weak accuracy, with errors ranging around five meters, while for indoor applications the recommended average error is around one meter [11], [17].

In order to connect and communicate a plethora of sensors employed in a localization system, many options of wireless technologies are available in the market. The remarkable and commonly used technologies on IPS are: Wi-Fi, Radio Frequency Identification (RFID), Zigbee, Ultra Wide Band (UWB) and Bluetooth [18]. Before choosing a wireless technology some important factors need to be noticed such as cost, energy consumption, baud rate and transmission range [19]. It is relevant to know that each technology possesses advantages and drawbacks when employed in localization, so it depends on each context and objective of the system.

These technologies are also named Radio Frequency (RF) based systems and are the most adopted for localization because they cover a wider area with low-cost hardware [18]. Its signals are able to cross obstacles such as walls and human bodies, leading to a greater coverage area and suffering less attenuation when compared to satellite, in addition, the existing infrastructure can be reused, which reduces the cost of deployment in some cases [20]. These wireless technologies can be classified according to their operating frequency, which reflects on their coverage capabilities and resistance to obstacles [18].

Comparing the listed technologies, Wi-Fi and Bluetooth possess compact size and low-cost devices. While Wi-Fi is a strong candidate due to Access Point (AP) availability inside buildings, the implementation of these APs was done with signal range coverage in mind rather than location implementations [11]. In terms of energy consumption, the latest version of Bluetooth, the Bluetooth Low-Energy (BLE) is more efficient compared to other technologies such as Wi-Fi and Zigbee [18].

Recent advances on low power wireless technologies have revolutionized number of devices in the market. The BLE beacon based devices, for instance, are generally small, low cost, and configurable, what affords broadcasting data packets, also known as beacons [8]. This device offers the benefit of completely wireless hardware, which does not need an external power supply, furthermore, due to the compact size and availability of the BLE protocol in most mobile gadgets, these systems can be easily deployed and scalable, significantly with no impact on the infrastructure of the environment, what makes the beacon device a popular choice for IPS [21]. The beacons are very short-duration packets, which are either data or advertisement messages and can be received by all nearby BLE-enabled devices [11], [22]. Through the information of this data packet it is possible to obtain the signal intensity value, which can be employed in positioning algorithms to estimate the beacon transmitter location [23].

The BLE-based indoor location implementations mainly employ the following methods: radio propagation modelling and Fingerprinting (FP) [24]. In the first case, from a radio propagation model it is possible to calculate the distance between an unknown point and the AP. After, it is able to estimate the position, solving a system of equations through Ordinary Least Squares (OLS) method, such as in the Trilateration and Multilateration (MLT) techniques [19].

In the second approach, a scene analysis is done independent of angle or distance, collecting information or features from a scene or observation and then estimating the position of an object in an unknown point by matching or comparing the collected information with another in an existing database [20]. This collected feature is also known as fingerprint, which represents unique information in the setting, e.g., the received signal intensity [18]. From these fingerprints, it is able to estimate the location of objects by matching online measurements of the same characteristic collected before, comparing with the nearest possible location that corresponds to the saved values in the database [16].

Although these techniques can be employed in indoor environments, some challenges may affect the radio wave propagation in a location service, one of them is the presence of numerous obstacles that attenuate the signal [24]. Furthermore, this non-linearity and random effects caused by external factors, which are not covered in equations or models, may decrease the accuracy of the system [18].

The emerge of the smart age increased the demand for a reliable and efficient IPS, so the purpose of this work is to evaluate an indoor localization scheme in a real-world scenario, aiming at decreasing uncertainty and improving the accuracy of positioning estimates. Therefore, a set of localization techniques and an optimization tool, also known as stochastic filtering, will be used.

1.1 Introduction to the Problem

For Indoor Positioning Systems typically based on wireless technologies, the signals received and transmitted are susceptible to amplitude attenuation by the transmission medium. The main influencing factors are: shadowing, path loss and multipath [25]. The pathway between transmitter and receiver may be blocked by multiple obstacles such as walls, buildings, people and furniture. The signal variation due to absorption, reflection or diffraction of the wave by obstacles is namely known as shadowing [20]. A signal transmitted through a wireless channel is subjected to a random variation due to shadowing phenomena, this event can be considered as a random Gaussian variable with zero mean and standard deviation that attempts to represent the shadowing effects present in the real scenario, following a Log-normal distribution [19].

The path loss is related to the distance, is the reduction in power density of an electromagnetic wave as it propagates through space [25]. This attenuation is represented by a factor namely path loss exponent, which varies according the environment, its typical range value is between 2 to 6 dB [26]. Since it depends on the distance between the transmitter and the receiver, the longer the distance the higher the attenuation, and the greater the signal's fading effect.

The fading is the deviation of the attenuation that a signal experiences propagating on multipath. The fading varies with geographical position, time and radio frequency [25]. The multiple ways that the signal propagates between transmitter and receiver, can create either destructive or constructive interference, amplifying or attenuating the signal power at the receiver [19].

Since a signal propagated over a wireless channel is subject to interference and exhibits random behavior, this affects the position estimates coming from the localization algorithms. The signal fluctuations caused by these phenomena will reflect in the calculation of the distance estimate for the case of MLT, for example, while for FP it will influence the fingerprint saved in the database during the offline stage and make it difficult to accurately compare the values measured over the online phase. In both cases, it will introduce errors into the system and consequently decrease its accuracy.

In order to mitigate these drawbacks, a stochastic filter can be implemented over the collected measures, which provide an improvement in the Signal-to-Noise Ratio (SNR) and minimize the signal variation [21]. Furthermore, the filtering process also improves the accuracy of an IPS, decreasing the system's estimate error [24].

Each localization technique has its respective limitations and disadvantages, e.g., the

MLT is in charge of a model that is an abstraction of reality, which ends up not bringing a faithful characterization of the phenomena to which the signal propagation is subject. The FP, on the other hand, depends on a characterization of the environment, leading to the technique being somewhat fixed, making any change and the construction of a generic system difficult. On the face of it, the intended solution will integrate both methods (MLT + FP) resulting in a hybrid system in terms of positioning algorithm. In addition, the Kalman filter (KF) will be implemented in order to mitigate the random behavior of the signal for each isolated technique aiming to reduce the positioning error. Finally, a third filter will be inserted into the system by combining the two positions estimated from each algorithm through a sensor fusion method, in order to reach a better accuracy.

The objective is to achieve a low-cost positioning system solution, reaching an accuracy level higher than those presented by each technique isolated and performing experiments in a real-world scenario aiming to evaluate it.

1.2 Motivation

The fast growth of wireless communications and mobile devices has prompted a significant development of location-based applications [27]. In this context, the number of location systems has increased, as well as the investment in this type of market. Some of the benefited areas that employ this system are the health sector, industry, transport, engineering, robotics, security, and a number of other branches [14]. In order to satisfy the user's necessities, all the information about the items and people needs to be independent, providing a generalization capability to the positioning applications [24].

The implementation of an IPS needs to take into consideration that compared to an outdoor application the challenge and complexity increases, due to the numerous obstacles and the fluctuations that a signal undergoes propagating in a wireless channel. Therefore, it is extremely important that the system is reliable and accurate, ensuring interconnectivity between user and objects. For instance in WSNs, location is an extremely essential factor and is implemented in many fields, such as in food companies where it is necessary to carefully monitor the temperature of the food and know the location of each product in the warehouse, allowing sensor nodes to execute an appropriate decision, thus preventing the spoiling of the goods [25].

Some of the remarkable scenarios that the purposeful location system can be used are: (i) locating objects in warehouse applications, helping a company contributor or a robot locate products inside the building. (ii) Locating people inside a building, such as in a hospital, facilitating the process of locating a doctor or a patient. (iii) Customer location within a mall or supermarket to attract attention, for example, when a store needs to promote a new product while people are near its location. In addition, the store can send out advertisements about its offerings and indicate where the products are within the store.

1.3 Objectives

1.3.1 Overall Objective

The main objective of this work is to design and implement a Hybrid Indoor Positioning System (H-IPS) in a real-world scenario, aiming at a low-cost solution and improving the accuracy of the system by applying stochastic filtering on the estimates of RSSI-based techniques (multilateration and fingerprinting) and implementing sensor fusion between both methods.

1.3.2 Specific Objectives

The previous referred main objective can be divided in the following sub-objectives:

- Search information about state of art about FP and MLT techniques, as well as sensor fusion and KF;

- Develop a positioning system employing FP technique;
- Develop a positioning system employing MLT technique;
- Evaluate the localization systems in a real-world scenario using BLE technology;
- Implement a KF and evaluate its performance operating with each previous localization method;
- Perform sensor fusion over the results from previous techniques;
- Compare and evaluate the results from each method combination of the system;
- Compare the system performance with the simulated system.

1.4 Publications

This work has generated a paper entitled "Low-Cost Indoor Localization System Combining Multilateration and Kalman Filter" that was presented in the *30th IEEE International Symposium on Industrial Electronics (ISIE2021)* [28], helded in the Kyoto, Japan, 20-23 June 2021, and published in the proceedings of the conference.

1.5 Document Structure

Apart from this introduction, the dissertation contains four more chapters. The Chapter 2 presents the literature review and describes the localization techniques. The purposed solution is presented in the Chapter 3 showing the system model, the testbed and the developed algorithms. In the Chapter 4 the results are shown, compared and evaluated. Finally, Chapter 5 rounds the master thesis up with the conclusions and points out the future work.

Chapter 2

Literature Review

The localization represents the tasks such as tracking the user's position, planning routes and guiding the user through the route to reach the desired destination [15]. Generally, localization requires a technical infrastructure, support of multiple contexts and an appropriate and accurate topographic representation of the scenario. For outdoor contexts, these requirements have been achieved over the years by the development of GPS [29]. Although, GPS cannot be used in indoor contexts due to the fact that the signal is compromised by obstacles and its implementation is expensive [20]. Therefore, as illustrated in the Figure 2.1, indoor localization has more challenges than outdoor localization due to obstacles, the characteristic of the signal propagating in a wireless channel, and noise surrounding the environment [18].

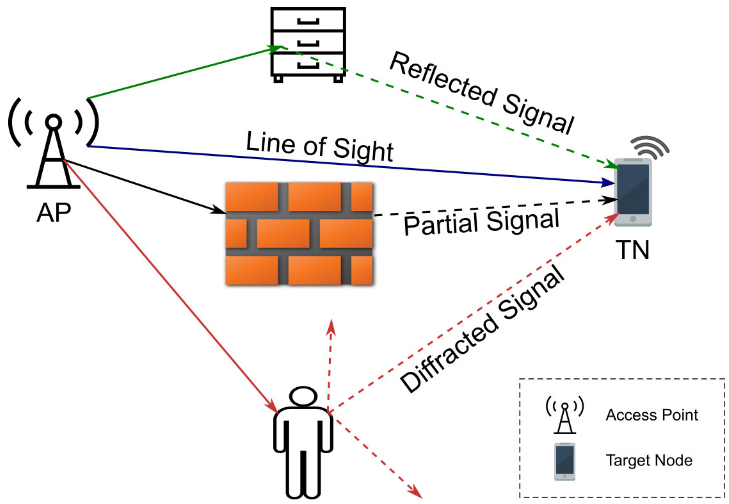


Figure 2.1: Impact of indoor environments on the propagation of a signal in a wireless channel.

A localization system originally is composed by three main stages [30], [31]: (i) Distance Estimation, (ii) Position Computation and (iii) Localization Algorithm. The distance estimation phase is responsible for estimating the relative distances / angles between the APs and the object also known as the Target Node (TN), using measurement techniques. Whereas the unknown coordinates are calculated in the position computation stage based on the available information of distances / angles and positions of the APs. The final step is the main part of the localization system, the localization algorithm, which determines how the information related to the position and distance is manipulated to allow most or all the objects to estimate their positions precisely. In addition, localization algorithm may embed other algorithms, in order to reduce possible errors and refine the position estimate.

The distance can be estimated through three conventional methods, including the Angle of Arrival (AoA), the Time of Flight (ToF), and the Received Signal Strength Indicator (RSSI). The location systems based on RSSI, typically adopt that the signal is transmitted according to a propagation model, from the RSSI values collected allow to obtain the distance between the APs, also known as anchor nodes, and the object [19]. Nevertheless, the models adopted in the system must consider that the transmitted and received signal is subject to radio frequency transmission effects, such as shading and multipath [26]. These phenomena cause fluctuations in the RSSI value and can alter the direction and phase of the wave during its propagation in the medium, which consequently influences the AoA method. The signal also varies over time and any obstacle can interfere with the temporal values used by the ToF technique [20]. Additionally, devices in the environment that operate in the same frequency range may interfere with each other, causing information loss [24].

In settings where the target moves and periodically communicates with the access points, it is possible to embedded solutions in order to improve the accuracy of the system [21]. Particularly in RSSI-based systems, it is possible to include in the IPS output a solution called Kalman Filter. This is a real-time estimator approach that handles measurement noise to track the status of randomly disturbed dynamic systems. It follows a physical model to provide its predictions and correct them, obtaining in the end estimates with less positioning error [32].

Positioning techniques, stochastic filtering, as well as sensor fusion will be explained in more detail in the following sections.

2.1 Distance Estimation Techniques

Most of the frequently applied techniques in the localization context are based on the received signal strength indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Angle of Arrival (AoA). Among all options, RSSI is the most popular and simplest method since no extra hardware is necessary, implementation complexity is low and time synchronization between devices is unrequired. [11], [18].

In the following subsections, these conventional techniques will be explained in detail, comparing their performance and justifying the choice of RSSI for the implementation at hand.

2.1.1 Time of Flight

ToF methods, such as ToA or TDoA, can convert signal propagation time into distance, based on the speed of the wave propagation ($u = 3 \times 10^8$ m/s) between transmitter and receiver through synchronized time references [20], as illustrated in Figure 2.2. In ToA the bandwidth is extremely important, when a signal's bandwidth is not wide enough, the ToA measurement may result in wide error range distance. If the receiver has 1 GHz bandwidth, the receiver resolution will be about 1×10^{-9} s, resulting in a maximum error of 0.3 m. While using 10 MHz bandwidth, the resolution will be about 1×10^{-7} s and the maximum error will be around 30 m [33].

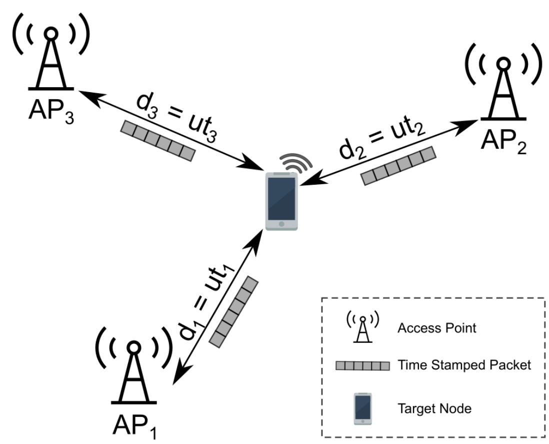


Figure 2.2: ToA-based localization.

Differently from ToA technique, which uses the absolute signal propagation time, TDoA employs the difference in signals propagation times from different transmitters, measured at the receiver [14]. A TDoA measurement is composed by the difference between two ToA measurements, so through three ToA measurements it is possible get two TDoA measurements [18]. The TDoA from at least three transmitters is requested to calculate the location of the target as the intersection of three (or more) hyperboloids [14], as represented in Figure 2.3.

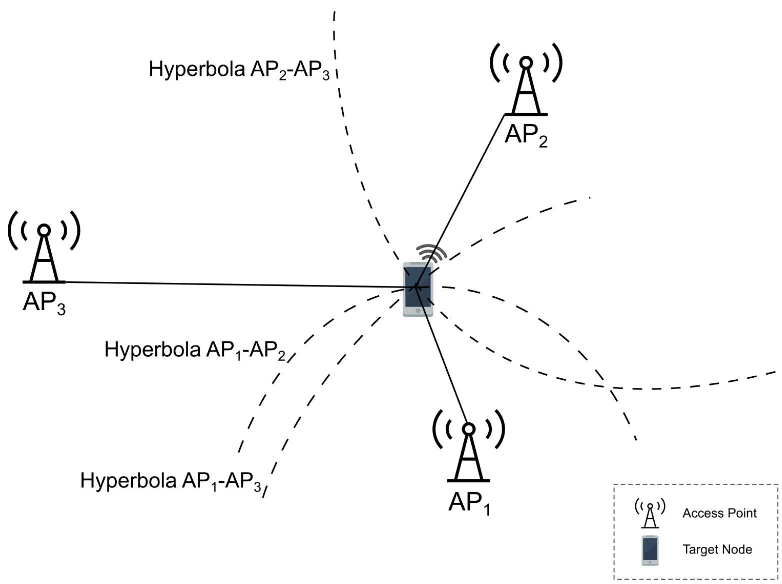


Figure 2.3: TDoA-based localization.

All sensors, including TN, need to be synchronized in ToA, since all the transmitted packets have a timestamp, while in TDoA just the APs need to have synchronized clocks. Moreover, the synchronism required for both methods implies on additional hardware, increasing the system's implementation cost [11].

2.1.2 Angle of Arrival

AoA determines the position by taking angular data of that object with respect to the orientation of the transmitters, as illustrated in Figure 2.4. Basically, AoA calculation works on an antenna array on one sensor node, which needs a minimum of three reference nodes coordinated in order to determine the position of the receiver [16].

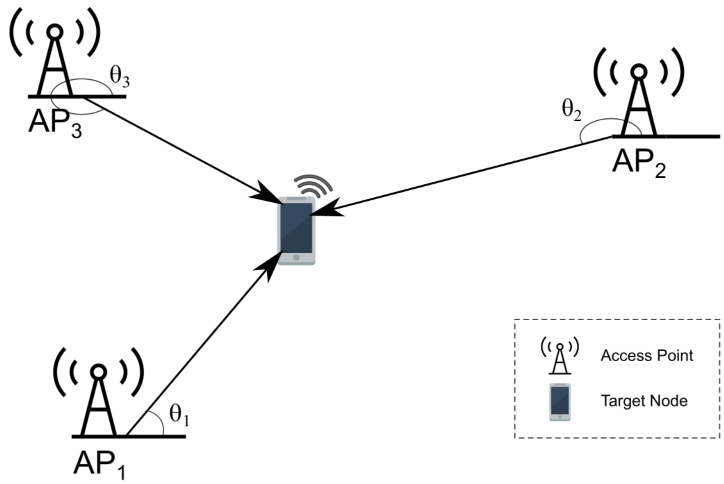


Figure 2.4: AoA-based localization.

AoA typically obtains the angle data using radio array techniques and can estimate by employing directional or multiple antennas. In multiple aerials, works by analyzing the phase or time variation among the signals at different array items that have detected locations regarding TN. In directional antennas, this acts by calculating the RSSI ratio between many directional aerials that are carefully placed to achieve similarity among their major beams [24]. In addition, AoA requires an exact antenna design, complex hardware and must be calibrated in order for an accurate positioning estimation [11].

2.1.3 Received Signal Strength Techniques

The RSS is an indication of the actual signal power level at the receiver's antenna, usually measured in decibel-milliwatts (dBm) or milliWatts (mW) [14]. In RSS-based systems the higher is the RSSI level, the stronger is the radio signal and closer is the target. Furthermore, the radio components report the current RSSI value each time a valid packet arrives [25]. As represented in Figure 2.5, this method relates the received signal's intensity with a reference distance, so that the distance between AP and TN can be calculated. In addition, when the signal strength becomes higher, the measurement is more reliable, incurring in better accuracy [11].

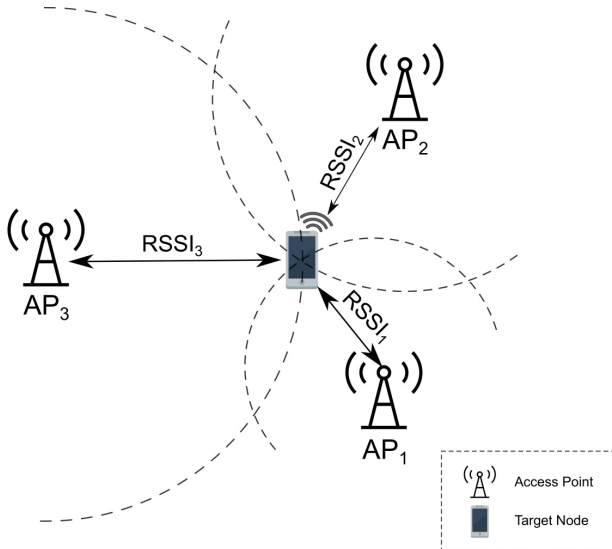


Figure 2.5: RSSI-based localization. Adapted from [14].

RSS technique is popular and simple since it requires no additional hardware and is available on any device that utilize any type of wireless communication technology [25]. In order to the high potential of indoor tracking applications, low cost, low complexity implementation and a plethora of devices that can be used, RSSI is a suitable option [34]. The RSSI parameter can also be measured from periodic broadcasted signals like beacons from a BLE device or even from unicast packets [19].

The RSSI technique can be classified in two main ways: a range-based and range-free approach. The first approach is based on mapping the radio propagation losses to distance according to the propagation model. Through the model, it is possible to obtain the corresponding distance between AP and TN from the transmitted signal. Just isolate the term of the distance in the chosen model and solve the achieved mathematical equation [24]. The main problem with this way is the difficulty of choosing which indoor propagation model is more suitable [19]. The RSSI allows to calculate propagation losses, since the signal intensity is inversely proportional to the distance of its shift in the propagation medium. The disadvantage of this approach is the precision and flexibility of the environment, when using three reference points in trilateration technique, although it is possible to improve it employing the distance from multiple reference points, employing

Multilateration technique [35]. The MLT is a technique to determine a device position through a set of reference points which have known locations, based on the measured distances between the anchor and TN [23].

The range-free approach use fingerprinting techniques (radio map) for localization, so that it does not require angle or distance measurements to find the position. The fingerprinting is composed by a database which contains a measurements series in strategical positions, in order to build a radio map of the environment that relates the position with its respective RSSI signature. The range-free approach reaches a greater accuracy compared to a range-based, but requires an exhaustive characterization of the environment. Moreover, it is very susceptible to changes, which triggers the need of a new characterization round [24].

2.1.3.1 Path-loss Model and Distance Calculation

The distance between AP and TN can be determined through a path-loss model. Considering the distance between transmitter and receiver as d_n, the $RSSI_n$ (in dBm) in the nth AP can be calculated through the log-normal propagation model as [26]:

$$RSSI_n = RSSI_{n,d_0} - 10\alpha \log_{10}(d_n/d_0) + X_\sigma, \tag{2.1}$$

where the d_n is the distance between the AP_n and the TN, the $RSSI_{n,d_0}$ is the RSSI value (in dBm) at AP_n when the target is at a reference distance d_0, the parameter α corresponds to the path loss exponent and $X_\sigma \sim \mathcal{N}(0, \sigma^2)$ represents the shadowing effect (in dB).

A signal propagating on a wireless channel varies according the logarithm of the distance that the signal travels. In addition, the RSSI value is affected mainly by some inherent characteristics of the device model like construction aspects, as well as the antenna orientation. In indoor environments that are complex and susceptible to reflection, refraction and obstacles to the signal, the RSSI value has an even bigger error due to the high momentary fluctuation of the signal level, which affects the system accuracy [18].

2.2 Localization Techniques

Among all existing wireless technologies, WLAN, also known as Wi-Fi is one of the most conventional choices for indoor location applications [11]. This is due to its availability, since all mobile devices now support this technology, and also to its ability to reuse the infrastructure already in place, not requiring any extra hardware, being able to use the access points previously installed for communication in environments [24]. On the other hand, Wi-Fi has a high energy consumption when employed in tracking applications, which ends up decreasing the battery life of the devices used for this purpose [11], [36]. In addition, the scanning time for the protocol is very long, about 3-4 s, which results in a low refresh rate and ends up causing positioning losses [24].

Another possibility could be an RFID-based system, which uses electromagnetic transmissions to transfer and gather data from a transmitter (RFID tag) to a compatible RF circuit (RFID reader) [20]. Tags can be active, passive, or semi-active. Active tags provide a range of up to 100 m, which is very useful for long-range locations, nevertheless achieving this large-scale coverage requires high power consumption and financial investment [18]. Passive tags have a limited range within 1-2 m and operate without any battery, they are smaller, lighter, and cheaper than active tags [37]. Passive tags are an alternative to the traditional barcode, especially in situations where the tag is not in the line of sight of the reader, however, due to its limited coverage it becomes unviable for IPS and the cost of the reader is significantly high [14].

Zigbee is also a promising candidate for location-based applications and is known to be a simple, low-power, and secure protocol [11]. Devices that utilize this technology are capable to manage their own data and avoid data loss using Carrier-Sense Multiple Access/Collision Avoidance (CSMA/CA). In addition, these devices are designed with some options such as power detection and link characteristics, which allows working with

RSSI-based methods [18]. Zigbee allows reaching long distances through its mesh network configuration to achieve the target, being favorable for sensor localization in WSNs. However, this protocol is unavailable on most devices, such as Wi-Fi, making it necessary to use extra hardware, which is in fact not recommended for indoor localization applications as it makes implementation more expensive [14].

UWB is also a widely used alternative in localization, this technology works by transmitting pulses with a duration of fewer than 1 ns, using a low duty cycle value between 1 to 1000. This allows the UWB signal to be transmitted in multiple frequency bands, resulting in an accurate solution for indoor localization and tracking [16]. This technology provides immunity to interference due to its different signal types and radio spectrum, allowing it to penetrate a variety of obstacles and also has a wide data rate, low power consumption, and multipath protection. UWB devices are centered on line-of-sight modifications, which allows accuracies of the order of centimeters to be achieved in a localization system [18]. However, a UWB-based localization system faces several challenges in achieving such precise positioning values, requiring sampling rate limits, device synchronization, shadow effects caused by the human body and antenna phase axis variation. A UWB implementation provides an accurate solution but requires a complex infrastructure and high financial investment [24].

One of the most popular options for IPS is Bluetooth Low-Energy (BLE), which uses short-range radio with minimal power consumption to operate over long periods of time, with coverage of 70 to 100 m and a transmission rate of 24 Mbit/s with consumption ranging from 0.01 mW to 10 mW [7]. BLE is available on most devices, such as smartphones, and when compared to technologies such as Zigbee and Wi-Fi, has a higher efficiency in terms of power consumption, a low level of implementation complexity, and a better-transmitted power per bit ratio [18]. But like Wi-Fi, it occupies the 2.4 GHz frequency band known as Industrial, Scientific and Medical (ISM), which can lead to interference in BLE channels [22]. In indoor location services, this technology has BLE beacon-based devices operating in a GAP configuration, which allows for configuration and operation modes such as scanning or advertising (non-connectable messages), and initialization and management (connectable messages). Operating in this configuration, the devices can function as either masters or slaves, where the masters receive advertising from the slaves by scanning BLE advertising channels [38].

Location systems require a technology that offers secure transmission, accuracy & precision, low cost, low complexity, scalability, low power consumption, and robustness. The BLE protocol satisfies the following system requirements: low power consumption, low complexity, low cost, robustness (the system can work even if one AP fails), and compactness [7], [38]. Therefore, BLE was chosen as the technology adopted in our proposed solution.

The following subsections are intended to explain the frequently employed localization techniques when a BLE-based localization system is implemented.

2.2.1 Trilateration

The trilateration method exploits the geometric properties of triangles to estimate the position of the target node. Through RSSI it is possible to estimate the relative distance between the APs and the TN, these distances are obtained from the calculation of the attenuation of the transmitted signal [20], according (2.1). The anchors represent the receivers of the system and need to be configured to receive the packets continuously in order to avoid information loss. Thus, allowing the transmitter positioned at the unknown location to be detected and to send its packets containing the RSSI values. The RSSI values are converted to an estimated distance d_n between AP_n and TN as [24],

$$d_n = d_0 10^{(RSSI_{n,d_0} - RSSI_n)/(10\alpha)}. \tag{2.2}$$

As presented in Figure 2.6, the distance between AP and TN is related to the received power. For 2D measurements, through two equations, there will be two possible solutions. In order to achieve a unique solution, three equations are required; the intersection of these equations will determine the location of the target node [18]. Being the TN coordinates

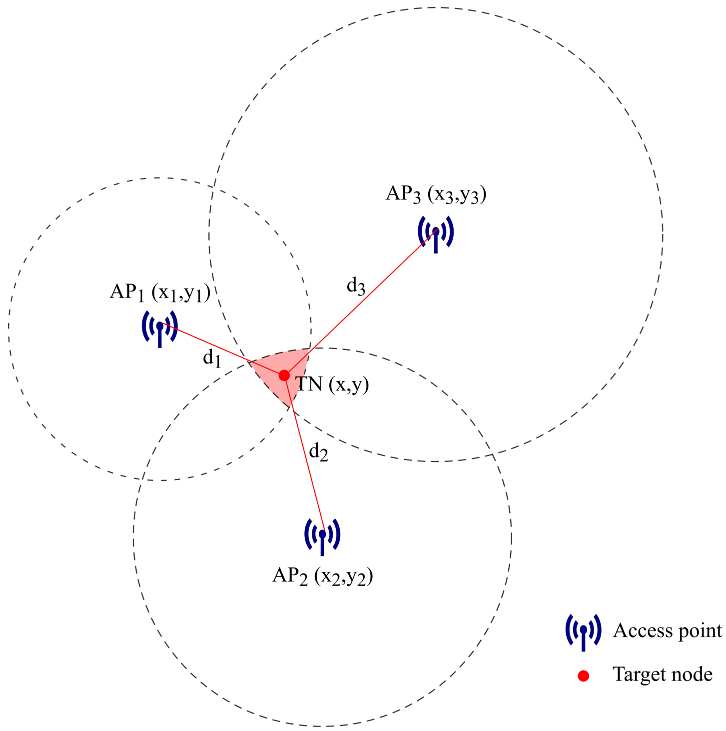


Figure 2.6: Example of Trilateration, considering the circles as the distances between TN and each AP. The area resulting from the intersection among the APs is the estimated location where the node is located.

(x, y), and the APs (AP_1, AP_2 and AP_3) coordinates, are (x_1, y_1), (x_2, y_2) and (x_3, y_3) respectively, the intersection of the three circles with radius d_1, d_2 and d_3, achieved from equation (2.2), represents the estimated position of the TN.

The geometric properties between anchors and node can be represented by the following system of equations [19]:

$$d_1 = \sqrt{(x - x_1)^2 + (y - y_1)^2}, \tag{2.3}$$

$$d_2 = \sqrt{(x - x_2)^2 + (y - y_2)^2}, \tag{2.4}$$

$$d_3 = \sqrt{(x - x_3)^2 + (y - y_3)^2}. \tag{2.5}$$

Solving the equations the location of the target (x, y) will be reached a unique solution, where two will be basic equations and the third is a linear combination from the other ones. The result is inferred based on the distances obtained using least square techniques.

2.2.2 Multilateration

Multilateration is an extension of the trilateration method with more than three RPs ($N > 3$) to estimate the target position. A RF multilateration method estimates the TN location using the strength of the signals received from many non-collocated and non-collinear transmitters [24]. The estimated distances between an AP_n and TN located in (x, y), can be calculated as [18]:

$$d_n = \sqrt{(x - x_n)^2 + (y - y_n)^2}. \tag{2.6}$$

The signal intensity measured from all of anchors in the environment are used to convert the signal power in distance through equation (2.2). Considering $\hat{d}_n \simeq d_n$, where $\hat{d}_n$ is the estimated distance from (2.2) and d_n the euclidean distance from (2.6), equating both terms, squaring and subtracting the Nth equation of the nth equation, which N is the total amount of APs and $n = 1, 2, 3, ...N$, reordering the terms, reaching a linear function in x and y [35]:

$$\begin{aligned} -x_n^2 - y_n^2 + x_N^2 + y_N^2 + (\hat{d}_n)^2 - (\hat{d}_N)^2 = \\ x(-2x_n + 2x_N) + y(-2y_n + 2y_N). \end{aligned} \tag{2.7}$$

Representing all terms in the form of a linear system of equations $\mathbf{b} = \mathbf{Ap}$, where $\mathbf{p}$

is the coordinate vector, as [35]:

$$\begin{bmatrix} -x_1^2 - y_1^2 + x_N^2 + y_N^2 + (\hat{d}_1)^2 - (\hat{d}_N)^2 \\ -x_2^2 - y_2^2 + x_N^2 + y_N^2 + (\hat{d}_2)^2 - (\hat{d}_N)^2 \\ \vdots \\ -x_{N-1}^2 - y_{N-1}^2 + x_N^2 + y_N^2 + (\hat{d}_{N-1})^2 - (\hat{d}_N)^2 \end{bmatrix} = \begin{bmatrix} -2x_1 + 2x_N & -2y_1 + 2y_N \\ -2x_2 + 2x_N & -2y_2 + 2y_N \\ \vdots & \vdots \\ -2x_{N-1} + 2x_N & -2y_{N-1} + 2y_N \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}. \tag{2.8}$$

Since $\{\hat{d}_n\}_{n=1}^N$ may present errors due to shadowing effect, the estimate position $\hat{p}_{MLT}$ is determined using a standard least-squares approach [35]:

$$\hat{p}_{MLT} = \hat{\mathbf{p}} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b}, \tag{2.9}$$

in order to minimize $\sum_{n=1}^N (d_n - \hat{d}_n)^2$.

The multilateration method has errors in the estimates, due to the uncertainty in distance calculation between anchor and target. This inaccuracy in estimation is due to several factors, including simplifications and uncertainties in signal propagation models, multipath losses or fading, and the complexity of indoor environments in maintaining LoS with APs [24].

2.2.3 Fingerprinting

In IPS, the FP localization is a recurrent method aiming at increasing position accuracy using range-free information in a building structure, reducing the hardware complexity and undesirable influence of multipath effect [20]. The FP technique finds a correlation based on RSSI values and normally is formulated in two phases: the offline phase (training/calibration) and online phase (testing/localization) [18].

2.2.3.1 Offline Phase

In the training phase, the spatial-temporal RSS data of each AP location is collected and stored in a database as coordinates of the current location, creating a radio map of the area. Therefore, for each fingerprint, a unique RSSI value and its location in the environment must be collected, segmenting the entire area into a grid with unique characteristics for each point of interest (also called Reference Point (RP)) on the map [39].

A set of measurements is required in order to achieve an average value for each measured point. Figure 2.7 shows a technique overview, presenting the both phases of the method. Each measured point has its respective set of characteristics associated with their coordinates and received signal power in that point. These dataset will be available in a database, containing information from each RP [22].

2.2.3.2 Online Phase

The built database in the offline step is used in the testing phase for comparing and recognizing the RSSIs collected from unknown locations, these processes are performed between the measured RSSI values and the closest RPs for position estimations [39]. The estimated position will be linked to the best suitable fingerprint or the geometric mean of the positions of K fingerprints close the TN.

In order to compare and recognize the RSSI measured values with database a localization algorithm is required, a typical choice is a deterministic algorithm, being the most widely adopted options: the Nearest Neighbour (NN) algorithm, which uses just one RP to estimate the TN position [40]; the k-Nearest Neighbour (KNN) being k the number of RPs considered in order to build a polygon which centroid will be the result estimation [18]. Finally, the Weighted k-Nearest Neighbour (WKNN) which applies the KNN algorithm with a weight employed in the neighbors, attributing different weight values for each RP in the environment [41].

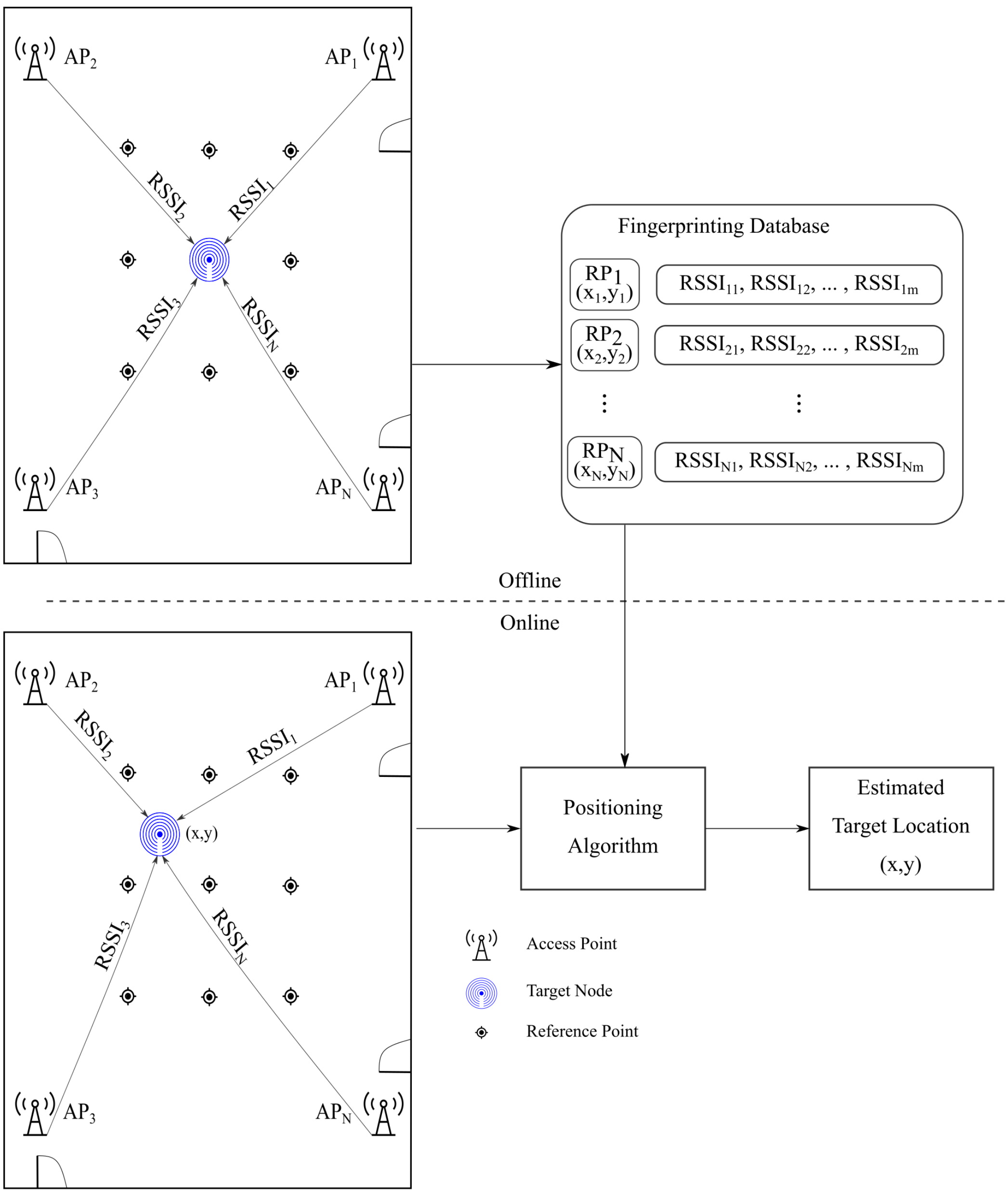


Figure 2.7: Fingerprinting-based positioning method overview.

The KNN algorithm is the typical choice since it does not need lot of data to work with, has low complexity and the accuracy is equivalent to modern techniques [39]. KNN algorithm is a deterministic approach, i.e., based on fixed known values, it is an instance-based learning method and memorizes all training data. Basically, a deterministic algorithm will find the optimal similarity between the new measurements of testing data and the database of the FP offline phase [14]. KNN uses the shortest distance between the RPs registered on database ($RSSI_{m,n}$) and the target position ($RSSI_n$), this algorithm employs the Euclidean distance as following equation [42]:

$$D_m = \sqrt{\sum_{n=1}^{N} (RSSI_n - RSSI_{m,n})^2}, \tag{2.10}$$

where D_m is the distance between the set of RSSI value from RP_m of the database, and the current RSSI measured from the tracked target by AP_n, which leads to a set of distances $\mathcal{D} = \{D_1, ..., D_m, ..., D_M\}$, with $|\mathcal{D}| = M$. The M distances are classified in ascending order and the k first points will be selected for calculating the estimated position, so that the estimated position is denoted as $\hat{p}_{FP} = (\hat{x}_{FP}, \hat{y}_{FP})$. Nevertheless, the principal disadvantage of FP-based IPS is the fact that the approach works only in the previously characterized area and any change in the environment can impact the method, making it necessary to carry out a recharacterization.

However, some modern solutions have emerged in order to provide easy construction of radio maps, consuming less time, with little effort, and reduced human workload. A Crowdsourcing-based FP system proposed by [43], where the user can get the RSSI values via a smartphone while performing their routine tasks, in order to subsequently employ this collected data in the radio map construction process. In addition, an automatic database update was developed at [44], in which a mobile robot was configured to acquire the RSSI in the environment while moving through the area.

Unfortunately, most of these new solutions require extra hardware or increase the computational cost. A typical methodology employed to smooth the problems with multipath interference in indoor environments, which causes a variation in the received signal level introducing errors in the measurements, are the stochastic filters, such as Kalman Filter and Particle Filter or Sequential Monte Carlo. These methods provide an improvement to the system mitigating the positioning error introduced by this phenomenon [34].

2.3 Stochastic Filtering Techniques

There are many stochastic filtering process options, such as Bayesian Filter (BF), Particle Filter (PF), KF and extended Kalman Filter (EKF) [24]. These approaches linear & non-linear are typically employed in IPS aiming to compensate the cumulative positioning error and they can also to attenuate the noise measurements [27], [40]. The filtering process may aid in obtaining a continuous trajectory and decrease the estimation error [24].

In state-space models, the tracking problem can be solved by Bayesian tracking, which employs the Bayesian filter. The principal idea of this filter is aimed at a continuous estimation of positioning, considering a situation of a complex indoor environment [45]. There are solutions as [46] that describe systems able to mix LoS and NLoS scenarios. As discussed in [47], it is also possible to combine linear and non-linear models to estimate the position through a BF by mixing data from a dead reckoning and UWB.

Particle Filter is an iterative estimation method, which can use human motion data, radio map information, and RSSI measurements recorded by APs [24]. The PF algorithm is based on the state equation method that allows solving nonlinear filtering problems [45]. A low-cost PF-based solution is proposed by [48], which solves the pedestrian map-matching problem by accurate positioning and tracking using a smartphone Microelectromechanical System (MEMS) sensors jointly PF.

KF and EKF are recursive Bayesian Filters, which have been employed to sequentially investigate positioning in tracking systems [24]. The KF allows to employ linear and quadratic models in real-time, improving performance in indoor positioning and navigation applications. It provides an accurate position estimation using a precise measurement model and Gaussian distribution of measurement noise [32]. However, the traditional KF uses Gaussian models to solve linear problems and being not recommended for non-linear applications [45]. On the other hand, the EKF is aimed at nonlinear processes, being widely used in probabilistic mapping problems in Simultaneous Localization and Mapping (SLAM) [24]. However, EKF requires an updated-time sensor data and for truly known mapping between the target and the AP [49].

Comparing the previously mentioned approaches, the traditional KF is the main choice for the proposed implementation as it allows working with linear motion models, is reduced complexity, and requires a lower computational cost in relation to EKF or PF.

Considering hardware limitations like memory, energy consumption and processing capability, KF proves be the most effective at reducing noise and improving indoor location accuracy [21]. The KF is typically employed in a time-discrete system. Considering some knowledge regarding the target motion model and including a Gaussian noise, the typical KF can produce effective results, especially for the linear motion model [50].

A frequently approach adopted in IPS is to apply KF over the RSSI measurements, in order to decrease the uncertainty, and then implement the localization algorithm. In [51] a BLE-based IPS is proposed, which a KF is employed filtering the signal's RSSI increasing the accuracy of the estimated position by the trilateration method. Reaching 0.53 m average error in a (5×5) m static scenario.

In [52] it was proved that a KF in an IPS enhances the precision up to 78.9%, showing an inexpensive solution. It was tested in three different configurations, allowing a smoothing of the surrounding noise in the environment, which is reflected in fluctuations of the signal power.

2.3.1 Kalman Filter

The Kalman Filter is a statistical method adopted due to its ability to reduce the overall uncertainty. It uses a series of measurements observed over time which contains random noise and produces estimations that tend to be more accurate by the fact of taking into account the past states and the covariance error. Furthermore, the Kalman Filter is usually employed in navigation and trajectory optimization applications [52].

In this way, the estimated position $\hat{\mathbf{p}}_j$ from the localization algorithm is exploited as an input to the Kalman Filter that considers a linear motion model to smooth the positioning error introduced by this previous localization technique, providing an enhancement of the system accuracy.

The linear motion model for example, assumes that the TN moves in the environment with a constant velocity in both axis, so the position varies a linear pattern. Thus, the state vector x_k is defined as a vector containing the true values of the state variables at the moment k, as represented in equation (2.11) [23]:

$$x_k = \begin{bmatrix} x(k) & y(k) & \dot{x}(k) & \dot{y}(k) \end{bmatrix}^T, \tag{2.11}$$

where $x(k)$, $y(k)$, $\dot{x}(k)$ and $\dot{y}(k)$ are respectively the location coordinates and velocity in x and y directions.

The measurement function is governed by the linear stochastic difference equation [32]:

$$z_k = \mathbf{H}_k x_k + v_k, \tag{2.12}$$

where $\mathbf{H}_k \in \mathbb{R}^{j \times p}$ is the measurement model that is related to the state with the estimation and $v_k \in \mathbb{R}^{j \times 1} \sim \mathcal{N}(0, \mathbf{R})$ represents the measurement noise, being $\mathbf{R} \in \mathbb{R}^{j \times j}$ the covariance matrix. The KF estimates a process using the feedback control, where the filter estimates the process state in a moment, getting the feedback through the measurements [32]. The KF process can be separated in two groups, namely the *time update* (which is responsible for the prediction) and *measurement update* (i.e. related to the correction or maintenance) [34], as presented in Figure 2.8.

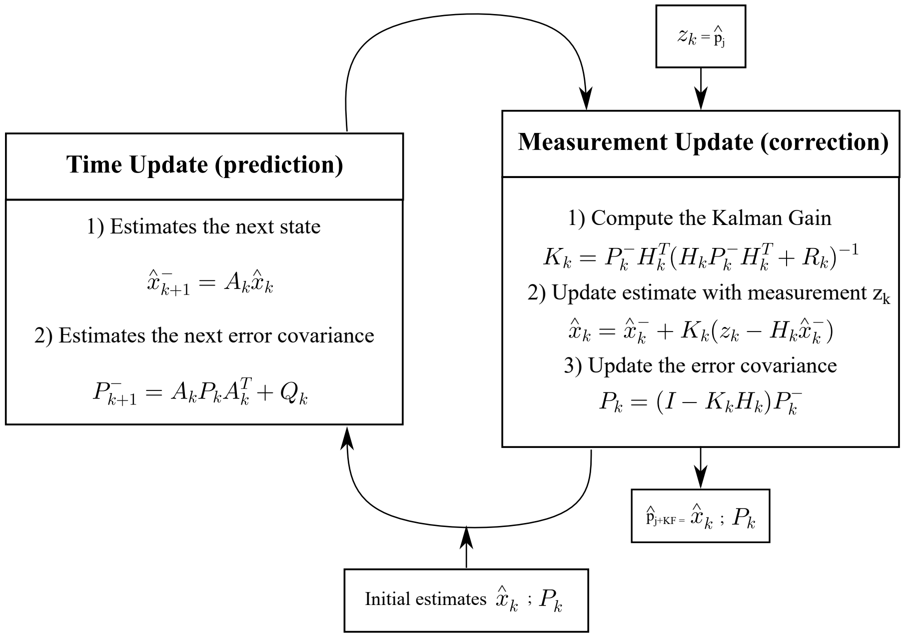


Figure 2.8: Kalman Filter Algorithm.

2.3.1.1 Time Update

The state variables from equation (2.11) are updated projecting forward the current state and estimating the error covariance to obtain the next state [32], [34]. In this model, $\hat{x}_{k+1}^- \in \mathbb{R}^{p\times 1}$ is the a priori estimation at the moment $k+1$, given the a posteriori estimation at the moment k, $\mathbf{A}_k \in \mathbb{R}^{p\times p}$ is the state transition model following the uniform movement (relating to states k and $k+1$), $\mathbf{P}_{k+1}^- \in \mathbb{R}^{p\times p}$ is a priori error covariance matrix that projects ahead the estimations at the instant $k+1$ given the a posteriori error covariance matrix at the instant k, $\mathbf{Q}_k = q\mathbf{I}_j \in \mathbb{R}^{j\times j}$ is the covariance matrix of the transition model and $q \in \mathbb{R}$.

2.3.1.2 Measurement Update

This stage adjusts the prediction projected via the measurement at the current moment, that is a combination from the prediction and measurements in order to refine the estimation [32], [34]. In this model, $\mathbf{K}_k \in \mathbb{R}^{p\times j}$ is the Kalman Gain that is responsible to adjust the balance between the prediction and the current measurement, $\hat{x}_k$ represents a posteriori state estimation given the measurements up to time k, $z_k \in \mathbb{R}^{j\times 1}$ is the real measurement at moment k and $\mathbf{P}_k$ is the a posteriori error covariance matrix at moment k.

Through the described mechanism, the output contains state variables with lower error levels when compared to the system measurements. Considering a tracking or positioning system, such information may be coordinates, velocity and trajectories of the target object [45].

2.4 Fusion of Localization Techniques

The combination of localization techniques is a recurrent tool in applications which need a system with more accuracy. In [39] a fusion using trilateration and FP techniques was implemented, providing an improvement to the system of 25% compared with FP technique standalone reaching an accuracy of 1.8 m. The proposed solution employs a path-loss model leading an estimate position that will be used as input to the KNN algorithm, which will search and compare with the fingerprints in database using a 2 m radius through trilateration estimate, in order to restrict the searching process and accelerate the KNN algorithm.

In order to decrease the influence of the interference, the authors in [27] developed an IPS with adaptive multilateration, which employs inertial sensing and adaptative ranging in a BLE infrastructure. A PF was used to combine the all information and improve the estimate result, reaching around 20% of enhancement.

MLT and FP are methods dependent of the number of anchors in the area. Probabilistic methods, on the other hand, are based on the Probability Density Function (PDF) of unknown variables by providing more accurate results with statistical framework [24].

Therefore, probabilistic methods besides considering the output of deterministic techniques (MLT & FP), provide mathematical treatment in order to merge the information reaching a better result [34]. Finally, the KF is an example of a tool that can be employed in IPS, in order to combine two position estimates achieving third information devoting to compensate the weak from the previous techniques applied. In [23] a hybrid IPS (H-IPS) that combines MLT and FP was presented, employing a KF based on uniform motion in order to improve the positioning error for each traditional method. In addition, their system provides a sensor fusion using KF called Track-to-track Fusion which takes the outputs from the original KF and combines the estimations achieving at the final a better accuracy. The proposed system outperformed the MLT 54% and the FP by 46%.

2.4.1 Sensor Fusion using KF

Increased performance and reliability requires a intelligent combination of data from multiple sensors leading to a less uncertain information about the desired state. The data fusion aim to produce a model or representation of the system handling a set of independent data sources, providing a perception of the external environment [53].

The combination of the information from the sensors and following estimation of the state of the scenario need to be done correctly, in order to reduce the uncertainty. A common application of data fusion techniques is the estimation of target position from multiple measurements from a single or multiple sensors [53].

Two essential processes are involved in positioning contexts: data association and state estimation. State estimation concerns the optimal estimation of position, velocity, acceleration, or angular position of the target [53]. The most popular and widely applied state estimator algorithm is the Kalman Filter [32].

The Kalman Filter became an attractive tool in data fusion problems and track fusion problems, in [54] is employed to collision avoidance and object recognition in autonomous vehicle context. It have been extensively applied to robot localization, guidance and navigation, as [55]. IPS is another field that can also use KF for data fusion applications, [56] presents a solution combining Wi-Fi and inertial sensors to provide a more accurate tracking system.

The conventional state-vector fusion and measurement fusion are two modalities based on KF data fusion [53], [57]. The conventional measurement fusion has lower estimation error in settings that sensors communicate each time they receive measurements or the process noise is zero, but a higher computational cost is required [58].

There are two principal methods for measurement fusion. The first just merge the measurements from two or more sensors into a new measurement vector [58]. The second approach is devoted to weight the individual measurements from each sensor and then track the fused measurements through a Kalman Filter obtaining an estimate of the state vector [59]. Since the measurements noise is independent for the sensors, the fusion process is a recursive form for a minimum mean square estimate [53].

In real-world scenarios targets are tracked by a plethora of sensors, the process involved in associating the tracks of the same target is a correlation problem, this is often solved employing a track fusion [53]. The combination of distinct information sources through sensor fusion results in a unique output which has lower uncertainty than each individual source. One of the widely used track fusion method is the track-to-track fusion algorithm [53], as illustrated in Figure 2.9.

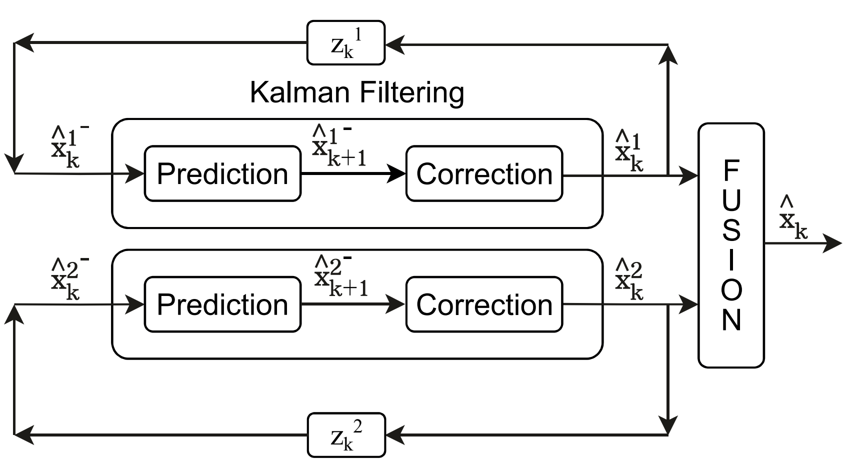


Figure 2.9: The track-to-track fusion algorithm. Adapted from [53].

This method performs the state vector fusion combining the estimated states $\hat{x}_k^1$ and $\hat{x}_k^2$ of sensors 1 and 2, respectively, in order to produce a new estimate state vector $\hat{x}_k$, the new fused state vector is generated given the following static linear estimation equation [53]:

$$\hat{x}_k = \hat{x}_k^1 + \left[\mathbf{P}_k^1 - \mathbf{P}_k^{12}\right]\left[\mathbf{P}_k^1 + \mathbf{P}_k^2 - \mathbf{P}_k^{12} - \mathbf{P}_k^{21}\right]^{-1}\left(\hat{x}_k^2 - \hat{x}_k^1\right), \tag{2.13}$$

where $\mathbf{P}_k^m$ is the covariance matrix regarding the state vector from the fusion $\hat{x}_k^m$, being m the index of different sensors $(m = 1, 2)$. $\mathbf{P}_k^{12} = \left(\mathbf{P}_k^{21}\right)^T$ is the cross covariance matrix between $\hat{x}_k^1$ and $\hat{x}_k^2$. The cross covariance matrix can be obtained from following recursive equation:

$$\begin{aligned}\mathbf{P}_k^{12} = &\left(\mathbf{I}_p - \mathbf{K}_k^1\mathbf{H}_k^1\right)\mathbf{A}_{k-1}\mathbf{P}_{k-1}^{12}\mathbf{A}_{k-1}^T\left(\mathbf{I}_p - \mathbf{K}_k^2\mathbf{H}_k^2\right)^T \\ &+ \left(\mathbf{I}_p - \mathbf{K}_k^1\mathbf{H}_k^1\right)v_{k-1}\mathbf{Q}_{k-1}v_{k-1}^T\left(\mathbf{I}_p - \mathbf{K}_k^2\mathbf{H}_k^2\right)^T,\end{aligned} \tag{2.14}$$

being $\mathbf{K}_k^1$ and $\mathbf{K}_k^2$ the Kalman Gain for sensors 1 and 2 respectively, at the moment k.

The equation (2.13) presents a suboptimal solution due to the fusion be the optimal solution for a linear estimator [60]. The advantage of this algorithm is a reduced computational cost, which turns this method into an attractive option to combine state vectors [53].

Another fusion method, is represented in Figure 2.10, which proposes that the resulting vector of the fusion will be used as feedback of the system to a single stage predictor. The output of the prediction step will be divided to two correction equations [53].

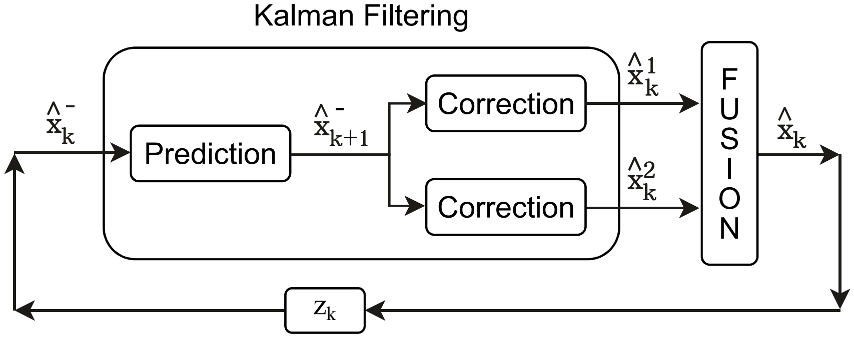


Figure 2.10: The modified track-to-track fusion. Adapted from [53].

In the modified state vector fusion, the prediction $\hat{x}^{-}_{k+1}$ is combined with the measurements z^1_k and z^2_k individually, generating two new state vectors $\hat{x}^1_k$ and $\hat{x}^2_k$, whose will be linked in the next iteration.

To summarize, in [53] when the fusion is applied in scenarios that the sensors or the measures present similar units, the original algorithm performs better than the modified solution. This happens because in the modified system there is an extra fusion procedure step, where the information from dissimilar sensors is fused and used as feedback for the subsequent stage of estimation, however, this process will not provide any new fused information in similar sensors settings.

2.5 BLE Beacon

The advance in low-power wireless technologies has caused an evolution in wireless communication devices, eliminating the hassles caused by traditional wired communication and allowing more dynamic data transmission between devices using air as the propagation medium [8]. Among them there is the BLE beacon device that is generally small and low cost wireless devices that work by repeatedly broadcasting packets to all nearby devices in a range of about 100 m. In addition, beacon devices does not rely on an external power source and are able to operate months or even years using a coin cell battery, thanks to its low energy consumption [21], [61]. However, one of the limitations imposed by the energy constraints is that the protocol operates under very small Protocol Data Unit (PDU) for the advertising packets [8].

The beacon device was explored by Apple introducing the iBeacons and Google with Eddystone in smartphones, which is used for localization within airports, malls, restaurants and supermarkets, where the area map is sent to the smartphone and the location is estimated using the BLE [18]. The ease of integration between BLE beacons and smartphones particularly, turns effective to diverse IoT applications, requiring less human workload to do several tasks [8], like opening a door through identifying proximity or locating some missed object inside a building.

A typical beacon-based system architecture is presented in Figure 2.11. After receiving a message from iBeacon, the smartphone reports to a server or to the cloud in order to identify the action associated with the received beacon. The action might be to send a discount coupon, to open a door or to display something on a monitor through the user's proximity of a specific location [14].

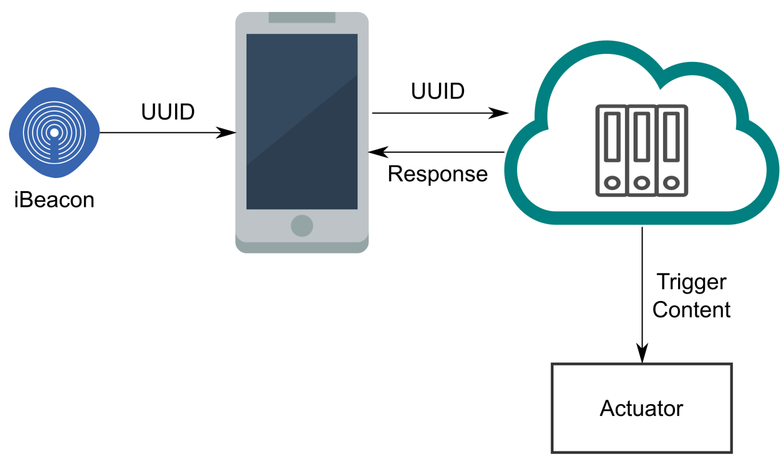


Figure 2.11: Typical architecture for iBeacon based systems. Adapted from [14]

.

Both the companies Apple and Google, work on the embedded information in the PDU and proposed their respective exclusive beacon technology [8]. Due to the limited PDU, beacon devices are only suitable to send small messages. The BLE-beacon symbol rate is up to 1 Mbit/s and an advantage is that is not necessary to pair the Bluetooth devices, since it is possible to just listen to the advertisement messages [8].

BLE beacon-based solutions are popular when compared to other existing solutions. The key factors are they low production cost, ease of deployment, and easy accessibility to users. Wi-Fi based solutions have limitations such as the number of APs and their inflexibility in deployment, Wi-Fi was first designed to signal coverage and not for localization applications. In [22] has been proved that BLE solution performs better than Wi-Fi based IPS, depending on deployment configurations and operation parameters, such as the BLE-beacons device deployment density, advertising interval and transmission power.

Setting up 19 beacons in an office, the authors achieved <2.6 m error 95% of the time in a beacon density of 30 m^2, beating the <8.5 m error achieved using Wi-Fi.

In IPS three remarkable factors are essential to be minded: the arrangement of the transmitters and receivers, the RSSI analysis and the wireless technology, that will be used in the implementation [19].

There are two possible forms of arrangement, the first in which the anchors transmit the beacons to the sensor tags to be located, and the other where the access points receive the signals from the target to be tracked [19]. In the proposed solution the second arrangement was adopted due to its low power consumption, fast response time, and reduced message volume when compared to the first option.

Regarding the RSSI analysis, the average of the readings was used to reduce the effect of the fast fading. It was preferred to work with the RSSI in order to avoid the need for synchronism and the low complexity of implementation. Therefore, two techniques were selected, namely FP and MLT, which allow the use of this indicator for positioning purposes. Both techniques end up introducing positioning errors in their estimates, errors caused by the model used in the method, the algorithm employed by the technique, the signal itself, and constructive aspects of the devices used in the implementation. To overcome these barriers a filtering process was introduced, which uses a KF to improve the quality of the estimates and increase the reliability of the results.

In the wireless technology concern, BLE was adopted because it has the lowest power consumption among other options, reduced complexity, availability, easy scalability, does not require extra hardware, and the low-cost presented by devices based on this type of technology [14], [38].

Chapter 3

Proposed Solution

Aiming at implementing a low-cost H-IPS solution while presenting low power consumption and better accuracy, a BLE-based approach was selected, that combines MLT, FP and KF techniques to smooth the statistical noise and reduce the position error. In addition, the track-to-track fusion (TTF) was employed combining the estimates from FP and MLT, producing a hybrid estimate position providing an accuracy enhancement.

The goal is to predict a TN position, which follows a linear motion model, i.e, constant velocity. The arrangement in which the APs receive the beacons, containing the RSSI values, transmitted by the TN was adopted. This arrangement was chosen because it provides low power consumption, shorter response time, and lower complexity. However if the opposite architecture was selected where the AP would represent the transmitter and the target the receiver, the sensor tag would have to be constantly available to listen to the transmitters and to respond to them, which would increase the level of messages, update time and power consumption (reducing the battery life of the beacon device).

The beacon device sends data packets which is subjected to multipath, shadowing and fading effects [26]. The fast-fading effect can be mitigated by averaging a huge amount of RSSI measurements [22]. As presented in Figure 3.1, the proposed system is composed by the following modules: distance calculation, database construction, position estimation, improving accuracy and sensor fusion.

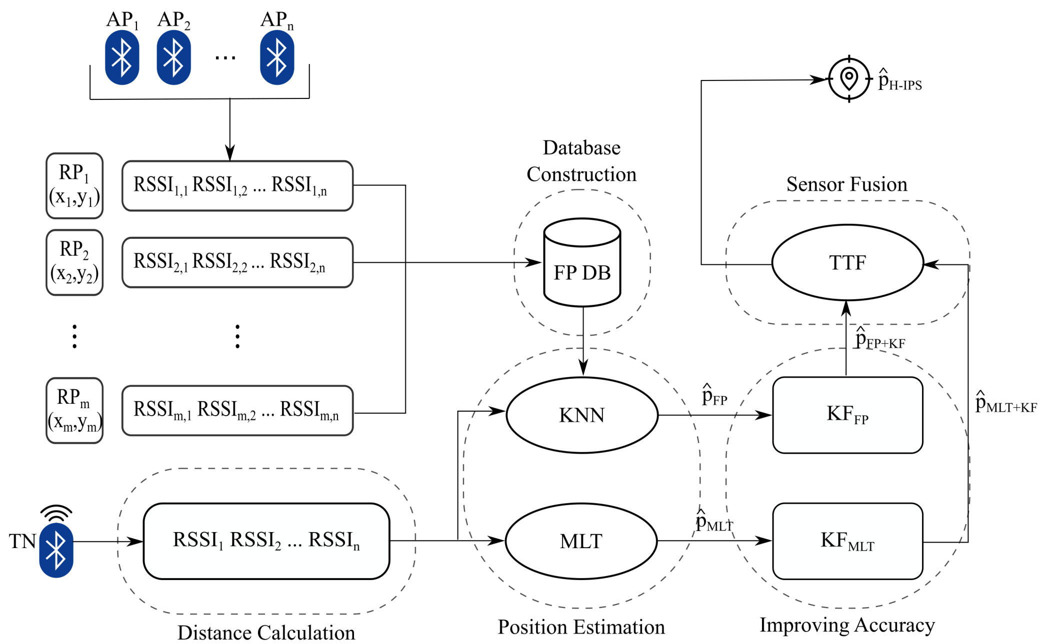


Figure 3.1: H-IPS model scheme proposed employing KF and TTF algorithm. Adapted from [23].

3.1 Distance Calculation

The RSSI coming from the beacon messages forwarded by the TN is denoted as $RSSI_n$, where each RSSI measurement will be used by the localization algorithms (FP and MLT) in order to estimate the target's position. In this stage of the solution, the distance between target object and the AP is estimated through (2.2). This distance corresponds to the radius established between object and the N anchors, that will be used in the MLT technique to estimates the TN position. To estimate the distance between the transmitter and receiver, the path loss model was adopted because of its ease in representing the propagation of a signal taking into account all the effects it is subject to. In addition, this model does not require any synchronism for calculation purposes, which is no longer the case with time-of-flight-based methods.

3.2 Position Estimation

In order to estimate the TN position, two RSSI-based approaches will be considered: MLT and FP, which will be detailed in the following subsections.

3.2.1 Multilateration

The MLT technique uses the estimated distance from section 3.1, in which the intersection of all the circles formed by the set of radius corresponds to the area which contains the estimated position $\hat{p}_{MLT}$, which is obtained through the minimization of $\sum_{n=1}^{N}(d_n - \hat{d}_n)^2$ using a standard least-squares method.

First of all, to implement the MLT technique is necessary to measure the $RSSI_{n,d_0}$ for each AP. Therefore, is extremely important ensure that the TN is positioned correctly at a distance d_0 from the anchor. Finally, is $RSSI_{n,d_0}$ obtained by averaging enough single measurements. This calibration is important, since an inefficient measurement will be reflected in the radius calculation, which then affects the position estimation in the least squares method.

MLT is a popular, low-complexity method, selected because it does not require extra hardware or a high computational cost. The Algorithm 1 demonstrates the MLT technique implementation, which was introduced in the subsection 2.2.2.

Algorithm 1: Multilateration

Input: $RSSI_n, d_0, \alpha, RSSI_{n,d_0}$
Output: $\hat{p}_{MLT}$

begin
  Initialization;
  for *n=1:1:N* **do**
    Estimate the distance between TN and AP_n by (2.2);
  Apply standard least square method in the system as (2.8);
  return $\hat{p}_{MLT}$;

3.2.2 Database Construction

For the FP technique it is necessary to build a database in the offline phase containing the measurements $RSSI_{m,n}$, representing a received signal intensity by $\{AP_n\}_{n=1}^{N}$, which a BLE-beacon device has sent in M RPs equidistant locations $\{RP_m\}_{m=1}^{M}$, when positioned in (x_m, y_m) coordinates inside the Area of Interest (AoI).

The output of the offline phase is composed by the identification of the AP_n and RP_m, linking their respective locations (x_n, y_n) and (x_m, y_m), as well as the measurement $RSSI_{m,n}$ associating $\forall n \in \{1, ..., N\}$, $\forall m \in \{1, ..., M\}$ [42]. The database needs to be connected to the APs so that they can estimate TN in online phase.

In this step, the scene is divided into a grid of RPs, where each RP is visited manually ensuring the reliability of the measurement and aiming to get a better characterization of the signal in the environment. All collected fingerprints will design a signal map of the scene. Finally, ensuring a good characterization of the environment will lead to better accuracy in the FP technique.

3.2.3 Fingerprinting

After the FP database is built as described in section 3.2.2, in the online phase the TN sends beacons. The RSSI values received by each AP are grouped in a set of readings and compared with the database stored values. Then an algorithm based on Euclidean distance is applied, calculating the distance between the RSSI stored in the database ($RSSI_{m,n}$) and the current value measured from TN ($RSSI_n$), as equation (2.10) [42].

The results lead to a set of distances $\mathcal{D} = \{D_1, ..., D_m, ..., D_M\}$, with $|\mathcal{D}| = M$. The TN estimated position, is denoted as $\hat{p}_{FP} = (\hat{x}_{FP}, \hat{y}_{FP})$, hence is achieved through KNN algorithm, which output will be the centroid $\hat{p}_{FP}$ of the polygon composed by the k nearby RPs with small D_m, i.e, the top k neighbours of the set $\mathcal{D}$, which is organized in an ascending order [39]. For this current implementation according to [62] was adopted a value $k = 4$ for the KNN, high values of k will contain a larger cumulative error, while if a low value of k is adopted, the results will not contain enough information and the position estimate will be unstable.

The FP technique is adopted because this approach allows a characterization of the environment, being able to better deal with the random variables surrounding the environment, aiming to achieve high system accuracy. The Algorithm 2 presents the FP technique implementation, as mentioned in subsection 2.2.3.

Algorithm 2: Fingerprinting

```
Input: k, RSSI_n, RSSI_{m,n}, ∀n ∈ {1, ..., N}, ∀m ∈ {1, ..., M}
Output: p̂_FP
begin
    Initialization;
    for m=1:1:M do
        Calculate D_m through (2.10);
        Add D_m in 𝒟 vector;
    Sort the vector 𝒟 in ascending order;
    Build a polygon with the RPs associated to the k small D_m;
    if collinear points then
        return mid point of the line;
    else
        return centroid of the constructed polygon;
```

3.3 Improving Accuracy

The estimated positions $\hat{p}_{MLT}$ and $\hat{p}_{FP}$ provided by MLT and FP standalone techniques respectively, are applied in the input of two distinct KFs. The vector z_k from each filter has the coordinates of $\hat{p}_{MLT}$ and $\hat{p}_{FP}$. Employing to the estimated position a linear motion model, it is possible to mitigate the positioning error introduced by the original localization techniques and improve the accuracy of the estimate. Therefore, two second order filters without external control were designed. The following state vector was considered (2.11), resulting in a 2D output as $\hat{p}_{f+KF} = (\hat{x}_{f+KF}, \hat{y}_{f+KF})\,, f \in \{MLT, FP\}$.

This step of the proposed model aims at reducing the noise in order to improve the position accuracy. It employs a series of measurements observed over time, containing a statistical noise and produces estimations that tend to be more accurate by the fact of taking into account the past states and the covariance error.

The Algorithm 3 shows the KF process, according to subsection 2.3.1.

Algorithm 3: Kalman Filter

Input: $\hat{p}_f, \mathbf{H}, \mathbf{R}, \mathbf{Q}, \mathbf{A}$

Output: $\hat{p}_{f+KF}$

begin

Initialization;

$z_k = \hat{p}_f$;

$x_k \leftarrow \begin{bmatrix} x(k) & y(k) & \dot{x}(k) & \dot{y}(k) \end{bmatrix}^T$;

As represented in Figure 2.8:

Calculate $\hat{x}^-_{k+1}$;

Calculate P^-_{k+1};

Calculate K_k;

Insert z_k vector to calculate $\hat{x}_k$;

Calculate P_k;

$\hat{x}^-_{k+1} = \hat{x}_k$;

return $\hat{p}_{f+KF}$;

3.4 Sensor Fusion

Finally, in order to get a better estimate position from the H-IPS proposed solution, a fusion is developed between $\hat{p}_{MLT+KF}$ and $\hat{p}_{FP+KF}$ through TTF original algorithm as (2.13), since to the sensor units are the same.

The TTF scheme was selected due to low computational cost, while showing better performance than modified TTF techniques when employed on similar sensors. In addition, the fused state estimate is the optimal linear solution, and is by definition better than individual KF state estimates [53]. The Algorithm 4 represents the TTF, as previously illustrated in Figure 2.9.

Algorithm 4: Track-to-track fusion

```
Input: p̂_{MLT+KF}, p̂_{FP+KF}, H, R, Q, A
Output: p̂_{H−IPS}
begin
    Initialization;
    P^{12}_{k|k} = 0;
    P^{21}_{k|k} = 0;
    x̂_{H−IPS} ← the results from (2.13);
    return p̂_{H−IPS};
```

Chapter 4

Implementation and Analysis of Experimental Results

The proposed H-IPS was implemented and experimentally tested in a laboratory facility that hosts the development of R&D activities as illustrated in Figure 4.1, consisting of an environment approximately 10×13 m, with several obstacles such as walls, office desks, workbenches, partitions and robot stations, which configures an environment that will affect the transmitted signal.

4.1 Implementation Setup

In this experimental setup, the target represents a transmitter that sends BLE advertisements acting as a BLE-beacon device. Five APs were deployed in the environment, acting as receivers, each one implemented in a Raspberry Pi (RPi) that is responsible to listen to the BLE advertisements sent by the TN.

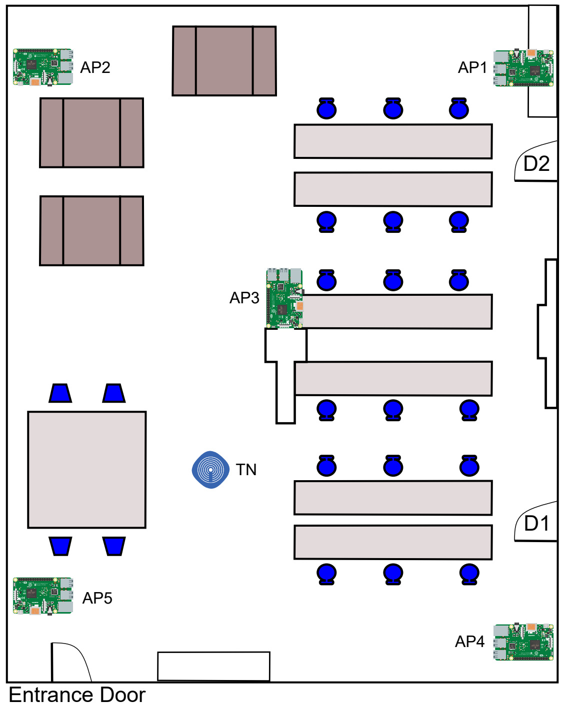


Figure 4.1: Overview of the case study environment layout.

4.1.1 Implementation Hardware

The BLE-beacon device used is the iBKS105 model from Accent Systems (Figure 4.2), which was configured to use iBeacon protocol, transmitting in a Transmit Power (Tx Power) level of 0 dBm and an advertising interval of 100 ms sending non-connectable data packets. For each time interval (i.e., the configurable time between advertisements), this device transmits sequentially the beacon messages (non-connectable advertisements), originally through three BLE channels (37, 38 and 39).

Figure 4.2: BLE-Beacon device employed.

Regarding the receivers were adopted the *Raspberry Pi 3 model B+* (Figure 4.3), the APs were placed in certain positions in order to avoid loss of the line of sight with the target and to facilitate access to electrical outlets. Four APs were fixed in the bounds of the environment and one AP was fixed near the center of the laboratory space (all of them placed approximately at the same height).

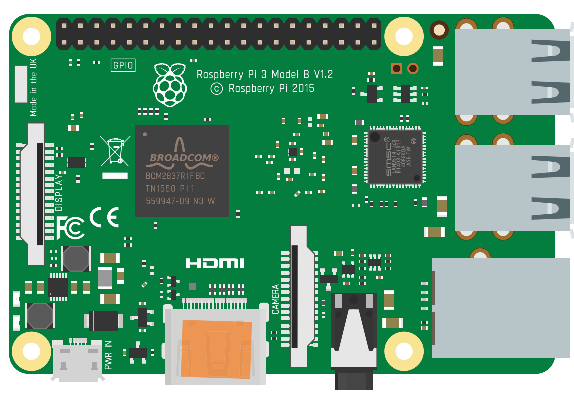


Figure 4.3: AP adopted in the implementation.

As the BLE protocol operates in the ISM frequency band, the same occupied by the Wi-Fi, there may be interference between the two technologies, and the sniffer appears as a solution to separate the BLE advertisement channels in order to read only the channel that possesses less influence of the Wi-Fi presence, avoiding packet losses and possible interference in the read values. Each RPi was used jointly with one Adafruit Bluefruit LE Sniffer (Figure 4.4), responsible for sniffing the beacons sent by the sensor tag. The

Adafruit module is a low-cost BLE device based on the *Nordic nRF51822* chipset with a RSSI measurement accuracy of ± 6 dB [63].

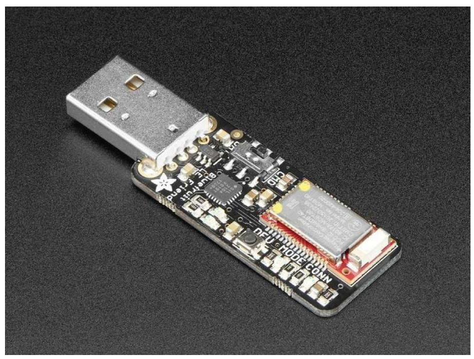


Figure 4.4: BLE sniffer used in the implementation.

The sniffer was configured to read a single channel due to the BLE's characteristics that occupies the same bandwidth of Wi-Fi (i.e. 2.4 GHz). Thus, the adopted solution receives the beacons and just analyzes the channel 39 since its central frequency is not affected by the Wi-Fi channels [22] as presented in Figure 4.5. Therefore, the RPis were programmed in *Python* language using the Adafruit API to configure the sniffers. It creates a socket connection identifying the MAC address of TN, and allows to listen to the beacons from the sensor tag, in addition, a smaller window interval to read than the target advertisement interval was set in order to avoid data packet losses. Finally, the APs jointly with the sniffer were responsible to acquire all RSSI measurements and save the readings in a file.

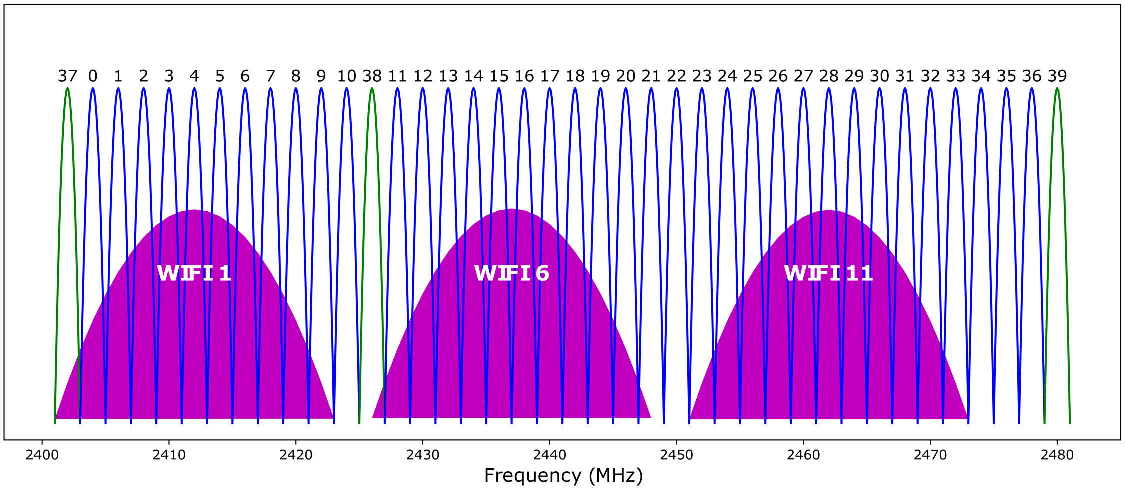


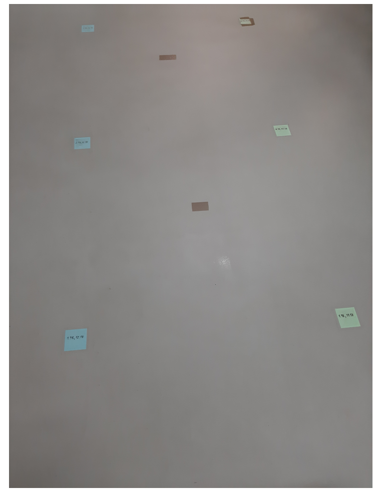
Figure 4.5: 40 BLE channels and the three commonly WiFi channels that cause interference. The BLE advertising only occurs on channels 37, 38 and 39. Adapted from [22].

4.1.2 Experimental Setting

The real-world setup is illustrated in Figure 4.6, each AP was placed on the wall using a double-sided Velcro tape to facilitate the removal of the receiver, as represented in Figure 4.6a. The beacon device was configured to an advertising interval of 100 ms operating with iBeacon protocol, in according to [22] aiming to maintain a balance between the energy consumption and the positioning update.

The tests were performed using a bench and a box as illustrated in Figure 4.6c, keeping the same height as the office desks in order to decrease the shadowing effect of the objects and simulate that the sensor tag was a card or a keychain. For the tests performed, the beacon device was positioned over the measured positions, keeping the same orientation of the antenna throughout the entire measurement, as represented in Figure 4.6d.

(a) AP deployment.



(b) RPs from FP database.

(c) Example of a developed test.

(d) Beacon position.

Figure 4.6: Real-world scenario implementation.

4.2 System Parameters & Coding Implementation

For the implementation of the H-IPS, the following parameters were considered:

The number of samples over trajectory is 50 (Figure 4.7), since the KF needs a minimal of samples to improve its covariance error matrix. Due to its recursive behavior, the Kalman Filter at each iteration updates the error covariance matrix to calculate a new gain in order to correct the model prediction, in addition, the measurements together with the calculated gain achieve a better state estimate [32].

Table 4.1: System parameters

Parameter	Value
Path loss exponent (α)	3.227 $*$
Room length (l)	9.77 m
Room width (w)	13.45 m
Reference distance (d_0)	1 m
$RSSI_{n,d_0}$	-59.0 dBm
Trajectory samples	50

Source: $*$(GOLDSMITH, 2005)

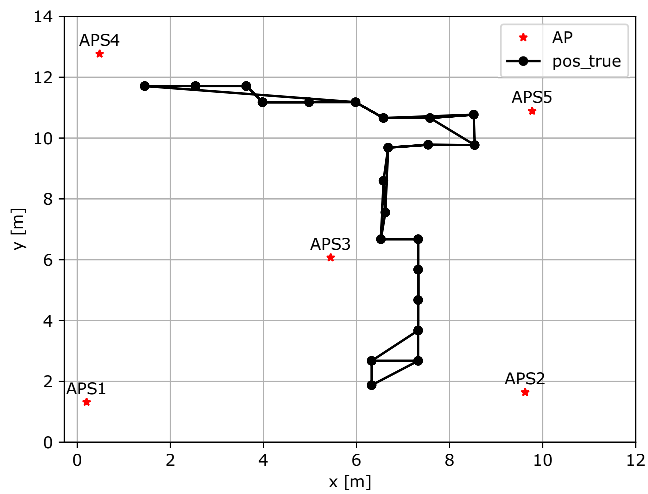


Figure 4.7: True position in scenario $l = 9.77$ m and $w = 13.45$ m, with a PRs grid size 1×1 m.

4.2.1 MLT Implementation

For MLT Technique, a calibration phase is extremely important, in order to determine the $RSSI_{n,d_0}$ the TN was positioned at $d_0 = 1$ m from each AP. Hence, 1000 packets were collected from all APs and an average value was computed, achieving a $RSSI_{n,d_0} = -59$ dBm, as illustrated in Table 4.1. During the tests the presence of multipath effect caused fluctuations in the RSSI.

To calculate the radius of the circles for the MLT technique, the path loss exponent was adopted the value of $\alpha = 3.227$, which was obtained experimentally in order to use a value that affords a better estimate. As indicated by the literature [26], a range of $\alpha = 1.6 - 3.5$ for an office building on the same floor.

The following *Python* implementation was used to calculate the radius through the measured RSSI values, employing the path-loss propagation model:

```
    # Function responsible to estimate the distance
    # between TN and AP through the measured RSSI.
def find_distance(TNRSSIdbm):
    RSSI0dbm = -59.0 # RSSI in the d0 distance
    s = 0 # Shadowing value in dB
    n = 3.227 # Pathloss exponent value
    d0 = 1.0 # Reference distance
    width = 9.775 # Width
    length = 13.45 # Length

    dist_buffer = []

    for i in range(5):
        # Calculates the distance between TN and AP
        dist = 10**(-((TNRSSIdbm[i]-RSSI0dbm+s)/(10*n))+np.log10(d0))
        dist_buffer.append(dist)

    return np.asarray(dist_buffer)
```

After the distance between the APs and TN is estimated, a least-square method was employed in order to predict the position, minimizing the function $cost\_fun$ using the Limited-Memory BFGS algorithm. The algorithm's target is to minimize the function over unconstrained the values of the real vector *pos* where $cost\_fun$ is a differential scalar function.

```
    # Calculates the euclidean distance between each AP
```

```
    # and the estimated position
def dist_fun(APsLoc, pos):
    res = []
    for i in range(len(APsLoc)):
        res.append(list((APsLoc[i, :] - pos) ** 2))

    res = np.sqrt(np.sum(np.asarray(res), axis=1))

    return res
```

```
def multilateracao(APsLoc, TNRSSIdbm):
    # Calculates the distance through path-loss propagation model
    dist_final = find_distance(TNRSSIdbm)
    dist_final = np.transpose(dist_final)
    pos_est_mlt = [] # Estimated position vector
    APsLoc = APsLoc.to_numpy() # AP positions vector
    # Calculates the error between the estimated distance
    # and the path-loss propagation model
    cost_fun = lambda pos: np.sum((dist_fun(APsLoc, pos)-dist_final)**2)
    # Initial condition
    cond_init = np.array([0.0, 0.0])
    # Estimates the position minimizing the fuction cost_fun
    location = scipy.optimize.minimize(
    cost_fun, # The error function
    cond_init, # The initial guess
    method='l-bfgs-b', # The optimisation algorithm
    options={
    'ftol':1e-5, # Tolerance
    'maxiter':1e+7 # Maximum iterations
```

```python
    })
    position = location.x
    pos_est_mlt.append(list(position))

    return np.asarray(pos_est_mlt)
```

4.2.2 FP Implementation

In the Fingerprinting Technique the RPs are placed in a (1×1) m grid as Figure 4.6b in order to build the FP database. To populate the FP database, the RSSI from 1000 beacons from each RP were averaged during the offline phase, as well as in the testing stage, in order to mitigate the fast-fading effect.

After building the database, in the online phase the KNN method was implemented that searches the database for the corresponding position based on the measured RSSI, leading to a matrix with a set of possible positions found.

```python
# Search in the database the first KNNs lower MSEs
xy_hat = np.zeros((KNN,KNN))

for b in range(0,KNN):
    # Seach the lower MSE
    min_mse_value = min(database[:,nAPS+3])
    # Search the corresponding position
    min_mse_index = np.argmin(database[:,nAPS+3])
    # Coordinate x of the lower MSE
    xpos = database[min_mse_index,1]
    # Coordinate y of the lower MSE
    ypos = database[min_mse_index,2]
    # Possible estimates matrix
    xy_hat[:,b] = [min_mse_value,min_mse_index,xpos,ypos]
```

```
        # Replace the found value by 200
        database[min_mse_index,nAPS+3] = 200
```

After achieved the possible positions, there are three possibilities: first the estimated position is the origin, when the sum of the possible coordinates was null; second if the possible points are not collinear, the corresponding estimated position will be the centroid of the convex hull formed by these points. Finally, case the coordinates are collinear the estimated position will be the average value of the points.

```
    # Case the sum of the possible coordinates was null,
    # the estimate will be (0,0)
    if sum(x1) == 0 and sum(y1) == 0:
        xest = 0
        yest = 0

    else:
        # Case the points are not collinear,
        # the estimate will be the centroid of the
        # convex hull formed by these points
        pos = np.array([x1,y1]).transpose()
        if not pointsAreCollinear(pos):
            hull = ConvexHull(pos)
            cx = np.mean(hull.points[hull.vertices,0])
            cy = np.mean(hull.points[hull.vertices,1])
            xest = cx
            yest = cy

        # Case the points are collinear, the estimate
        # will be the mean of the possible points
        else:
```

```
        xest = np.mean(x1)
        yest = np.mean(y1)
```

4.2.3 KF and TTF Implementation

As commented in subsection 2.3.1, the parameters $\mathbf{R} = r\mathbf{I}_2$ and $\mathbf{Q} = q\mathbf{I}_4$ corresponding to the covariance matrices, where $r, q \in \mathbb{R}$. In the KF tuning, each technique was adjusted separated, the MLT was adopted $q = 0.667$ and $r = 2$ while FP was selected $q = 0.00877$ and $r = 0.05$, all of the values were achieved experimentally in order to reach parameters that reduce the positioning error. For the MLT it was preferable to use a higher uncertainty, trusting more in the system model, while in FP because of the offline phase a lower uncertainty was adopted, relying more on the measurements. Aiming to improve the system accuracy and mitigate the RSSI fluctuations, the KF was implemented following a linear motion model:

```
    hat_x_me = np.append(hat_x_me,Phi.dot(hat_x_ma[:,k].reshape(4,1)) +
                         np.random.normal(0,Q,1),axis=1)
    P_me = Phi.dot(P_ma.dot(np.transpose(Phi))) + Q
    K = P_me.dot(np.transpose(H).dot(np.linalg.inv(
                H.dot(P_me.dot(np.transpose(H)))+R)))
    hat_x_ma = np.append(hat_x_ma,(hat_x_me[:,k+1].reshape(4,1) +
    K.dot(z[k,:].reshape(2,1)-H.dot(hat_x_me[:,k+1].reshape(4,1)))),
          axis=1)
    P_ma = P_me-K.dot(H.dot(P_me))
    P_buffer.append(P_ma)
```

Finally, to get the maximum performance of the system the TTF was implemented combining the FP and MLT methods according equation 2.13, considering the cross covariance matrices null. Reaching the optimal linear solution, being by definition better than the position estimate achieved employing just the technique standalone or the technique + KF.

```
pos_fusion.append(pos_FP_KF[k+1,:].reshape(4,1)+P_FP[k+1].dot(
                np.linalg.inv(P_MLT[k+1]+P_FP[k+1])).dot((
                pos_MLT_KF[k+1,:].reshape(4,1)-
                pos_FP_KF[k+1,:].reshape(4,1))))
```

The implementation code is available in [64].

4.3 Evaluation of System Performance

The entire estimation process was implemented on a desktop platform, aiming to estimate the position of the sender according the information received by the access points, i.e., the experimental tests considered an offline framework that allowed to test and evaluate the system performance, as illustrated in Figure 4.8. However, the developed system can work with an online framework in a similar or in a different testbed, but it is necessary a re-characterization of the environment in order to update the FP database.

From Figure 4.8 it is possible to compare the results obtained by each method (MLT, FP and H-IPS) with the real trajectory, it is noted that the MLT technique presents the largest values of distance from the true position, i.e. presenting a more significant error, while FP and H-IPS achieved more accurate estimates. Although the Fingerprinting performed better than the Multilateration, the fusion method turned out to be the most accurate resulting in more reliable estimates and shorter distances from the true trajectory points, providing a smaller positioning error.

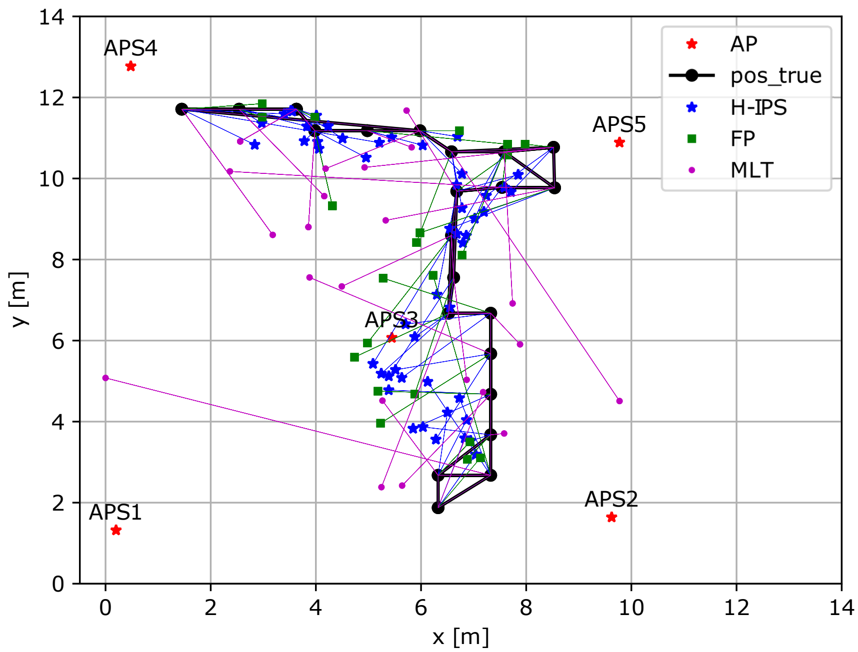


Figure 4.8: True position, H-IPS, MLT and FP, in scenario $l = 9.77$ m and $w = 13.45$ m, with a PRs grid size 1×1 m.

The proposed H-IPS performs better than standalone FP or MLT. MLT has the worst performance among the schemes.

Table 4.2: System position average error (in meters)

Average positioning error	
MLT	2.9991
FP	1.8121
MLT+KF	2.5341
FP+KF	1.4567
H-IPS	1.4307

The results presented in Table 4.2 are in accordance with [23], since the H-IPS performs better than the other solutions, reaching an average error of approximately 1.43 m, which represents an improvement of 52% over MLT original method and 21% in comparison to FP standalone technique.

As illustrated in Figure 4.9, the probability that the proposed solution presents an error < 2 m is 80%, while the same probabilities for the FP and MLT original techniques are 56% and 20%, respectively.

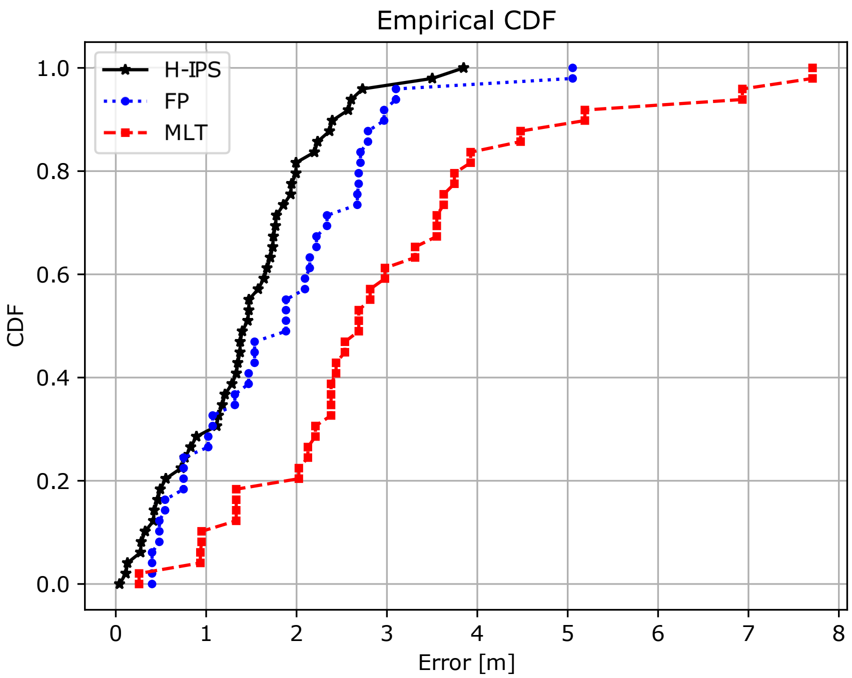


Figure 4.9: Cumulative Distribution Function (CDF) of distance error of the proposed IPS.

As stated in [53], in scenarios where the sensors have the same units, the original TTF works better than standalone techniques or even than Kalman Filtered techniques. Thus, sensor fusion is a viable solution to enhance the system accuracy.

The proposed solution was based on BLE and uses RSSI techniques to estimate the target position, providing a low complexity system when compared to other options, such as time-based arrangements that employ synchronism between the devices or angle methods that apply extra hardware and require a thorough calibration. Moreover, the proposed solution provides a low implementation cost where it uses inexpensive and commercially available equipment, striking a total investment of hundreds of euros, while UWB-based structures for example this value is around of thousands of euros.

Chapter 5

Conclusion and Further Work

An IPS aims to locate an object inside a building, with the solutions being usually based on applying techniques to calculate the distance between the object and several APs, combined with optimization algorithms that allow a faster positioning estimation and improve the accurate system. The main challenges addressed in this field are related to combine low cost implementations with low energy consumption and good position accuracy.

The IPS can be employed in a lot of scenarios and promotes the development of a plethora of technologies, like the BLE-beacon devices. This device is extremely versatile, being a interesting solution to warehouse and shopper solutions. The low-cost and low complexity of BLE technologies are important factors that makes these devices so attractive, increasing the user's adoption.

Considering the all advantages of BLE protocol, in this implementation was selected popular methods in localization solutions converting the RSSI values received from beacon messages in distance. In addition, employing FP and MLT techniques, schocastic filtering process and sensor fusion method, a notable enhancement was achieved, overcoming the standalone techniques performance. Emerging a hybrid indoor system.

The results proved that the H-IPS increases the accuracy in 52% over MLT original method and 21% in comparison to FP standalone technique. Finally, the probability of the proposed solution presents a error < 2 m is 80%, while the same probability of error to FP and MLT original techniques is 56% and 20%, respectively.

Future work will devoted to include an external antenna in the APs, in order to improve the signal reception, enhancing the performance of the MLT technique. Another point to work on is a model to tuning the KF parameters in real-time, improving the accuracy of the system and further mitigating the random variables surrounding by the environment.

Other possibility to explore could be to replace the MLT technique by another technique and compare the achieved results with other existing solutions, aiming to make the system more adaptive. Finally, a crowdsourcing solution may be an interesting tool to include in order to accelerate the calibration phase of FP, allowing easy update the database and facilitating the re-characterization to scenario changes.

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