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Sensory fusion of UBW-TOF-based location systems for mobile robotics

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Resumo

Com a necessidade crescente de robôs móveis em aplicações industriais, os sistemas de localização em tempo real, que é um ponto crucial nestas aplicações, têm atraído a atenção de muitos investigadores em todo o mundo. Assim, a localização de um robô é o processo de determinação da posição e orientação do mesmo no seu ambiente.

Os sistemas de localização que utilizam a tecnologia Ultra-WideBand (UWB) têm sido amplamente utilizados em ambientes urbanos e de interiores complexos. Consequentemente, uma tag UWB em movimento pode ser localizada com recurso à medição das distâncias a âncoras UWB fixas, cujas posições são conhecidas antecipadamente. A dificuldade desta abordagem reside no facto de as medições não serem perfeitas. Ou seja, haverá sempre algum ruído nas medições, e por isso, a determinação da posição pode conter alguns erros que podem resultar numa menor precisão.

Neste trabalho, é estudado e implementado num robô móvel o desempenho dos módulos da Pozyx como uma solução tecnológica de tempo de voo Ultra-Wideband (UWB) de baixo custo, através de um esquema de localização baseado em marcos. Assim, a fim de reduzir o impacto do ruído de medição e perturbações do sistema, as leituras de odometria, as medidas dos Pozyx e a informação das linhas do caminho de navegação são fundidas para melhorar a localização estimada do robô móvel. Desta forma, o objetivo desta integração é melhorar a precisão da localização para robôs autónomos de interiores. Para tal, primeiramente, foi estudado a caracterização do erro de medição dos módulos da Pozyx, sujeitando-os a diversas condições de teste. Em seguida, um algoritmo de filtro de Kalman estendido (EKF) foi implementado, integrando-o com duas heurísticas que permitem a libertação do filtro, de modo a este convergir para a pose correta do robô, após este ter começado a divergir. Por conseguinte, os resultados obtidos, a partir dos diferentes testes de localização realizados, são apresentados e comparados, de forma a apresentar a precisão atingida e comprovando as inúmeras vantagens da utilização das heurísticas.

Em suma, a inclusão do sistema Pozyx na elaboração deste trabalho mostrou ser uma ferramenta adequada e eficaz para melhorar a localização de um robô num ambiente interior desafiante, dado a sua boa relação de custo/precisão.

Palavras-chave: Robôs móveis, Localização, Ultra-wideband, Fusão sensorial, Filtro de Kalman estendido.

Abstract

With the increasing need for mobile robots in industrial applications, real-time location systems, which is a crucial point in these applications, has attracted attention from many researchers around the world. Thus, robot location is the process of determining the robot position and orientation in its environment.

Location systems using Ultra-WideBand (UWB) have been widely used in complex urban and indoor environments. Consequently, a moving UWB tag can be located by measuring the distances to fixed UWB anchors whose positions are known in advance. The difficulty of this approach remains in the fact that the measurements are not perfect. There will always be some noise in the measurements, and because of this, position determination could contain some errors that may result in decreased accuracy.

In this work, the Pozyx performance, a low-cost Ultra-WideBand (UWB) Time-of-flight (TOF) technology solution, is studied and implemented on a mobile robot, through a beacon-based location scheme. In order to reduce the impact of measurement noise and system disturbances, the readings of odometry, Pozyx measures and the information of the lines of a known navigation path are fused to improve the estimated location of the mobile robot. Therefore, the goal of this integration is to improve the accuracy of location for indoor autonomous robots. Firstly, was studied the characterisation of the Pozyx measurement error among several test conditions. Then, an Extended Kalman Filter (EKF) algorithm is implemented using two heuristics that allow the release of the filter so that it converges to the correct robot pose after it has started to diverge. Consequently, the results obtained from the different location tests performed are presented and compared, to present the precision achieved and proving the several advantages of using heuristics.

Overall, this work with Pozyx system showed that it is a proper and effective tool to improve the robot location in a challenging indoor environment given its good cost/accuracy trade-off.

Keywords: Mobile robot, Location, Ultra-wideband, Sensory fusion, Extended Kalman filter.

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Tiago Regallo Soares

“Tell me and I forget.
Teach me and I remember.
Involve me and I learn.”

Benjamin Franklin

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Abbreviations and Symbols

AOA	Angle of Arrival
DoF	Degrees of Freedom
DIEKF	Distributed Iterated Extended Kalman Filter
ESKF	Error-State Kalman Filter
EKF	Extended Kalman Filter
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning Systems
GUI	Graphical User Interface
IPS	Indoor Positioning Systems
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IR	Infrared
IEKF	Iterated Extended Kalman Filter
KF	Kalman Filter
LOS	Line of Sight
LPS	Local Positioning Systems
LBS	Location-Based Service
MD	Mahalanobis' distance
MCL	Monte Carlo Localization
NLOS	Non-Line of Sight
PF	Particle Filter
PLA	Polylactic Acid
PRF	Pulse Repetition Frequency
RF	Radio-Frequency
RFID	Radio-Frequency Identification
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RSE	Recursive State Estimators
SLAM	Simultaneous Localisation and Mapping
SD	Standard Deviation
TDOA	Time Difference of Arrival
TOF	Time of Flight
UWB	Ultra-Wideband
UKF	Unscented Kalman Filter
WLAN	Wireless Local Area Network

Chapter 1

Theme Introduction

Robot localisation is the process of determining the robot position and orientation in its environment. For that reason, localisation is one of the most fundamental capabilities required by an autonomous robot. Thrun, in his book "Probabilistic Robotics" [1], describes mobile robot location as "the most basic perceptual problem in robotics". One of the biggest problems, when it comes to location, is extracting the robot position and orientation from the information gathered by different sensors [2].

With the increasing need for mobile robots in industrial applications, real-time location estimate, which is a crucial point in these applications, has attracted attention from many researchers around the world [3].

It is important to be aware that accuracy is the primary evaluation metric for estimated positions, so it is essential to obtain accurate information in terms of relative or absolute position [4]. Consequently, high positioning accuracy enables many applications that were not possible before. For example, a drone or robot can be programmed to navigate through a building without bumping into things.

One of the most commonly used methods of positioning uses basic geometry to estimate the position. By measuring the distance to some anchors with a known position, it is possible to obtain our position. The difficulty of this approach remains in the fact that the measurements are not perfect. There is always going to be some noise on the measurements, and because of this, position determination could contain some errors that may result in decreased accuracy.

1.1 Context

Indoor positioning and navigation technologies have the potential of transforming users' experience and creating new opportunities for businesses, in the same way, like the Global Navigation Satellite Systems (GNSS) had changed the outdoor navigation experience and created the consumer navigation industry [5].

Positioning in an indoor environment is one of the most important and exciting topics in a navigation system that still present numerous open problems to investigate. Many researchers are attempting to investigate technologies able to reach valid location in an indoor space, where the well-known GNSS positioning systems are not able to operate, due to the none signal existence [6].

In indoor environments, a mobile robot needs to localise itself accurately because of the limited workspace and because of their increasing demand, it has become in an active research area in which different solutions have been proposed.

Many indoor location technologies have been developed in recent years for research and commercialisation [7]. Among these technologies, the relatively new Ultra-WideBand (UWB) method has gained extensive attention due to its high accuracy (few centimetres), low-cost, and easy deployment.

Location systems utilising Ultra-WideBand (UWB) have been widely used in dense urban and indoor environments. A moving UWB tag can be located by measuring the distances to fixed UWB anchors whose positions are known in advance. Although UWB technology has many strengths, its applications suffer from many technical challenges, including [8]:

- Possibility of interference with nearby RF systems.
- Time-consuming processes for signal acquisition, synchronisation and tracking with very high precision.
- Technical difficulties from the design and implementation of the antennas for UWB systems.

Because of these difficulties, some estimate errors can be incurred, which can reduce our precision.

Furthermore, UWB technology cannot provide information about the orientation, and because of that, so there is a need for another way to achieve that information. Additionally, it will be used a wheel encoder which is a simple device that converts the wheels' angular motion to a digital signal. With this signal, a robot's posture can be calculated by odometry. Finally, as the path the robot will be navigating is known, information from each path line will be used to improve our accuracy in estimating the position and orientation of the robot, also known as the pose.

1.2 Motivation and Objectives

Due to the influence of the building structures in indoor environments, techniques have to be further developed to cope with different issues. The main problems that can be witnessed are varying Line of Sight (LOS) and Non-Line of Sight (NLOS) or multiple delayed copies which can be created by reflections in walls and ceilings. These situations provoke noise and system disturbances and consequently, errors presented in the sensor measurements.

That means that a single solution will not be valid for every location, and a combination of different technologies are required to cover a particular place fully [5].

In order to reduce the impact of measurement noise and system disturbances, the readings of odometry and UWB modules and the information of the lines of a known path are fused to improve the estimated localisation of the mobile robot.

The goal of this integration is to improve the location accuracy for indoor autonomous robots [9]. So, all the information are merged to combine the complementary advantages of each system, and if one fails, the estimate can be enhanced with the others. This information fusion is accomplished through the use of a filter. Where an Extended Kalman Filter (EKF) will be used since a nonlinear system is being handled.

The idea of this thesis was inspired by the competition Robot@Factory Lite of the Portuguese Robotics Open. This competition simulates a simplified industrial environment on a small scale, where a mobile robot follows lines placed on the floor to move around the factory. Thus, the robot developed for this competition was improved, placing encoders on the wheels, and replacing some components in it.

Following these motivations and goal, the main objectives of this thesis can be summarised as follows:

- Study the approaches and implementations used with the Extended Kalman Filter (EKF) to similar problems.
- Study the implementation of a low-cost Time-of-Flight (ToF) sensors for an accurate localisation system.
- Develop the robot with the proper improvements and its control.
- Increase the accuracy of the location estimates generated by the filter to decrease existing measurement noises.
- Compare the different results obtained with different combinations of information sources delivered to the filter and draw conclusions from the results achieved.

1.3 Structure of the Document

The dissertation has been divided into 7 chapters. Following chapter 1 (introduction), the document has been organised as follows:

- Chapter 2 that presents the literature review for indoor location technologies, UWB solutions in the market and fusion algorithms;
- Chapter 3 presents a high level architecture of the developed solution and describe each module present in this solution;
- Chapter 4 formulates the algorithms implemented along with their explanation and introduces the problem of the robot beacon-based location;
- Chapter 5 describes the different performance and location tests performed and introduce the robot and the Pozyx system used in the tests;
- Chapter 6 illustrates the results obtained in each test as well as reflections on each result;
- Chapter 7 enumerates the different conclusions along the dissertation and presents some considerations regarding future improvements.

Chapter 2

Literature Review

This Chapter presents the literature review of indoor location technologies, UWB solutions in the market and fusion algorithms. First, Section 2.1 introduces the problem of positioning in the world. Next, Section 2.2 extends to indoor positioning and its the fundamental challenges, followed by the technologies and techniques used. Then, Section 2.3 focuses on UWB positioning and the challenges that this technology faces, followed by the solutions in the market. Finally, Section 2.4 features some algorithms used in data fusion problems.

2.1 Positioning Introduction

In this subsection, a brief overview of Global and Local positioning systems will be presented.

Firstly, positioning is the process of determining the positions of people, equipment, or other objects. Furthermore, in general, only two things are needed to perform the positioning [10]:

- **Measurements:** In a sense, almost everything that can be measured depends on the position, and can be used for positioning. Nevertheless, it is wiser to measure things that are very sensitive to the position. For example, measuring the temperature can tell which continent it was measured on, but that is not very accurate. However, measuring the distance or the angle to some point, it is probably more accurate.
- **Reference points:** It is only possible to describe a position relative to some reference points. Reference points can be a home, a lighthouse, the north star or some satellites in the sky.

Indeed, positioning systems are broadly categorised into two main categories Global Positioning Systems (GPS) and Local Positioning Systems (LPS). Thus, Global Positioning Systems are the systems that use satellites to provide location information to the user. In contrast, Local Positioning Systems provide location information with the help of base stations or anchors. Where the coverage of LPS is limited, and localisation is achieved only within the coverage area of the network [11].

Moreover, LPS can be categorised based on different network criteria. Where, it is generally categorised by the availability of computing, environment and medium for transmission. Due to every positioning system heavily depends on the environment, different LPS have been developed for different environments. These LPS can be classified into three categories based on the environment, i.e., outdoor LPS, indoor LPS and underwater LPS [11]. The former is performed outside buildings, while indoor positioning is performed inside buildings such as houses, hospitals, malls and others [12].

Depending on the type of applications, it may require different types of positioning technologies that fit their needs and constraints [10]. For example, in comparison with outdoor environments, sensing location information in indoor environments requires higher precision and is a more challenging task due in part to the expected various objects (such as walls and people) that reflect and disperse signals [12].

Furthermore, the research and use of positioning and navigation technologies outdoors have seen exponential growth. Based on that success, there have been attempts to implement these technologies indoors, leading most of the algorithms, techniques and technologies, that have been implemented outdoors, to numerous studies. Thus, several technologies have been proposed and implemented to improve positioning and navigation indoors [13].

As a result, indoor location sensing systems have become very popular in recent years. Those systems provide a new layer of automation known as automatic object location detection [14].

2.2 Indoor Positioning Systems

An indoor positioning system (IPS) is a system which continuously and real-time resolves the position of a person or an object within an indoor environment and can be applied in several applications, see Figure 2.1. For instance, providing indoor navigation systems for blind and visually injured people, locating devices through buildings, finding the emergency exit in a smoky environment, aiding tourists in museums, tracking kids in crowded places, tracking expensive equipment, among other examples. Consequently, indoor positioning applications may require different quality attributes, so IPSs should be carefully selected to meet the requirements of the application that depends on the context [10].

Besides, IPSs use numerous positioning approaches, which vary significantly in terms of accuracy, cost, precision, technology, scalability, robustness and security [10].

There are two main questions that developers need to address indoor positioning systems [10]:

1. What are the suitable technologies for implementing the desired IPS?
2. How can the most attractive trade-off between the different quality metrics be achieved to obtain an effective IPS?

Despite the numerous studies in the literature on indoor positioning area during the past decade, it remains an active and open research area. By that reason, IPS are attracting scientific and enterprise interest because there is a big market opportunity for applying these technologies. Additionally, studies predict that the market value for indoor LPS worth 10 billion US dollars by 2020 [11, 12, 15].

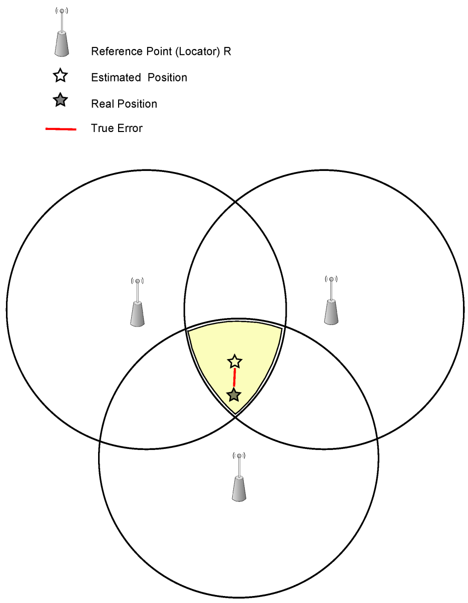


Figure 2.1: Positioning using reference points [10]

According to what was said in the previous section, indoor environments are more complex, which is characterised by a large number of obstacles, signal fluctuations, noise, environmental changes, and non-line of sight communication, accurate indoor LPS are required for satisfactory indoor location-based services (LBS) [11, 15].

Because of that, indoor localisation has been a challenging task in robotics for years, due to obstruction on GPS signals. In fact, outdoor positioning technologies such as satellite-based Global Positioning System (GPS) cannot be used in an indoor environment, since signals of GPS cannot penetrate through buildings and that they are hugely affected by indoor surroundings, becoming impractical for many indoor environments [12, 16, 17].

2.2.1 Fundamental Challenges on Indoor Environments

Following the previous section, many characteristics make indoor positioning different from outdoor positioning. Thereby, in comparison with outdoor environments, indoor environments seem to be more complicated due to the existence of several objects. Indoor environments usually rely on non-line-of-sight (NLOS) propagation in which signals cannot travel directly in a straight path from an emitter to a receiver (see Figure 2.2) causing inconsistent time delays at the receiver [10, 12].

Moreover, the existence of objects leads to high attenuation and signal scattering. Consequently, indoor positioning suffers from signal stability, as signal strength tends to fluctuate steadily due to the existence of numerous interference sources around us such as mobile devices, wireless devices, Zigbee devices, WiMAX devices, Bluetooth devices, cordless phones, microwave ovens, and fluorescent lights [10, 12].

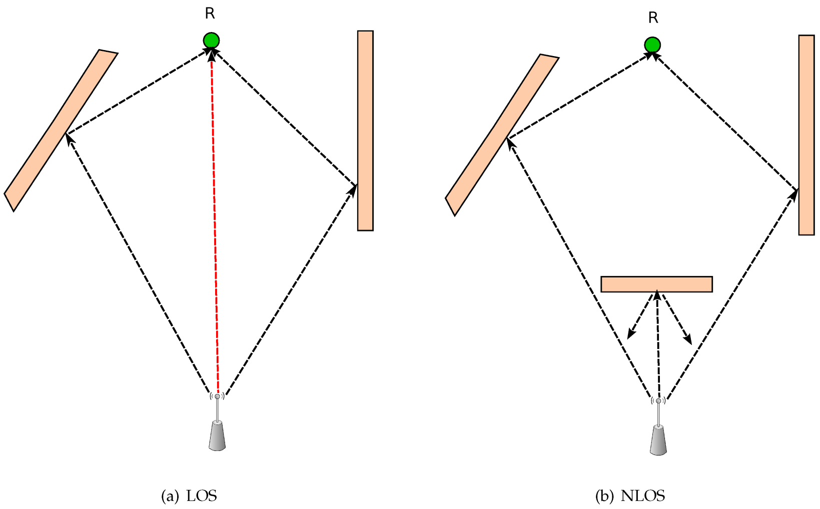


Figure 2.2: (a) Line-of-Sight (LOS) vs. (b) Non-Line-of-Sight (NLOS) [10]

Additionally, relative to outdoor environments, indoor environments are subject to structural movements in which structures, including reference points, may be moved from one place to another [10].

Typically, indoor positioning deals with relatively small areas and existing obstacles comparing to outdoor positioning. However, there are some characteristics of indoor environments that facilitate positioning. As an example, several factors can help in performing positioning within a small coverage area: predetermined infrastructure, corridors, small temperature and humidity gradients, entries and exits, and slow air circulation. Besides, indoor environments are less dynamic because objects move at a slower speed within them [10, 12].

2.2.2 IPS Performance Metrics

It is not enough to measure the effectiveness of a positioning technique only by observing its accuracy. IPSs use numerous positioning mechanisms which vary tremendously in terms of cost, accuracy, precision, technology, scalability, robustness, and security. For example, some applications might require low-cost IPS, whereas others may require high accuracy IPS. For this reason, in this section, the different performance metrics of IPSs are described. Table 2.1 presents the definition of each metric [10, 14].

Accuracy: This term has been defined as "the closeness of agreement between a measured quantity value and a true quantity value of a measure." or in other words, location error, and is an essential requirement of positioning systems. Usually, it is the average Euclidean distance between the estimated position and the exact position. Briefly, the higher the accuracy, the better the system. However, some compromises might need to make between "suitable" accuracy and other performance metrics [10, 14].

Availability: Availability is the percentage of time through which the positioning service is available, considering the needed accuracy and integrity. An IPS integrity is related to the confidence which should be placed in the output of a system. Besides, the availability might be affected by some factors such as communications congestion and routine maintenance. Usually, availability can be divided into three levels [10]:

- Low availability: under than 95%.
- Regular availability: between 95% and 99%.
- High availability: higher than 99%.

Coverage Area: Describe the spatial extension field performed by the IPS. Each IPS has a specific range. Commonly, for positioning systems, there are three levels of coverage: local, scalable, and global [10].

- Local coverage: relates to a limited area that is well-defined and is not extendable (e.g. a single room or building).
- Scalable coverage: regards to the ability of a system to increase the area by adding hardware.
- Global coverage: points to a system that has worldwide coverage or covers a specific desired area, but this can be extendable (e.g. GPS).

Scalability: Although the positioning system might position objects in multiple environments, the number of objects that the system might be capable of positioning, over a given time, is limited. Scalability of an IPS describes the adaptive ability of a positioning system to allow many instances of the technology to operate independently without interfering with each other and at the same time, while the system stability is still maintained. Usually, the positioning performance degrades when the distance between the transmitter and receiver increases. Thereby, a location system needs to scale on two axes: geography and number of users [10, 14, 18].

Cost: The cost of an IPS may depend on many different factors: important factors include money, time, space, and energy. The cost for system installation and maintenance involves cost required for installation and any fees that are required to maintain the system functionality. Thus, the cost for infrastructure components and positioning devices might cover the costs of buying components and preparing them, as well as space and energy required to operate those components. Some IPSs, especially those that reuse existent infrastructures such as the network, are more cost-effective. Additionally, energy is considered a critical cost factor in IPSs. For example, RFID tags are completely energy passive, while other systems consume energy. Consequently, the overall cost trade-offs will depend on how many hardware infrastructures are deployed [10, 14, 18].

Privacy: Privacy is one of the most important factors for users that utilise IPSs, so a powerful access control over how users' personal information is collected and used is crucial. To enhance, users' privacy, security mechanisms should be implemented and maintained to preserve data from intrusion, theft, and misuse [10].

Table 2.1: Performance metrics of indoor positioning systems (IPSs) [10]

Metric	Definition
Accuracy	"The closeness of agreement between a measured quantity value and a true quantity value ofa measure".
Availability	The positioning service availability in the sense of time proportion.
Coverage Area	The area covered by an IPS.
Scalability	The extent to which system guarantees the normal positioning function when it scales in one of two dimensions: geography and number of users.
Cost	Can be measured in different dimensions: time, space, money or energy that could be affected on different levels of the system: system installation and maintenance, positioning devices, and infrastructure elements.
Privacy	Reliable access control over how users' personal information gathered and used.

2.2.3 Indoor Positioning Technologies

Different indoor positioning technologies might be used simultaneously to reach the advantages of each one. The suitable indoor positioning technology should be chosen carefully for making the proper balance between complexity and the performance of IPSs. Researchers classify indoor positioning technologies in several ways [10, 12].

In 2003, some authors categorised indoor positioning technologies into two classes according to the necessity of hardware: technologies that require specific hardware in the building and self-contained technologies [10, 12].

Secondly, other authors provided a different classification of indoor positioning technologies in 2009, wherein they split them into two distinct categories based upon their needs for existence of networks: network-based and non-network-based technologies. The authors further classified indoor positioning technologies according to system architecture into three classes [10, 12]:

1. Self-positioning architecture, in which objects determine their positions by themselves.
2. Infrastructure positioning architecture that estimates the locations of the objects, using the infrastructure to obtain it, if the object is in the range area, and track it.
3. Self-oriented infrastructure assisted architecture which depends on the system that determines their positions and then sends them to the tracked object in response to its request.

Consequently, they classified indoor positioning technologies into six categories based on the surrounding environment for determining positions [10, 12]:

- Infrared (IR) technologies.
- Ultra-sound technologies.
- Radiofrequency (RF) technologies.
- Magnetic technologies.
- Vision-based technologies.
- Audible sound technologies.

In 2011, other authors categorised indoor positioning technologies into fixed indoor positioning systems and indoor pedestrian positioning systems. Such classification is very similar to the categorisation introduced in 2003 [10, 12].

Similarly, Chliz et al. divided the indoor positioning techniques into two categories: parametric in which a position is computed based on the prior knowledge and non-parametric where a position is computed by processing the data considering several statistical parameters [10, 12].

Besides, Rainer Mautz provided another classification of indoor positioning technologies in 2012. He classified them into thirteen categories: camera, infrared, tactile polar systems, sound, WLAN and Wi-Fi, RFID, ultra-wideband, high sensitivity GNSS, pseudolites, other radio frequencies, inertial navigation, magnetic systems, and infrastructure systems [10, 12].

Unlike the previous classifications, a new classification for indoor positioning technologies, according to the infrastructure of the system that uses them, was presented, see Figure 2.3. The new classification has two main classes: building dependent and building independent. Building dependent indoor positioning technologies are referring to technologies that rely on the building in which they would operate. They are dependent either on existing technology in the building or on the map and structure of the building. Building dependent indoor positioning technologies may be divided into two significant classes: indoor positioning technologies, which demand dedicated infrastructure and indoor positioning technologies that use the building's infrastructure. The necessity for dedicated infrastructure is determined according to the overall structure of most current buildings. For example, most buildings contain WIFI, while almost none contains radio frequency identification [10, 12].

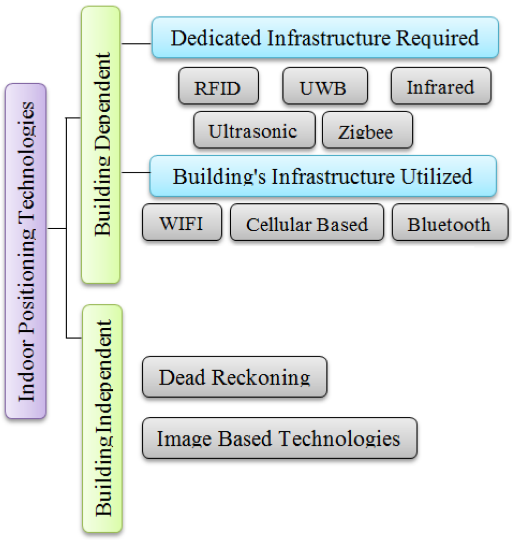


Figure 2.3: Classification of indoor positioning technologies [10]

(1) Radio Frequency Identification (RFID): Radiofrequency Identification uses radio waves to transmit the identity of an object (or person) wirelessly. RFID technology is most used to identify objects in large systems automatically. It relies on exchanging different frequencies of radio signals between these two main components: readers and tags. Tags produce radio signals that are received by readers and vice-versa. Both use predefined radio frequencies and protocols to send and receive data between them. Tags are connected to all the objects that must be tracked. There are two kinds of tags: active tags and passive tags. By contrast, an RFID reader consists of various components, including an antenna, transceiver, power supply, processor, and interface, to connect with a server. Even Though different positioning methods might be used with RFID, proximity is the most used one. Besides that, received signal strength (RSS) could be used with RFID [10, 12, 13, 15, 17, 19, 20].

(2) Ultra-Wideband (UWB): Ultra-wideband (UWB) utilises a radio wave generator (emitter) and antennas (receiver) to detect static and moving objects. The transmitted signal in UWB is sent through multiple frequencies band. So, it is a communication channel which spreads information across a large portion of the frequency spectrum. This fact enables the UWB transmitters to forward large quantities of data while consuming a small transmit energy. Researchers and industry frequently use UWB in several fields such as indoor positioning in order to present enhancements in terms of achieving high range measurement resolution and accuracy, low probability of interception, multipath immunity, and the capability to combine positioning and data communication in one system. Moreover, UWB technology is highly scalable and can be used at low cost with low energy consumption. Localisation systems based on UWB technology accomplish an accuracy of centimetres. UWB can be used for positioning by leveraging the time difference of arrival (TDOA) of the RF signals to get the distance between the reference point and the object [10, 12, 13, 15, 17, 19, 20].

(3) Infrared (IR): The infrared technique is like the idea of infrared light. The only difference is that it estimates its local position rather than estimate an object position. Infrared communication makes use of the invisible spectrum of light just beneath the red edge of the visible spectrum, making this technology less intrusive than indoor positioning that relies on visible light. IR can be applied in two different ways: direct IR and diffuse IR. Infrared Data Association (IrDA) is one example of direct IR which uses a point-to-point ad-hoc data transmission standard designed for very low-power communications. IrDA requires line of sight (LOS) communication between the devices over a short distance. Another side, diffuse IR, has stronger signals than direct IR, so it has a more extended reach (9–12 m). Diffuse IR utilises wide-angle LEDs which emit signals in many directions. Consequently, this enables many connections and requires no direct line of sight. Differential phase-shift, proximity and angle of arrival (AOA) positioning algorithms are often used with Infrared technology [10, 12, 13, 15, 17, 19, 20].

(4) **Ultrasonic:** Ultrasonic location-based systems utilise sound frequencies higher than the audible range (beyond 20KHz) to determine the object position calculating the time taken for an ultrasonic signal to travel from a transmitter to a receiver (TOA). Besides, it does not interfere with electromagnetic waves and has a relatively short range. Ultrasonic positioning systems use building material and the air as a propagation medium. Emitters localisation can be evaluated by multilateration from three (or more) measures to some fixed receivers (deployed at known locations). Ultrasound systems, as well as many other IPS, can be active or passive [10, 12, 13, 15, 17, 19, 20].

(5) **Zigbee:** ZigBee builds on standard IEEE 802.15.4 and is concerned with the physical and MAC layers for low cost, low data rate and energy saving. It delivers network security and application support services. In other words, ZigBee is a short distance and low rate wireless personal area network. There are two distinctive physical device types used for ZigBee nodes: full function device (FFD) and a reduced function device (RFD). An IPS based on ZigBee consists of a network of sensors and wireless sensor network algorithms. Most of the algorithms that are used in these systems use RSSI values to estimate the location of the target. Besides, phase shift measurement is a new approach which was recently introduced to estimates the positioning of the target [10, 12, 13, 15, 17, 19, 20].

(6) **Wireless Local Area Network (WLAN):** The Wi-Fi (IEEE 802.11 WLAN standard) was approved in June 1997. WLAN or Wi-Fi is a technological communication standard for wireless data transmission, which uses electromagnetic waves for transmission of data. Wi-Fi is another excellent wireless way to estimate location, which is based on the strength of the signal received. Besides, the effective range of Wi-Fi standard is comparatively broad with such a coverage range of between 50 to 100 m. However, using RSS, the accuracy of WLAN positioning systems is approximately 3 to 30 m. Moreover, using Wi-Fi in indoor positioning and navigation systems depends on knowing a list of wireless routers which are available in an area where the system operates [10, 12, 13, 15, 17, 19, 20].

(7) **Cellular Based:** Global System for Mobile Communications (GSM) networks are accessible in most countries and can field service the coverage of WLAN with a lower positioning accuracy. Several systems have used a global system of mobile/code division multiple access (GSM/CDMA) mobile cellular networks for estimating the location of mobile clients. GSM works in licensed bands and prevents interference from other devices that operate at a similar frequency (unlike WLAN). However, it is only possible to use indoor positioning, on a mobile cellular network, if one or more base stations cover the building with strong RSS. The most common approach of GSM indoor positioning is fingerprinting, which relies on the power level (RSS). So, the accuracy of the method using cell-ID is generally low [10, 14].

(8) **Bluetooth:** Bluetooth is a wireless communication technology which uses digitally embedded data on radio frequency signals. Originally designed for data exchange in short distances, it was defined in standard IEEE 802.15.1. Main goals of the technology are to facilitate communication between mobile users, for eliminating cables and connectors between devices and facilitating data synchronisation between personal devices. Bluetooth is designed for a deficient power technology for peer-to-peer communications. In comparison with WLAN, the bit rate is lower, and the range is shorter (approximately 10 cm to 10 m), making it less effective for longer-range applications. Although Bluetooth is also regarded as another secure, low power (BLE), low-cost wireless technology. Finally, Bluetooth technology uses proximity and RSS methods to estimate positions [10, 14, 15, 17, 18, 19].

(9) **Dead Reckoning:** With dead reckoning, an object can roughly estimate its current position by knowing the past position and the velocity whereby it moves. This estimate is achieved through either incrementing the known location based upon its velocity or the known, travelled distance. With the right number of absolute location updates, dead reckoning's linearly growing position errors might be suppressed within predefined boundaries. In order to improve its accuracy and decrease error, dead reckoning must use other technologies to adjust the location of the object after each interval [10, 18].

(10) **Image-Based Technologies:** Image-based indoor positioning technologies, sometimes known as optical methods, contain camera and computer vision-based technologies. Different kinds of cameras can be used like mobile phone cameras, omnidirectional cameras, and three-dimensional cameras. However, their effectiveness varies depending on the amount of information that can be extracted from their images. Since cameras provide a picture of a place, this place might be trained by neural networks in order to provide an estimate of the current position. Image-based positioning systems can be divided into two main categories: ego-motion systems, that uses a camera's motion concerning a rigid scene to estimate its current position and static sensor systems that detect moving objects in the images [10, 17].

(11) **Pseudolites:** Pseudolite is a shortening term of pseudo-satellite. Considering that satellites signals cannot penetrate most indoor environment, such as buildings, coal mines, long tunnels and others, pseudolites can be used to create signals like GPS which can be used within indoor environments in order to enable GPS device to keep receiving signals from those transmitters, rather than satellites. Besides, to deal with a less accurate clock inside pseudolite transmitters, that produces the clock errors, different techniques were developed. Pseudolites for indoor environments are still negatively impacted by multipath, signal interference between pseudolites, weak time synchronisation due to less accurate clocks inside the pseudolites, and carrier phase ambiguities [10].

Additionally, an Inertial Navigation System can be arranged in order to complement any of the technologies above.

(12) **Inertial navigation system (INS):** An INS is a compound indoor/outdoor location identification technology that uses an inertial measuring unit (IMU), such as accelerometer and gyroscope, to estimate the position and angular motion of the object, relative to an initial starting point. Of course, this is a very rough estimate. Thus, it continuously calculates, by dead reckoning, its orientation and velocity. Moreover, because INS includes estimate of target position from a known initial position using direction and speed measurements, it is exposed to drift and cumulative error [15, 18].

Moreover, it is possible to observe in Figure 2.4 the accuracy accomplished by all the different technologies used for indoor positioning, outdoor and other environments. It is quite clear from this figure that the accuracy requirements will vary depending on the scale of the transmission.

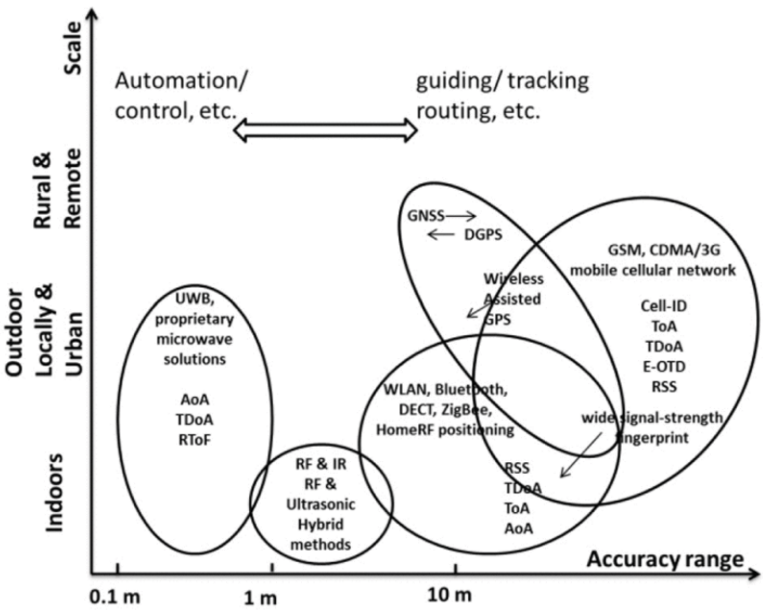


Figure 2.4: Overview of the accuracy accomplished by all the different technologies [19, 20]

The Table 2.2 provides a comparison between indoor positioning technologies presenting the advantages and disadvantages of each technology which needs to be counted during the IPSs a selection procedure.

Table 2.2: Comparison between Indoor Positioning Technologies [10, 12]

Technology	**Advantages**	**Disadvantages**
RFID	It can penetrate solid and non-metal objects. It does not require LOS within RF transmitters and receivers.	The antenna changes the RF signal. The positioning coverage area is small. Cannot be integrated easily with other systems. RF communication is not intrinsically secure and consumes more power than IR devices.
UWB	It as a high accuracy positioning, even in the presence of severe multipath, effectively goes through walls, equipment, and any other obstacles. UWB do not interfere with existing RF systems if properly designed.	Some of UWB equipment has a high cost. Even Though UWB is less susceptible to interference relative to other technologies, it is still under interference caused by metallic materials.
Infrared	Because IR signals cannot penetrate through walls, it is appropriate for sensitive communication because it will not be available outside a room or a building.	It does not penetrate walls, so it is typically used in small spaces like one room. IR communication is obstructed by obstacles that block light which consist of almost everything solid. It requires LOS between transmitter and receiver when using direct IR. One problem with diffuse infrared systems is their low performance in locations with direct sunlight or fluorescent lighting because the infrared emissions, from the light sources, may interfere with the signals.
Ultrasonic	Does not require LOS and do not interfere with electromagnetic waves.	Does not penetrate solid walls. The signal can be lost because of an obstruction; Reflections can cause false signals and it can have interference caused by high frequency sounds (e.g., keys jangling).
Zigbee	Its sensors require low energy and it is a low-cost technology.	Zigbee seems vulnerable to interference caused by a variety of signal types that use the same frequency. This might disrupt radio communication. It is suitable for networks where conversation between two devices takes some few milliseconds which allows the transceiver to switch to sleep mode quickly.
WLAN	It uses existing communication networks that may cover more than one building. Many devices available nowadays are equipped with WLAN connectivity. WLANs exist almost in most buildings. LOS is not required.	Main disadvantage of WLAN fingerprinting systems is the recalculation of the predefined signal strength map in case of changes in the environment (e.g., open or closed doors and the moving of furniture in offices).
Cellular Based	There is no interference with devices that operate at the same frequency. The hardware of the usual mobile phones can also be used.	It has low reliability due to varying signal propagation conditions.
Bluetooth	Does not require LOS between communicating devices. It is also embedded into most smartphones, personal digital assistants, etc.	The greater the number of cells, the smaller the size of each cell and consequently better accuracy, however more cells increase the cost. It requires some relatively expensive receiving cells. Requires a host computer to locate the Bluetooth radio. Because the 2.4 GHz spectrum that Bluetooth uses is unlicensed, new uses are expected for it and as the spectrum becomes more widely used, radio interference is more likely to occur.
Dead Reckoning	Does not require additional hardware such as sensors.	The Dead Reckoning calculates only an approximate position.
Image based technologies	They are relatively cheap compared with other technologies such as ultrasound and ultra wideband technologies.	Requires LOS and its coverage is limited.
Pseudolites	They allow to extend the coverage area much farther to several kilometres and provide great flexibility in deployment that can be optimised for some application and it is also compatible with existing GPS receivers.	They are negatively affected by multipath, signal interference among pseudolites, low time synchronisation due to less accurate clocks inside pseudolites and carrier phase ambiguities.

2.2.4 Indoor Positioning Techniques

Aside from indoor positioning technologies, there are a few indoor positioning techniques which can be applied to different indoor positioning technologies. Accordingly, positioning techniques serve to specify which is the foundation technique of the algorithm to be applied to obtain the position of the object. One or more techniques could be applied simultaneously to compensate for the limitations of a single positioning technique. Therefore, several techniques exist to determining position which has been classified by Gu et al. in 2009 into four classes (see also Figure 2.5) [12, 13, 14]:

1. Triangulation.
2. Fingerprinting.
3. Proximity.
4. Vison Analysis.

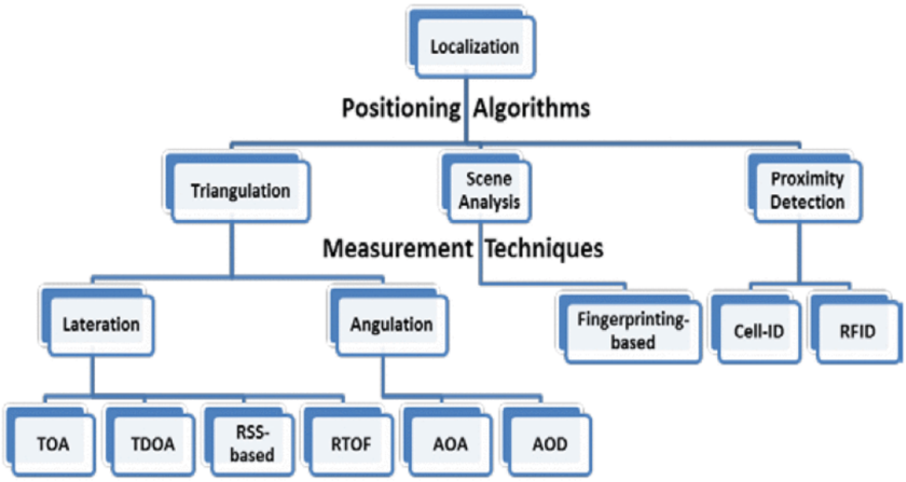


Figure 2.5: Classification of localisation methods [20]

Triangulation: The triangulation location detection technique uses geometrical properties of triangles to compute object locations. Triangulation could be divided into three techniques since to find out where a target is, required multiple distance measurements, multiple angle measurements or by a combination of angle and distance. These three approaches are often referred to as trilateration, multilateration, and angulation [12, 13, 14, 18]:

- **Lateration:** Trilateration or Multilateration, also called a range measurement technique, computes the position of objects by measuring its distance from multiple reference points. Besides, calculating the object's location in two dimensions (2D) requires distance measurements from 3 non-collinear reference points, while distance measurements from 4 non-coplanar points are necessary for three dimensions (3D) locations.

- **Angulation:** It resembles lateration. However, angulation uses angles to determine the position of an object as well as distances. Namely, an object can be located by computing angles relative to several reference points. Generally, two-dimensional (2D) angulation requires two angle measurements as well as one length measurement (e.g., the distance between the reference points). In three dimensions (3D) angulation is required, one length measurement, one azimuth measurement, as well as two angle measurements, are required to achieve a precise position.

Both trilateration and multilateration utilise the time of propagation of the signal (TOF) or the received signal strength (RSS) as a foundation of measurement. Whereas that angulation technique utilises the direction angle of the arrival (AOA) of the signal received [12, 13, 14, 18].

Thereby, when two or three reference points are used to identify the position, it leads to a simple and low-cost system. However, when the coverage area is broader, with several reference points, position determination might contain some errors that can lead to decreased accuracy [12, 13, 14, 18].

Fingerprinting: The position estimate in fingerprinting is made independent of angles or distances. In fact, instead of determining the distance between an object and a reference point and triangulating the object's location, fingerprinting location is based in a database correlation. Through which the distance between a beacon and transmitting objects is detected by comparing the received signal strength (RSS) pattern with a pre-recorded measurement pattern in the database. This technique presents two stages: offline stage (training or survey) and online stage (query, test or positioning). In the offline stage, also called training stage, signals from each position node at every training location are collected, by identifying the received signal strength indicator (RSSI), and recorded in vectors or radio maps. Whence, the construction of the radio map begins by splitting the area of interest into cells with the aid of a floor plan. Each RSSI vector constitutes the fingerprint of every known training location and stored in the database for further comparison and matching. Secondly, in the online stage, also called serving stage or run time stage, a location positioning technique uses the currently observed signal strengths (RSS) and previously collected information to figure out an estimated location. Once a user submits a location query with its current RSS fingerprint, positioning algorithms recover the fingerprint database and return the matched fingerprints plus corresponding locations [12, 13, 14, 18].

Thereby, the main challenge for this kind of technique, based upon location fingerprinting, is the fact that received signal strength (RSS) might be affected by diffraction, reflection, and scattering in the propagation indoor environments [12, 13, 14, 18].

Fingerprinting offers better positioning accuracy and performance compared to propagation techniques and proves effective in the presence of non-line of sight (NLOS). However, fingerprinting becomes inefficient in the offline phase, since it suffers considerably due to over-head from creating vectors. As a result, fingerprinting suffers from high cost, high complexity and low speed [12, 13, 14, 18].

Proximity: Unlike triangulation, proximity does not provide an absolute or relative position estimate because it just provides position information. To provide the information, a grid of detectors with known positions used to specify the position of the target. When a detector detects an object, its position is thought to be in the proximity area marked by the detector. There are three common approaches to detecting proximity. The first and most basic type of proximity detecting approach is detecting physical contact with objects. Another approach is when an object is detected in motion, where the closest detector is used to compute its position. Lastly, if the object is detected by more than one detector, the detector with the strongest signal is used to compute its position. All these approaches are relatively simple to implement. Generally, in proximity technique, the position of the object is specified using the RSS algorithm. Besides, accuracy utilising proximity detection is associated with the density of the detectors and the signal range of each one. However, whether high accuracy is required, the excessive concentration of detectors might lead to complexity and high cost. Finally, it can be implemented throughout different types of physical media. Especially, the systems which use infrared radiation (IR) and radio frequency identification (RFID) are often based upon this method. A further example is the cell identification (Cell-ID) or the cell of origin (COO) method [12, 13, 14, 18].

Vision Analysis: The vision analysis technique estimates locations from images received at one or multiple points and is achieved by utilisation of camera sensors. Usually, one or multiple cameras are installed in the tracking area of an IPS covering the entire place and take real-time images. The camera sensor is used to acquire visual features and images and estimate the motion of the target about specific features or landmarks that serve as references for determining the image position of the target. Furthermore, the vision analysis approach also uses a stored image database marked with position information of the cameras. Once an image query is received, perform an image matching between the query image and the database images by using an efficient algorithm like the vocabulary tree. Finally, Vision analysis location identification provides a low complexity, as the approach often requires no pre-installation of any dedicated infrastructure that serves as a crucial advantage. However, this technique suffers from several disadvantages: First, the approach is invasive in the nature resulting in the use of low-resolution cameras. Second, the approach becomes untrustworthy in blockage situations where objects are blocked by camera detection, which leads to low-resolution recognition and poor accuracy [12, 18].

The next Figure 2.6 summarises the characteristics of the positioning techniques.

Positioning algorithm	Signal property	Pros	Cons
Triangulation	AOA	Simple, low-cost and high accuracy at room level	Complex, expensive and low accuracy at wide coverage
Trilateration	TOA/TDOA	High accuracy	Complex and expensive
Proximity	RSSI	High accuracy	Complex and expensive
Scene analysis/fingerprinting	RSSI	High performance	Complex, expensive, medium accuracy and time consuming

Figure 2.6: Summary of positioning algorithms Positioning [13]

2.3 UWB Positioning

Ultra-Wideband (UWB) is an emerging technology in the field of indoor positioning that has demonstrated better performance in comparison to others. The antecedent technology of UWB is known as baseband, impulse, and carrier-free technology. Furthermore, the US Department of Defense was the first using the term ultra-wideband. Nevertheless, UWB technology only became commercially available in late 1990 [10, 16].

The UWB technology is a technique of spectrum access that can offer high-speed data rate communication through personal area network space. Moreover, UWB relies on transmitting extremely short pulses and uses techniques that provoke dissemination of the radio energy, within a broad frequency band, along with a meagre power spectral density. Consequently, this high bandwidth delivers high data throughput for communication. Additionally, the low frequency of UWB pulses allows the signal to traverse obstacles like walls and objects effectively [10, 16].

There are three main application areas whereby UWB is used [10, 16]:

- Communication and sensors.
- Positioning and tracking.
- Radar.

UWB positioning techniques might give real-time indoor precision tracking for multiple applications like mobile inventory and detector beacons for emergency services, indoor navigation for blind and visually damaged people, tracking of people or instruments, and military scouting. Therefore, UWB signals provide precise position and location estimate for indoor environments. However, depending on the required accuracy of the positioning system, the density of sensors can be adapted accordingly [10, 16].

2.3.1 Why UWB has gained attention

Broadly, UWB technology has different characteristics that are being explored in the literature. First and foremost, its high data rate which can reach 100 Megabits per second (Mbps), making it an excellent solution for near-field data transmission. Besides that, the high bandwidth and extremely short pulses waveforms help reduce the effect of multipath interference and to facilitate the decisiveness of TOA for transmission between the transmitter and corresponding receiver. Consequently, it makes the UWB a slightly more attractive solution for indoor positioning than other technologies. The duration of a single pulse defines the minimum differential path delay while the period pulse signals define the maximum observable multipath delay in order to perform multipath resolution explicitly. Additionally, the low frequency of UWB pulses allows the signal to go through obstacles such as walls and objects, which improves accuracy. Indeed, UWB provides a high accuracy rate which can minimise its error to just a few centimetres. For this reason, UWB is considered one of the most proper options for critical positioning applications that require highly accurate results. Finally, UWB technology, unlike any other positioning technologies like infra-red and ultrasound sensor, requires no line-of-sight and is unaffected by the presence of other communication devices or external noise owing to its high bandwidth and signal modulation (PPM, PAM, BPSK, QPSK or OOK). Moreover, the cost of UWB equipment is low, and it consumes less power compared to other competitive solutions [10].

2.3.2 How does it work

As has been presented before, an estimated position of any object can be attained by measuring distances to reference points. UWB technology uses this principle and measures the time of flight (TOF) of a wave that is sent by the transmitter to the reference point, also known as anchors in this context. Because UWB is based in radio waves, that travel at the speed of light, the TOF can be simply divided by the speed of light to achieve the distance travelled. However, owing to radio waves travels this fast, into a single nanosecond, a wave has travelled almost 30 centimetres. So, if a centimetre accurate ranging perform is required, the system must be able to measure the time very precisely [21].

In physics, there is something known as Heisenberg's uncertainty principle. The principle says that it is impossible to know both the frequency and time of a signal. If, for instance, a sinusoid is considered, this signal has a well-known frequency but an extremely undetermined time of signal (the signal does not have a beginning or end). However, when several sinusoidal signals are combined with a slightly different frequency, a pulse with a more defined timing can be established, i.e., the duration of the pulse peak. This pulse pike is visible in the following Figure 2.7 that is a result of the sum of several sinusoids to obtain a sharper pulse (X-axis: time and Y-axis: signal strength received) [21].

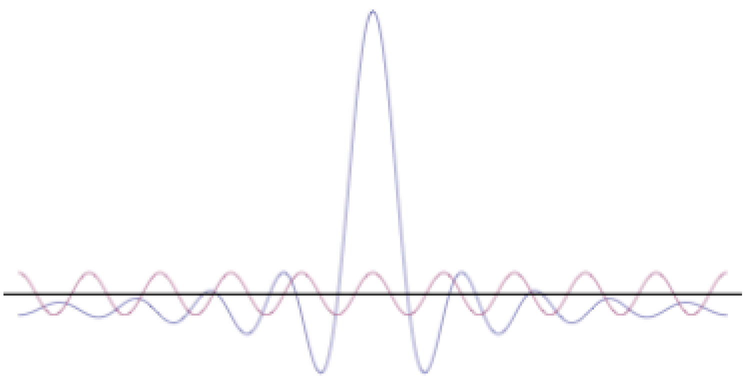


Figure 2.7: Representation of the pulse pike [21]

The UWB signal has a bandwidth approximately around 500 MHz resulting in pulses of 0.16 ns of duration. Thanks to this time resolution, the receiver can distinguish several reflections of the signal, see Figure 2.8. Hence, it is possible to achieve accurate ranging even in places where there are many reflectors, like indoor environments [21].

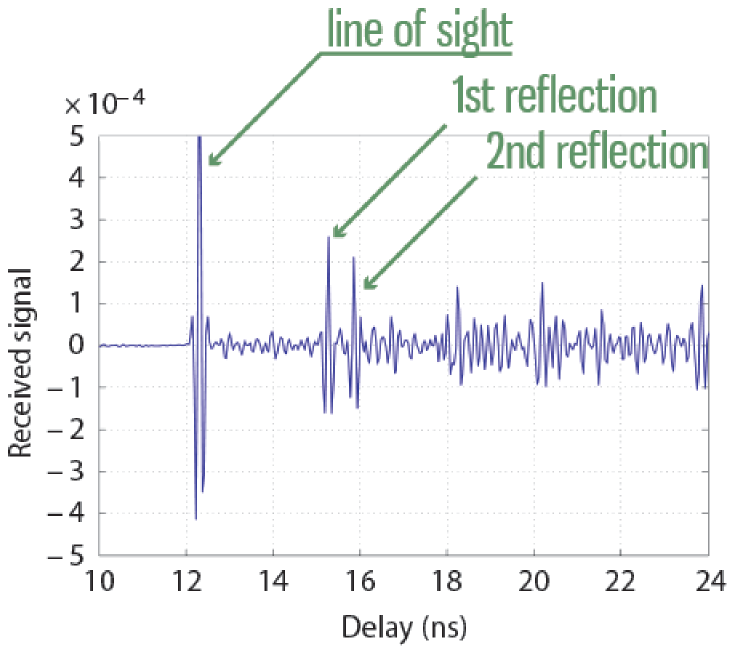


Figure 2.8: Representation of several receiving reflections [21]

Furthermore, UWB systems are only allowed to transmit meagre power (the power spectrum density must be lower than -41.3 dBm/MHz). Consequently, this very rigid power restriction means that a single pulse cannot reach far, i.e., at the receiver, the pulse will probably be below the noise level. In order to address this issue, a train of pulses is transmitted to constitute one bit of information. On the receiver, the received pulses are gathered, and with enough pulses, the power of the accumulated pulse is going to rise above the noise level, and reception is possible [21].

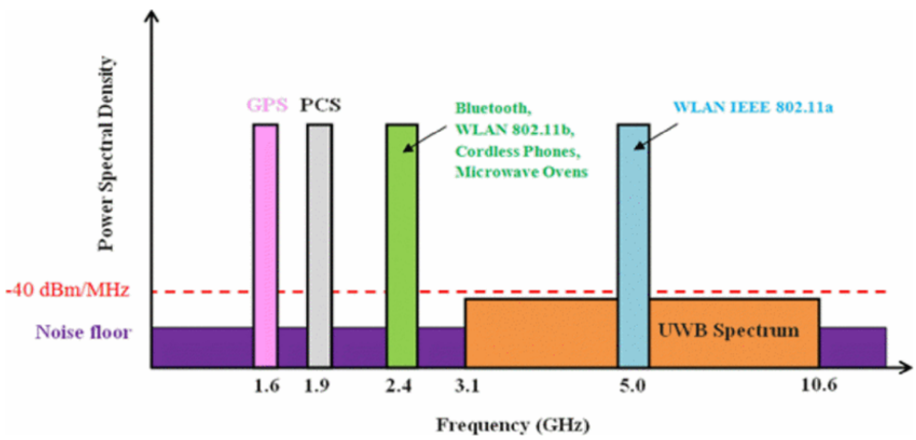


Figure 2.9: Regulated UWB spectrum [6]

2.3.3 UWB Positioning Algorithms

Positioning algorithms specify how to estimate the position of a target object. Put differently, these algorithms convert the captured signal properties into distances and angles and then calculates the actual position of a target object. Additionally, positioning algorithms have unique advantages and disadvantages [13].

There are many positioning algorithms which can be classified into four main categories based upon some estimating measurements [10]:

- Time of Arrival (TOA).
- Angle of Arrival (AOA).
- Received Signal Strength (RSS).
- Time Difference of Arrival (TDOA).

Time of Arrival (TOA)

Time of arrival algorithm relies on the intersection of circles centred in multiple transmitters, see Figure 2.10. The radius of those circles corresponds to the distance between the transmitter and the receiver. This distance is obtained through the calculation of the one-way propagation time among them. However, the time synchronisation of all transmitters is mandatory, whereas the receiver synchronisation is unnecessary. Any possibility of considerable delays must be accounted for during the calculation of the correct distance. When the anchor receives the signal, it calculates the distance to the target object based on the speed and the measured time of the signal, like was presented in the previous section. Then, the location of the target is estimated by using triangulation. Finally, TOA provides high accuracy. However, hardware complexity increases consequently [10, 12, 13].

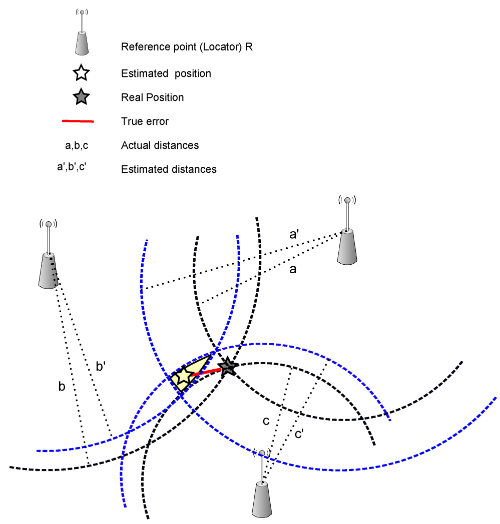


Figure 2.10: Time of arrival (ToA)-based algorithms [10]

Angle of Arrival (AOA)

Angle of Arrival is the angle and distance calculated concerning two or multiple anchors (reference points) through the intersection of direction lines to these anchors. In the AOA, the estimate of the receiving signal angles, with at least two anchors, is performed by comparing either the signal amplitude or carrier phase across multiple antennas. From such calculations, the target position is triangulated through the intersection of the angled line from each signal source (anchors). AOA estimate algorithms are highly sensitive to many factors, which can lead to errors in their estimate of the target position. Additionally, AOA estimate algorithms have higher complexity in comparison with other methods. Finally, increasing the distance between the target object and anchor may decrease accuracy. Besides, the hardware tends to be complicated and expensive. Figure 2.11 demonstrates the AOA positioning algorithm [10, 12, 13].

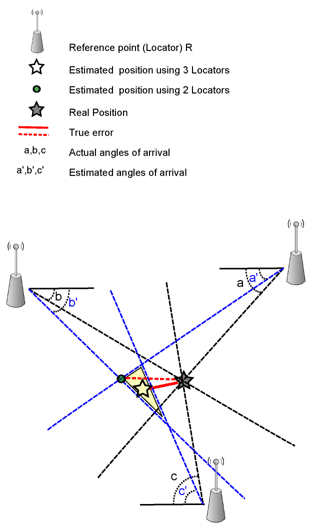


Figure 2.11: Angle of arrival (AOA)-based algorithms [10]

Received Signal Strength (RSS)

In contrast to angular and distance-based metrics, RSS is a measurement of the power level of the Received Signal Strength (RSS) present in the UWB radio wave. Thanks to the measurement of the RSS from multiple transmitters, it can be estimated the distance between the target object and the anchor. Although, RSS is susceptible to multipath interference and a small-scale channel effect that triggers a random deviation from mean received signal strength. Consequently, the accuracy of RSS for non-line-of-sight (NLOS) and the multipath environment is low, which clearly shows that RSS is not the proper estimate method for indoor positioning systems. However, RSS-based algorithms have some advantages over other algorithms which make them attractive in some cases [10, 12, 13].

Time Difference of Arrival (TDOA)

Time Difference of Arrival algorithm measures the propagation time difference among the target object and multiple anchors and obtains the distance difference from the time difference. Put differently, TDOA is based on measuring the time difference of arrival of a signal sent by a target object and received by three or more anchors, see Figure 2.12. Thus, the location of the object (transmitter) will be determined. Also, the scenario can be reversed so a single anchor can identify the target location through measuring the delta in arrival times of two transmitted signals. Typically, only one transmitter is available, which requires multiple anchors to share the data and cooperate to estimate the location of the transmitter. Consequently, from the geometric perspective, the position will be at the intersection of hyperboles set by the measured time differences. Additionally, the anchors must have the same notion of time, so their clocks must be accurately synchronised. As a result, the anchors will periodically communicate with each other through UWB to synchronise their clocks. Despite synchronisation, anchors still need precise clocks to enable TDOA [10, 12, 13].

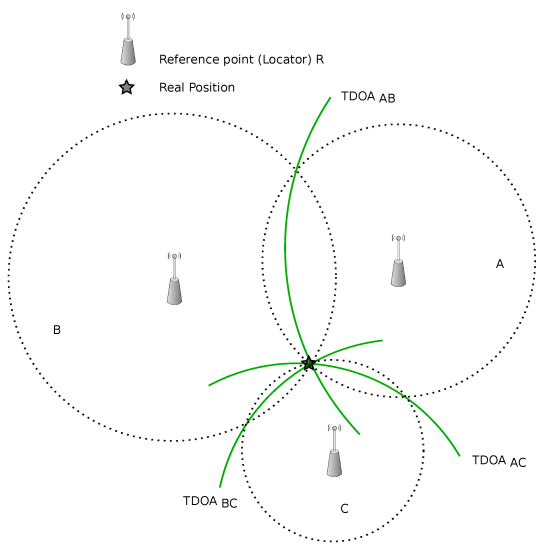


Figure 2.12: Time difference of arrival (TDoA)-based algorithms [10]

2.3.4 Comparison of Positioning Algorithms

After the presentation of the four general positioning algorithms, the following table 2.3 represents a comprehensive comparison of them. As a result, it can be concluded, that AOA is less practical versus other algorithms due to the difficulty of implementation and the cost of maintaining the required large dimensions of antenna arrays and sensors. Also, AOA requires close coordination between sensors and is subject to accumulated errors. Alternatively, the RSS algorithm does not effectively use the high bandwidth of UWB concerning other algorithms. For instance, Hatami and Pahlavan showed that RSS is better suited for systems that use narrowband signals, whereas the TOA algorithm works better in wideband systems as UWB-based systems. Finally, using RSS, the large bandwidth does not have a positive effect in increasing the achievable accuracy. Because of that, the RSS algorithm is less attractive compared to time-methods, that offer higher accuracy [10].

Table 2.3: Comparison between Indoor Positioning Algorithms [12]

Algorithm	Advantages	Disadvantages
TOA	It is the most accurate technique, which can minimise multipath effects in indoor situations.	It is complex to implement because it requires precise time synchronisation of all the devices which represents a high cost.
TDOA	It only needs to synchronise the base stations participated in the positioning, without the precise synchronisation between the target and the base station as on TOA.	It requires some preliminary knowledge to eliminate the position ambiguity, and it is influenced by multipath of signals.
AOA	Since all necessary transmitter time information is encoded in the signal, a receiver does not need to maintain phase coherence with the time source of any beacon.	It demands additional antennas with the capacity to measure the angles, and consequently, that increases the cost of the AOA system implementation. It is affected by multipath and NLOS propagation of signals, as well as reflections from walls and other objects. Owing to these factors, it can significantly change the direction of signal arrival and thereby degrade the accuracy. The position accuracy decreases with the increasing distance to the source.
RSS	It is easy to deploy compared with techniques that use the angle of arrival (AOA) and time difference of arrival (TDOA). It does not need dedicated hardware at the mobile station (MS).	Existence of obstacles may cause the different attenuation coefficient for RF signals. So the establishment of accurate indoor propagation model is complicated.

2.3.5 Challenges using UWB in indoor localisation

In this section, there is a highlight of some significant challenges that exist in indoor localisation. Like was introduced before, one of the most significant advantages of using UWB compared to other solutions is the fact that UWB is a radio technology that can easily penetrate objects. Some UWB solutions on the market are based on the transmission of an ID and timestamp over UWB and not merely on signal strength (RSS) as many other Bluetooth/Beacon-based solutions. Consequently, there is only a small loss in accuracy and range, even when the signal is heavily obstructed. However, there are some limitations while using UWB [22].

Clear Line of Sight (LOS)

The term clear Line of Sight means that the antennae of all target object, in the field, can "see" each other without any obstruction. Clear LOS is the ideal scenario and is when the system has both the best range and accuracy [22].

Radio transparency for each material

For wireless radio technology, the effect of obstacles on radio performance depends on the material of the obstacle and its radio transparency. Generally, when a signal goes against an obstacle, one portion partially penetrates the object, other is absorbed, and the remainder is reflected. Depending on which type of material the signal will go through, the absorbed and the reflected amount varies. When there are obstacles which create an obstruction, generally the literature named non-line-of-sight (NLOS) to this situation [22].

The type of materials can be split up into two categories: insulators and conductors. Since all the radio waves are electromagnetic waves, these material categories have a significant impact on a signal. Within the conductor class, the most common elements are metals, along with a well-known exception of saltwater [22].

- **Insulators:** Materials such as wood, plastics, glass, cardboard, insulating foam, fabrics, fibres, brick, etc. are excellent insulators and very transparent to radio waves. Meaning that if one of those materials obstructs the path between the transmitter and the anchor, the effect would generally be negligible [22].
- **Metals:** Conductors, generally, will reflect most of the radio waves and the remainder goes through the obstacle. Consequently, this causes two harmful properties [22]:
  - The signal will have less power and hence reduced range.
  - The signal will spend more time attempting to get through the material, reducing accuracy.

  However, if the obstacle is a thin sheet of metal, the impact will be low, albeit with a few cm reductions of accuracy. The issue exists with concrete walls with plumbing, wiring, and metal supports structures, where the signal will hugely be affected. The signal will get through, but the accuracy will be reduced, and the range following the obstruction will be concise [22].
- **Liquids:** Like happens with metals, liquids absorb radio waves. The saltier the liquid is, the more it absorbs the radio waves, which leads to a reduced range. Furthermore, radio waves travel slower in liquids (about 30% lower), resulting in a reduction of accuracy by several centimetres in technologies based on TOF. Additionally, the influence of the liquid obstruction on the signal is directly related to its volume [22].

2.3.6 UWB solutions in the Market

In order to provide an efficient UWB-based indoor solution, many companies have manufactured UWB chipsets and hardware. In this section, it is presented some commercially implementations using UWB, followed by a comparison between them based on accuracy and coverage and then cost, complexity and application area [10, 16].

(1) **Ubisense (Dimension4):** Ubisense is a successful real-time positioning system based on UWB technology for building Smart Space applications. In a Ubisense system, the target object carries the tag that transmits UWB signals to fixed anchors which use that signals to estimate the user's positions, taking advantage of TDOA and AOA techniques in order to provide the flexible capability of location sensing. The system is scalable and enables many users for arbitrary range and application. Moreover, the system provides higher accuracy to round the 15 cm, a sensing rate of up to 20 times per second and long-life battery of 1 year. Additionally, the selection of the required frequency of user positioning is of considerable importance since it heavily affects the battery life of Ubisense tags. However, discrete cell architecture increases installation cost and increase the complexity of installation tuning. As a result, Ubisense introduced a new innovative UWB-based solution to assist manufacturers in maintaining continuous flow, decreasing the error and improving efficiency in assembly processes by gathering location and systems data that provides real-time operational awareness. BMW has successfully adopted the solution in its facility at Regensburg, Germany [10, 16].

(2) **DecaWave (DW1000):** Decawave is another company who uses UWB technology to estimate the distance among target objects and fixed-location anchors, to assist in various applications such as inventory management, manufacturing flow monitoring and management, retailing monitor and customer behaviour. This technology uses low power and is functionally, economically viable to successfully deploy even in difficult access locations. Decawave introduced a DW1000 chip that is based on IEEE802.15.4-2011 standard. This chip provides a precision of 10 cm in indoor localisation, trying to locate the targets on a real-time basis. Thanks to the help of consistent receiver techniques, the chip allows an excellent communication range of up to 300m. Besides, the chip supports both two-way ranging and one-way ranging methods based on TOA and TDOA [10, 16].

(3) **BeSpoon (UPosition):** Another RTLS system was developed by BeSpoon and provided a high precision indoor positioning solution. BeSpoon is a start-up that developed this system that integrates UWB chips inside smartphones without any interference to the way the smartphones work. This integration opens a big range of practical applications such as finding someone's belonging, avoiding leaving smartphones behind, and customising the smartphone based on current indoor location. As a result, the company has manufactured UPosition module, which is easily integrated into existing hardware. The system uses a two-way ranging method [10, 16].

(4) **Time Domain MDS Tracking:** Another company is Time Domain that has developed UWB solutions aiming to release the full potential of UWB technology. Time Domain implementations rely on consistent signal processing which allows the signal energy to spread across multiple pulses delivering with increased energy per bit and an enhanced SNR. The company develops the PulsON chipset that is built upon five generations of custom UWB silicon. PulsON 410 (P400) incorporates advanced positioning and sensor communications features directly into products. Although the system takes benefit of extended operating range, this leads into a complex system with an increased number of measurements, hence reducing the update rates [16].

(5) **Zebra Technologies (Dart UWB):** Zebra Technologies has developed Dart Ultra-Wideband solutions designed for accurate tracking of equipment and personnel for indoor and outside localisation. Zebra's UWB based applications offer the lowest cost-of-ownership in the industry by improving ease of installation, visibility, scalability, performance, asset-tracking and tag management. The system uses Dart Hub, which maximises the coverage area with minimum sensor number and thus, demonstrates exceptional performance in a very multipath environment. Dart sensors are positioned throughout the area of interest and are connected in a daisy chain arrangement. The system offers a long tag battery life of up to 7 years and a blink rate of 1 Hz. For instance, the system is working in the Washington Hospital centre to guarantee emergency care goals. The solution has enabled asset location granularity down to items within one to two feet of each other, reducing the purchase cost of medical equipment [16].

(6) **Multispectral Solutions Ltd (PAL650):** Multispectral Solutions Inc. has also developed many systems representing a variety of short-pulse electromagnetic applications. The company has introduced many precision asset location systems (PALS). The PAL650 is the first commercial UWB system in hospitals and industrials facilities. The system uses the TDOA positioning method with 4 ANs, operational centre frequency of 6.2 GHz and a battery life of more than 3.8 years. With a short pulse RF waveform, this system offers absolute tag position accuracy of more than one foot. This system consists of two separate receivers connected in a daisy-chained arrangement. However, it is replaced by the hub-spoke configuration to avoid a single point of power failure in serial communication [16].

(7) **IST (EUROPCOM):** EUROPCOM, by Information Society Technologies (IST), is a positioning and communicating system specifically designed for the searching and rescue of emergency personnel within a disaster zone. The most differentiate feature of the system is a self-calibrating location-aware ad-hoc network of nodes. The system consists of base units (BU) which coordinates with GPS as it is deployed outside the building on any emergency service vehicle. Additionally, a set of four or five mobile units (MU) work within the building uses a TDOA method to estimate their position. In order to increase the network density, the system encompasses additional dropped units (DU), while moving further into the building. Finally, these coordinates are then sent to the control unit (CU) with the support of a high-speed network (HSN). Furthermore, the system provides absolute position accuracy of 1m or less under NLOS conditions [16].

Apart from these companies, many other companies such as Intel Corporation, Motorola and Freescale Semiconductor are amongst the chip manufacturers in the field of UWB based positioning systems [16].

Considering what was presented before, in dedicated infrastructure (the main class of UWB), metrics such as position accuracy, coverage area, scalability and cost are of great importance when choosing technology system, additionally will be considered the complexity of implementation as a metric. Based on these parameters, a comparison of different UWB-based positioning systems is shown in Tables 2.4 and 2.5.

Table 2.4: Comparison of different UWB IPSs based on accuracy and coverage [16]

Technology System	**Method**	**Accuracy**	**Coverage**
Ubisense (Dimension4)	TDOA and AOA	> 30 cm	up to 400 cm
DecaWave (DW1000)	TDOA and TOA	10 cm	up to 300 m
BeSpoon (UPosition)	RTT	-	-
Time Domain MDS Tracking	RTT and odometry data	2cm - 1m	Large
Zebra Technologies (Dart UWB)	TDOA	up to 30 cm	up to 200 m
Multispectral Solutions Ltd (PAL650)	TDOA	> 1 ft.	> 200 ft.
IST (EUROPCOM)	TDOA	within 10 cm	1000 m

Table 2.5: Comparison of different UWB IPSs based on cost, complexity and application area [16]

Technology System	**Cost**	**Complexity**	**Application**
Ubisense (Dimension4)	Moderate	Low	Industrial Process
DecaWave (DW1000)	Low	Low	R&D and Chipset
BeSpoon (UPosition)	Very High	Moderate	Sports and Office Logistics
Time Domain MDS Tracking	High	Very High	R&D and Chipset
Zebra Technologies (Dart UWB)	High	Moderate	Military, health care and asset tracking
Multispectral Solutions Ltd (PAL650)	Moderate	Moderate	Industrial and Commercial
IST (EUROPCOM)	Moderate	Low	Rescue operations

2.4 Fusion and Estimate Algorithms

In an ideal world, all the technologies presented before can directly or indirectly deduce the exact robot's position. However, in practice, there is uncertainty related to such a task that can arise from several reasons like the influence of the ambient environment or sensor constraints such as resolution and noise. Therefore, the capacity to deal with that is a critical system requirement. Probabilistic algorithms are generally used to help increase system accuracy and robustness based on two key objectives:

1. Deal with ambiguous measurements and sensors noise, identifying sudden interferences from the surrounding environment.

2. Can be used to the fusion of different technologies information. Even Though most of them could be used independently, a multi-sensor fusion could increase the redundancy in the state estimate.

Despite the existence of other types of estimators, such as the batch estimators, the emphasis of this subsection will be placed on the Recursive State Estimators (RSE), the most commonly used in robotics. These share a typical representation of the x state of the system based on Bayes' Theorem (2.1). In the equation 2.1 the p(x|y), known as posterior probability, represents the belief of the system on being in the state x given the measured data y. For instance, in localisation systems, the state is usually the robot's pose. It should be noted that past and future data is not dependent if the current state is known. As a result, knowledge of the immediately preceding state and current measurements are enough to predict the current state [1].

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)} \tag{2.1}$$

2.4.1 Gaussian Filters

Gaussian filters are the most popular filter techniques in the state-of-art localisation algorithms. All Gaussian filters share the basic idea that beliefs are represented by a well-known uni-modal distribution multivariate Gaussian distribution that can be characterised by the mean and the co-variance. Despite some flaws, in several practical problems, Gaussian filters are deemed to be a robust estimator. The best known are the Kalman Filter and its extended versions.

Kalman Filter

The Kalman Filter is one of the oldest and most studied techniques for implementing Bayesian inference in state prediction and filtering. The particularity of this filter lies in the linearity of the representation of state and measurement probabilities. Usually, the algorithm follows the state estimate and the uncertainty of this estimate in two different phases: the Prediction and Correction steps. The Prediction step predicts the new state through the input of the previous estimate and its uncertainty, along with the motion data into a state transition model. The Correction step integrates all the sensors information within the calculated state in the previous step and outputs the final estimate and its uncertainty. In fact, most real-world localisation systems rarely fulfil the linearity restriction of the Kalman Filter. In order to overcome the linearity restriction of this filter, an extension of the Kalman Filter was created, the Extended Kalman Filter (EKF) [23, 24].

Extended Kalman Filter

In the Extended Kalman Filter, the state transition and measurement models are first-order derivative functions. The state is still characterised as a Gaussian distribution of joint probability on the variables. However, this probability is now just an approximation to real belief and not the exact one. So, the main idea is to linearise the state around the current estimate by the first-order Taylor Expansion (2.2).

$$f(x) = f(a) + f'(a)(x-a) \tag{2.2}$$

EKF is undoubtedly the most popular tool for estimating the state in robotics [25, 26, 27, 28, 29, 30].

The principal advantages lie in its computational efficiency and simplicity because of the uni-modal Gaussian representation. Additionally, computational complexity only depends on the measurement and state vectors dimensions [31, 32]. Therefore, it is more efficient than Non-Parametric filters whose algorithms utilise more extensive and more sophisticated representations of the world.

This filter is also the most widely used algorithm for state estimate and data fusion in robotics [33, 27]. However, the EKF still experience performance issues when dealing with highly non-linear systems.

Unscented Kalman Filter

The Unscented Kalman Filter (UKF), was suggested by Julier and Uhlman [34], in order to respond to the error caused by the linearisation of the EKF. The state continues to be approximated as a gaussian random variable although now is only linearised in a smaller set of sampled points. The computational complexity is almost the same as the EKF. However, the procedure for selecting the sigma points involves a bit more effort.

Comparisons between UKF and EKF implementations have been presented in [35, 36, 37]. A different performance was presented in [38], concerning an outdoor scenario for a quadcopter UWB location system, where the EKF showed more consistent results against UKF that demonstrated some sensitivity toward the weights of the sampled points in different anchor configurations. In conclusion, if the models take into account are reasonably stable, the EKF is simpler and reaches a reasonable accuracy. Quite the opposite, if the models are highly non-linear, UKF is desirable.

2.4.2 Non-parametric Filters

This type of filters removes the assumptions used in Gaussian filters, which means that it removes the fixed distribution of the beliefs. Briefly, in non-parametric filters a finite set of points are dispersed throughout a specific region of space and to each point is assigned a probabilistic value. When compared to Gaussian filters, these filters are best suited for dealing with global uncertainty, complex non-linear systems and feature matching. However, these come with the cost of an increased computational demand depending on the number of parameters used in the model. Non-parametric filters are generally divided into two primary filters: Histogram Filters and Particle Filters.

Histogram Filters

Histogram filters decompose the state-space into regions and assign to each one a certain cumulative probability (as a histogram representation). The belief of the state is now characterised by a probability density function and by selecting the "most likely sampled region" the estimate can be completed. Besides, in Histogram filters, the robot environments are discretised into a grid map where each cell represents the probability that the robot's location is there. So, with the correct resolution, this filter can be a great approach to the localisation problem. However, when choosing high resolution grids, slow algorithms and massive memory consumption can be achieved. Finally, several researchers have implemented solutions with this filter. In the article [39], a promising solution is presented that uses the oct-trees concept to redefine the grid size dynamically.

Particle Filter

The concept of Particle filters is similar to histogram filters. However, the process of spreading samples, here called particles, around the space is done differently.

The most popular particle filter used in robot localisation context is Monte Carlo Localization (MCL) [40]. In MCL, each particle is representing a possibility of the robot being in a specific pose. At the end of the spreading process, the denser region is, the more probable and the state converge into that region.

Compared to Histogram filters, this one can decrease the memory consumption and the process requirements. PF is also deemed more accurate than the Histogram filters with fixed cell size [40].

Although PF is commonly a better solution than KF, the required computational cost makes it useless for low-cost systems.

The Particle Filter is one of the most popular approaches in mobile robotics, and so several studies have been done so far [41, 42, 43, 44].

2.5 Related Work

Over the last decade, there was an increasing interest in indoor positioning due to the rapid demand for many location-aware services. Because of this, many researchers focus their attention on global positioning in given infrastructures. However, many IPS surveys that have been published are just outdated, because of technology evolution or new methods found, due to the rapidly changing area such as IPS.

Thus, a series of articles were collected and analysed later in order to investigate the approaches implemented by researchers and the technologies used to obtain an accurate estimate in indoor environments. As a result, in the tables, 2.6 and 2.7 will be presented each article found and to be considered as well as the technologies used, and the approach adopted to obtain an estimate position. Next, the conclusions obtained by the authors and future work to be considered is presented.

Table 2.6: Description and analysis of the related work

Related studies [reference]	**Deploy Technology**	**Description**	**Conclusion**
[45]	UWB(TOA) + IMU	In this paper, they present an approach that combines measurements from inertial sensors with time-of-arrival measurements from an ultrawideband (UWB) system for indoor positioning. Throughout that work, the UWB measurements are modelled by a tailored heavy-tailed asymmetric distribution to account for measurement outliers. Their algorithm uses a tightly coupled sensor fusion approach. Using this approach, it was possible to assume more general measurement distributions. They also present an easy-to-use algorithm to calibrate the UWB system (i.e., the receiver positions and their clocks offsets have to be computed) using a maximum-likelihood formulation.	They conclude that the heavy-tailed asymmetric distribution works well on experimental data by analysing the position estimates obtained using the UWB measurements via a novel multilateration approach. Besides that, they also verify that the position estimates obtained using the heavy-tailed asymmetric distribution are considerably better than the ones obtained using either a Gaussian distribution or a Cauchy distribution. In the end, they conclude that their model leads to accurate position estimates, even from challenging data containing a relatively large amount of outliers.
[46]	Comparing different UWB-based systems	In this paper, they compare three commercially available UWB systems (Ubisense, BeSpoon, and DecaWave) under the same experimental conditions, in order to do critical performance analysis. The testing space includes areas under line-of-sight (LOS) and diverse non-LOS conditions caused by the reflection, propagation, and the diffraction of the UWB radio signals across different obstacles. Finally, they analyse the 3-D positioning estimate performance of the three UWB systems using a Bayesian filter implemented with a particle filter and a measurement model that considers wrong range measurements and outliers.	They conclude that under all the conditions of the testing (LOS and NLOS conditions), the performance of the DecaWave system is slightly better than the BeSpoon system and significantly more reliable, in terms of accuracy and outlier content, than the Ubisense system. They also refer that the performance results of the Ubisense equipment are lower than DecaWave and BeSpoon when it only uses TDOA data and when using the integrated localisation solution that fuses TDOA and AOA.
[47]	UWB + IMU	In this paper, they propose an approach to fuse IMU inertial and UWB ranging measurement for relative positioning between multiple mobile users without any knowledge of the infrastructure. Therefore, they incorporate the UWB and the IMU measurement into a probabilistic-based framework, allowing to cooperatively position a group of mobile users and recover from positioning failures. So, a dual particle filter is additionally used to incorporate the UWB ranging measure. As a result, by merging the measurements from IMU and UWB during a period, they could take advantages of both sensors and cooperatively estimate the relative positions of mobile users.	In their work, a simulation was set up to show the efficiency of their approach. They also implemented their approach in a real scenario for multiple users relative positioning and evaluated the performance of their system through experiments. They do not conclude anything about their performance and the results they obtain but looking at their figures, which show the results, is clear that they have many errors of position estimate. In the end, they conclude that they need to improve the accuracy of the IMU itself to enhance the overall relative positioning accuracy.
[48]	UWB + IMU	In this paper, they describe an IPS that fuses an UWB-based sensor positioning solution with an IMU sensor-based positioning solution to obtain a robust and optimal positioning performance. The sensor fusion was accomplished through the use of an Extended Kalman Filter (EKF), a tightly coupled filter, which calibrates the IMU systematic errors using the measured ranges from UWB radio sensors, providing position corrects for data fusion. Fault detection, identification, and isolation are built into the EKF design to prevent the corrupted UWB sensor measurement data due to obstructions, multi-path and other interferences from degrading the positioning performance.	In the end, they present a general system architecture and data processing for the proposed IPS tracking a 6 DOF platform motion. Taking into account motion profiles, they have done a computer simulation, and the results indicate an improvement in the performance of more than 100% on the positioning solution based on the UWB sensor, and that can be obtained through the fusion solution of sensors proposed. The IPS performance obtained from their laboratory tests correlated very well with the simulation results.
[49]	hybrid UWB-Doppler radar	In this paper, they present an improved indoor localisation performance using a hybrid UWB-Doppler radar system that was fused by a Kalman Filter. Experiments were conducted in a large complex indoor environment to demonstrate the feasibility of the proposed indoor localisation method further.	In the end, they conclude that the optimised measured trajectory with the use of Kalman Filter has shown better performance with more limited error range, compared with the previous work of this system without the use of a Kalman Filter.

Table 2.7: Continuation of the description and analysis of the related work

Related studies [reference]	**Deploy Technology**	**Description**	**Conclusion**
[50]	UWB + IMU	In this work, an improving distributed iterated extended Kalman filter (DIEKF) for INS/UWB integrated human positioning is proposed. It utilized an iterated extended Kalman filter (IEKF) as a local filter for the data fuse in each wireless channel, and the distances measured by the UWB and that values measured by the IMU are both sent to the IEKF. Then, the primary filter works with the output of the local IEKF and output the estimate of the INS position error. In other words, the distances measured by the UWB and that values measured by the IMU are both sent to the Distributed Iterated Extended Kalman Filter.	The test results show that the performance of the proposed method is better than the traditional EKF in position accuracy.
[51]	UWB + IMU	This paper present a useful system framework of INS/UWB integrated positioning for autonomous indoor mobile robots. To deal with the time-varying noise and outliers in UWB measurements caused by the multipath effects and NLOS factor, a robust INS/UWB integrated positioning approach is proposed based on the Sage–Husa fuzzy adaptive filter, which is a fuzzy logic filter.	As a result, the capture ability to outliers was enhanced, and the accuracy of covariance estimate was guaranteed. The effectiveness of what they proposed was demonstrated through simulation and experimental results, which achieves excellent positioning performance with strong robustness for mobile robots in complicated indoor environments.
[3]	UWB-based + odometry	This paper describes a method using Particle Filter for fusing UWB range measurements with odometry to acquire a real-time posture estimate of a wheeled robot in an indoor environment.	In the end, they conclude that the estimate method shown to perform sufficiently well for the robot to maintain a position for a period and to run along a simple path. Furthermore, experiments show that the interferences caused by dynamic obstacles could be partly alleviated.
[7]	UWB + IMU	In this paper, they present an accurate and easy-to-use method for UWB anchor self-localisation, that uses the UWB ranging measurements and readings from a low-cost Inertial Measurement Unit (IMU). The locations of the anchors are automatically estimated by freely moving of the tag in the environment. Their method was inspired by the Simultaneous Localisation and Mapping (SLAM) technique used by the robotics community. So, a tightly-coupled Error-State Kalman Filter (ESKF) was utilised to fuse UWB and inertial measurements, producing UWB anchor position estimates and six Degrees of Freedom (6DoF) tag pose estimates.	As a result, the simulated experiments demonstrate that their proposed method enables accurate self-localisation for UWB anchors and smooth tracking of the tag.
[9]	UWB + IMU	In this paper, a method to accurately locate mobile robots with sensor fusion was proposed. The acceleration from an inertial measurement unit (IMU) and the 2-D coordinates received from the Ultra-Wideband (UWB) anchors are fused in an Extended Kalman filter to achieve an accurate location estimate.	Considering that the experiment was done with LOS between UWB anchors and tags. The measurement results show considerable improvements in the accuracy of the location estimate, which can be used in different Indoor Positioning System (IPS) applications requiring precision. Although further tests with the movement of the autonomous robot are needed to verify their system entirely, the error for their system was reduced by 75% of its original error. So they conclude that the fusion of different sensor systems and evaluation using Kalman filtering enables, therefore, real-time capability.

Chapter 3

Project Overview

As previously mentioned, this thesis arose from a robotics competition called Robot@Factory Lite. The concept was to take the existing robot of the competition and improve it. Thus, the aim was to make it able to communicate with other equipment via wireless and create a location layer, capable of knowing in real-time what robot pose is on the map, among other improvements.

Therefore, for a better understanding of the core of the project is presented in Figure 3.1 a block diagram that represents a high-level architecture of the developed solution.

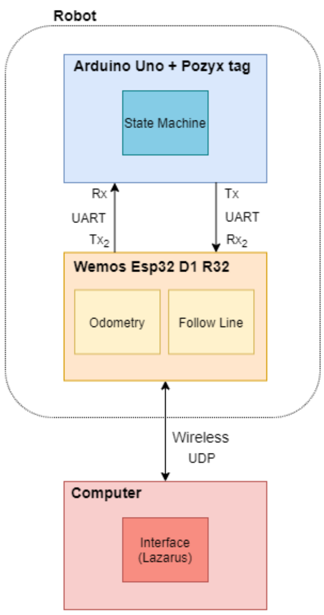


Figure 3.1: High-level architecture of the developed solution

Consequently, it can be verified the presence of three main modules. The computer module is where the interface is established to visualise what is happening with the robot. The Wemos Esp32 module is where all robot control is consolidated. Finally, the Arduino UNO module that is connected to the Pozyx tag, is where measurements of distances to anchors are carried out.

3.1 Computer module

Beginning with the computer module, it can be said that this is where the centre of all operations is located. It means that it is from the computer that all orders are sent to the robot via wireless. In other words, can be affirm that this communication follows a master-slave architecture, where the computer behaves like a master, sending the necessary orders to the robot, and the robot behaves like a slave, receiving orders and executing them.

Thus, for a better interpretation of the entire flow of information between the computer and the robot, a Graphical User Interface (GUI) was developed. The idea was to create a control system that allows a user to perform commands on the computer through the use of buttons or other graphics elements, in order to interact with the robot. Furthermore, since the computer behaves like the master, it was there that the entire robot pose estimate algorithm was implemented, based on the messages received by the robot. Finally, this GUI was developed in Lazarus.

Lazarus[1] is a professional open-source, cross-platform IDE using the Free Pascal compiler. This platform has a variety of components ready for use and a graphical form designer to create complex graphical user interfaces easily.

As a result, the developed GUI as a Header and four primary tabs. Into the header is the place where the type of communication desired with the robot can be chosen, which can be through a serial port or wireless (UDP packages) connection. Moreover, previous measurement log files can also be loaded from the computer to visualise again the histogram result or even the offset and standard deviation of that test. About the tabs, the first is the general configurations tab related to the project. Figure 3.2 shows the interface with this tab selected.

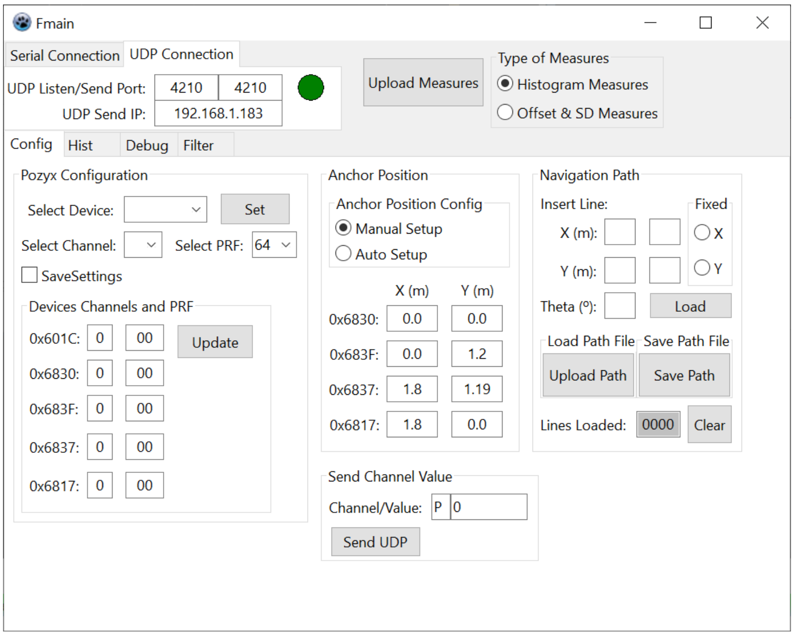


Figure 3.2: General Configuration tab of GUI

[1] https://www.lazarus-ide.org/

Presented in this tab, four group boxes can be seen. The first on the left named “Pozyx Configuration” is where the user will be able to change the Pozyx settings by selecting the device that wants to set up and the desire channel and PRF. Additionally, the possibility for the user to select whether to save these settings in the device memory has been introduced. This possibility is an essential option since this information is stored by default in the flash memory that has a finite number of program/erase cycles. So, if a simple test is going to be performed, with different settings, there is no need to deteriorate the integrity of the storage. Finally, the current settings of each Pozyx device can be visualised at the bottom of that group box by pressing the button “Update” to request such information to the robot.

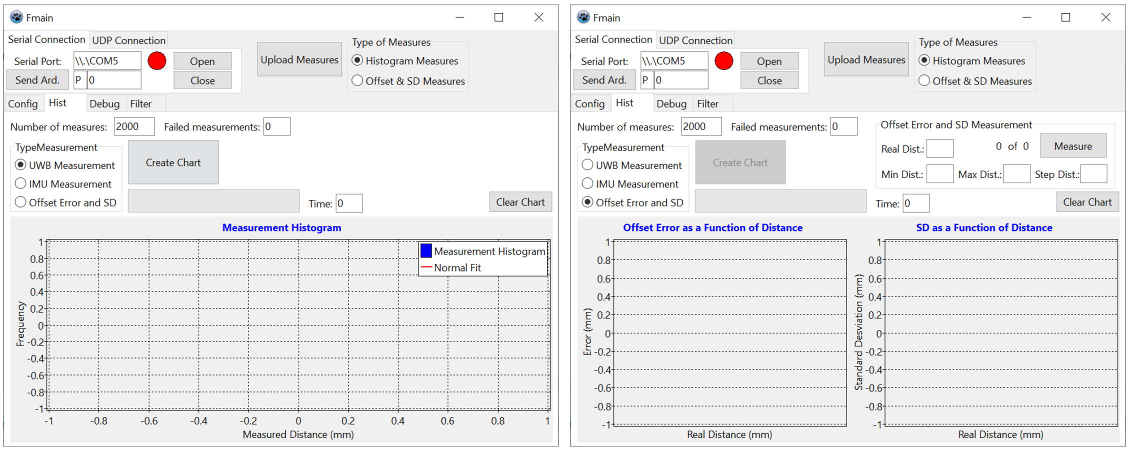
Next, there is the group box “Anchor Position” where all the anchors positions can be set manually or automatically. The option to execute an automatic setup is possible since Pozyx offers a code stack that contains a function that allows us to find the positions of each anchor automatically. Basically, what the anchors are going to do is measure the distances between them in order to calculate their positions regarding a global reference, specified by us. It should be noted that these measurements contain measurement errors, and therefore the final positions are not exact. Lastly, this data will be used by the algorithm which is going to estimate the pose of the robot.

On the right side, the group box “Navigation Path” is where the path where the robot is navigating can be configured. If a log file with the path is already saved, then it can be upload to the interface and at the bottom of the group box will be displayed the number of lines uploaded from that path. If that file does not already exist or if the user wants to create a new path, there is also the possibility to do so in the interface. To do this, the user loads one line at a time, until the path is complete. In the end, it can be stored the currently existing path in the interface to a file, for future use. Lastly, this data will also be used by the algorithm which is going to estimate the robot pose.

Finally, the last group box provides the possibility to send a raw message to the robot through wireless, using UDP packages. The communication protocol and structure of the messages exchanged will be presented later in this chapter.

The second tab is the tab on which the measurements are performed to characterise the error of Pozyx measures. Here there are two types of measurements. Figure 3.3 illustrates the interface for these two types of measurements. It is noteworthy that both types of measurements must be done through a serial port connection to avoid so many packet losses because if wireless communication is used, there is a greater probability of losing measurements over time.

The first type “UWB Measurement” is where the user place the tag and one anchor with a fixed distance and then perform the number of measures chosen on the first text box. As a result, the histogram, with all measures performed, will be displayed on the chart with its normal distribution fitting that histogram. Additionally, the user can also visualise the measurement progress on the progress bar under the button as well as the time that the measurements took and the number of failed measurements.



(a) Histogram characterisation Measurement (b) Offset and SD characterisation Measurement

Figure 3.3: Measurement error characterisation tab of GUI

The second type "Offset Error and SD" is where the offset and standard deviation can be checked depending on the measurement distance. To perform this test, the user have to specify the minimum and maximum distance of this test as well as the step between measurements and then place the tag and one anchor in the different distances and perform the number of measures chosen on the first text box for each distance. At the end of all distances, two different charts will be displayed, one to the offset and other to the SD, both as a function of the different distances.

The third tab is only for code debug or to visualise the messages that are being received. This tab also allows visualising all the loaded lines of the path in its internal code structure, thus allowing a quick debug if they are stored correctly. Figure 3.4 demonstrates the interface with this tab selected.

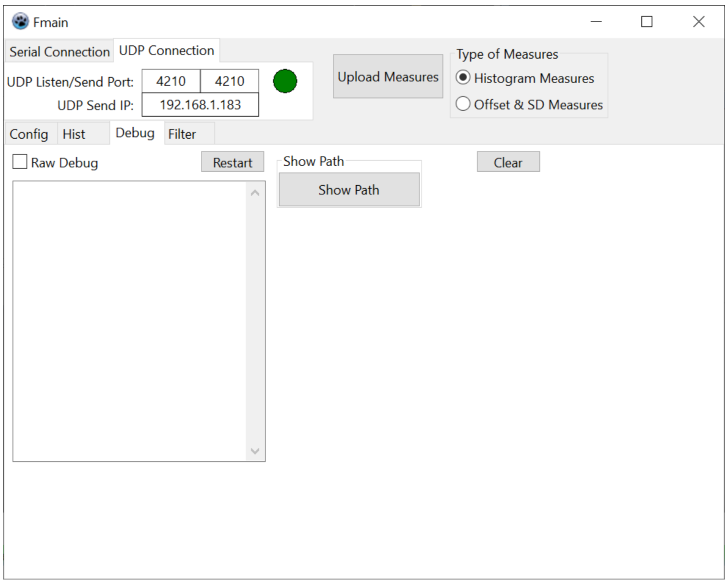


Figure 3.4: Debug tab of GUI

The last tab is dedicated to the filter responsible for estimating the robot's pose. Within this tab, four other tabs are presented. The first tab "Config Filter", presented on figure 3.5, is where the initial values of the filter can be set and where the user can start and stop the filter. Besides, the current pose estimate of the filter and the number of failed measurements at each anchor can also be viewed. Additionally, all the messages received from the robot can be stored to further use with the filter without the need of the robot being turn on. To perform this type of test with the filter, the user have to select the option "File Measures" on "Type of Measures" group box.

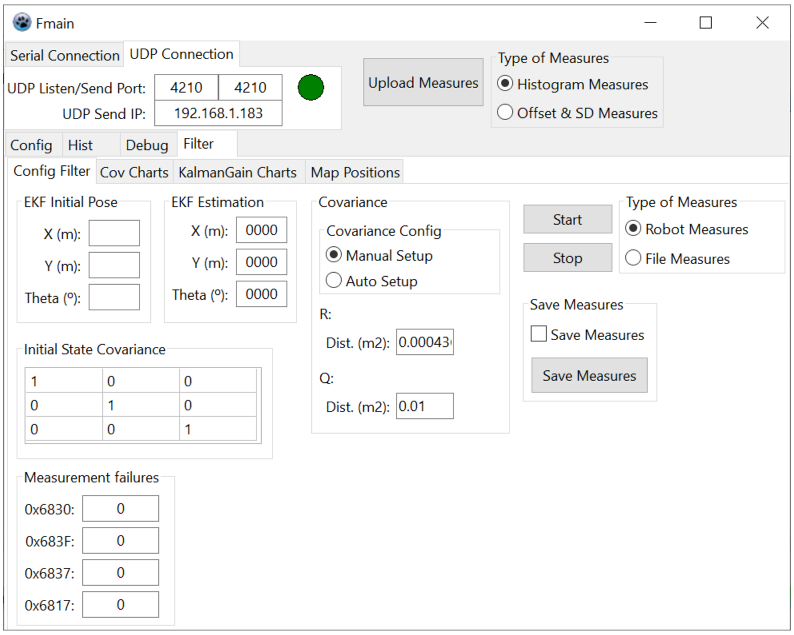
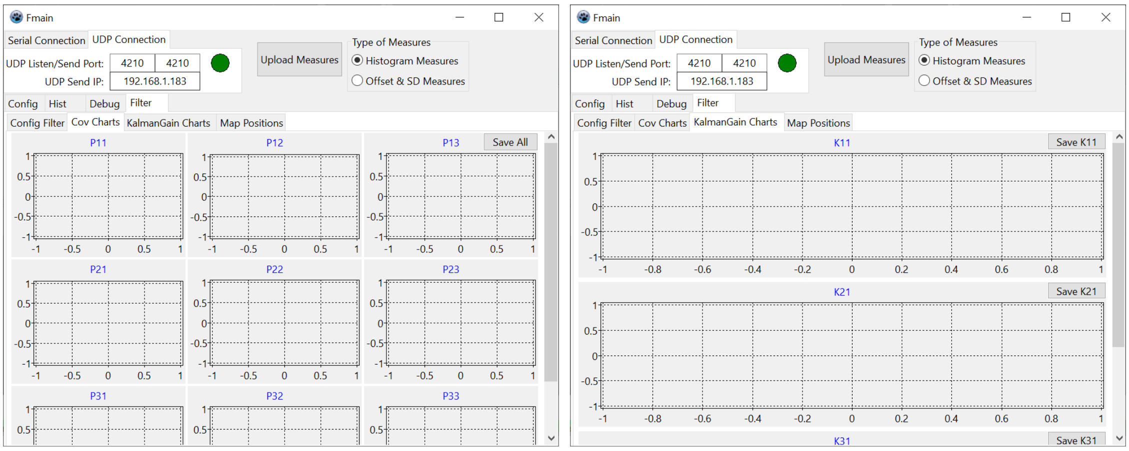


Figure 3.5: Configuration Filter tab of GUI

The second and third tab, shown in Figure 3.6, serves only to debug the filter behaviour over time graphically. In the "Cov Charts" tab, the chronological evolution of each element of the covariance matrix of the state estimate can be seen. In the tab "KalmanGain Chart" the principle is the same, however now the evolution of the covariance of the observation estimate can be visualised.

In the last tab "Map Positions", exhibited in Figure 3.7, is where the position estimates generated by the filter can be seen in the map. This map also displays the positions of all anchors as well as the previously loaded path to the interface.



(a) Chronological evolution of Covariance state estimate matrix

(b) Chronological evolution of Kalman filter gains matrix

Figure 3.6: Tabs of Filter behaviour over time of GUI

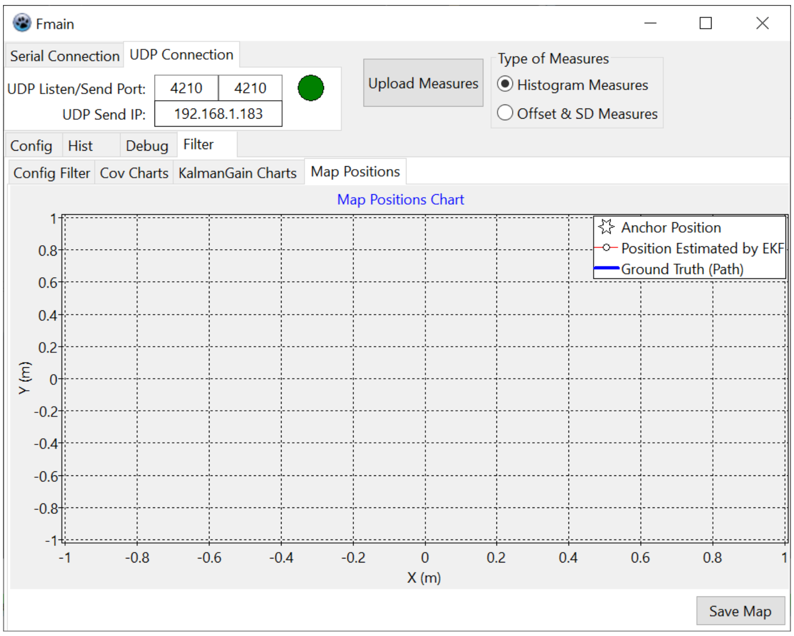


Figure 3.7: Map Position tab of GUI

3.2 Wemos Esp32 module

As mentioned above, this module acts as the robot control unit. Regarding the robot's control, it is divided into two main tasks. The first is the control of the robot's odometry, and the second is the control of line tracking.

3.2.1 Odometry Control

The robot used in this project is a robot with differential drive steering geometry. This type of robots has two driving wheels rotate around the centre of the robot and, additionally, one or two ground contact points can be added to improve the stability of the robot. Our robot has one ground contact point, which is a spherical ball.

Consequently, it is necessary to compute the robot's relative motion using the odometry equations, further presented in this document. All these calculations are done within this module, inside Wemos Esp32, with the help of the encoders readings present on both wheels of the robot.

3.2.2 Follow Line Control

Concerning the control of line tracking, as mentioned above, the path is formed by black lines on the ground. Thus, the navigation of the robot is performed by following these lines, in order to travel the desired path selected by the user.

Consequently, with the support of five infrared sensors, it is possible to produce a very stable line follower. Thus, it was possible to implement a control capable of following the left side of the line, the right side of the line and also the centre of the line. Additionally, this control is also able to detect when a robot passes through a crossing of lines. All these features are useful to make the robot navigate the map so that it can travel the desired path.

Regarding the scope of this thesis, this line tracking control is crucial, because as it is considered that the robot's navigation path is known, it must follow the lines properly so that the final estimate of the robot pose is as accurate as possible.

3.3 Arduino UNO module

The Arduino UNO module, as presented before, is responsible for performing the measures of the distance to all the anchors present on the field. To the Arduino UNO is connected the pozyx tag, that is embedded in a shield which includes headers to easy connection to the Arduino UNO. This Pozyx tag is a UWB technology that measures the TOF of a radio wave and is responsible for the distance measurements to a fixed anchor. Thus, given that this project had several goals concerning the use of this pozyx label, a state machine was implemented in Arduino UNO, which is represented in Figure 3.8. As a result, since the entire robot behaves like a slave in this relationship with the computer, this state machine is by default in a stop state (idle), waiting for new requests from the computer.

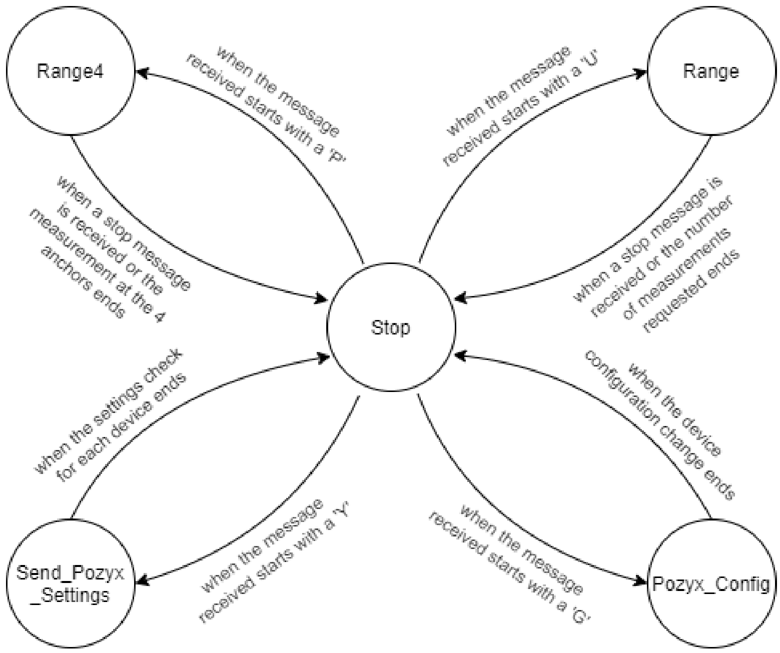


Figure 3.8: State machine that controls the Arduino UNO

Consequently, this state machine is composed of four more states, representing four different functionalities available. The state “Pozyx_Config” is the state responsible for changing the settings on the target device. When the message is received, it contains the target device and all the parameters chosen by the user as well as if these settings should be saved or just setup. The difference between saving or not the settings on the target device is whether it is stored in volatile or non-volatile memory. As a result, the state machine replies to the computer with the result, which may be an error message because the target device may not be within range or for other reasons.

The state “Send_Pozyx_Settings” is the state liable for verifying the current settings on each device. When the message to update the current settings is received, the state machine responds with a per-device message to the computer, which is composed of the current settings or an error message if it is not obtained.

The state “Range” is the state responsible for performing several asked distance measures to an anchor. When the message is received, it contains the number of measures that should be completed. Therefore, the state machine replies with one message per measure with the respective measured distance. If one measure fails, the state machine tries it again until a successful measurement is obtain. In the end, a message is sent with the number of failed measurements. It must be noted that this process can be interrupted at any time by a received stop message.

Lastly, the state “Range_4” is in charged to perform a distance measure to each anchor within the range. When the message to start ranging is received, the state machine selects an aleatory order to measure the distance to each anchor. The purpose of this random order is to minimise the errors introduced by each measurement in the final filter estimate. Towards the end, the state machine replies with one message per anchor with the respective measured distance or an error message if the measurement fails. Here, there is no interest in repeating the measurement in case of failure because, on the computer side, the filter is waiting for this information and therefore it is not intended to waste much time. In this state, it must also be noted that this process can be interrupted at any time by a received stop message.

3.4 Communication Layer

Ultimately, communication is what allows the connection and exchange of messages between the blocks previously presented. Thus, in order to obtain further robust communication and more accessible to detect failures, a communication protocol was created by using its own structure for the messages exchanged. Before presenting the structure of the exchanged messages, it is crucial to explain the management of the message flow. Consequently, as mentioned above, communication between the computer and the robot is performed wirelessly. Therefore, since this communication is made between the computer and the Esp32, the robot's control unit, it is important to have different messages for this module and the Arduino. As a result, Esp32 when receiving a message checks whether it is directed to the control or the Arduino. In case this message is not addressed to the control, it forwards it to the Arduino through its second available and programmable serial port. On the other hand, communication in the reverse direction is much easier. When the Arduino sends a message, through a serial port connection and the Esp32, after receiving it, resends it to the computer, since no message is directed from the Arduino to the control.

As regards the structure of messages, they are composed of two components. The first one is called the Channel and is represented by a non-hexadecimal character that indicates what type of message is being sent. Then eight hexadecimal characters represent the message to be sent. The set of these characters is called the value. As a result, each message exchanged between modules has the corresponding size of two bytes.

Finally, in Figure 3.9, it is presented all messages exchanged between the computer and the robot. On the top all the messages that the computer sends to the robot and on the bottom all the messages that the robot sends to the computer, where on the left side are the Arduino messages and on the right side the Esp32 messages.

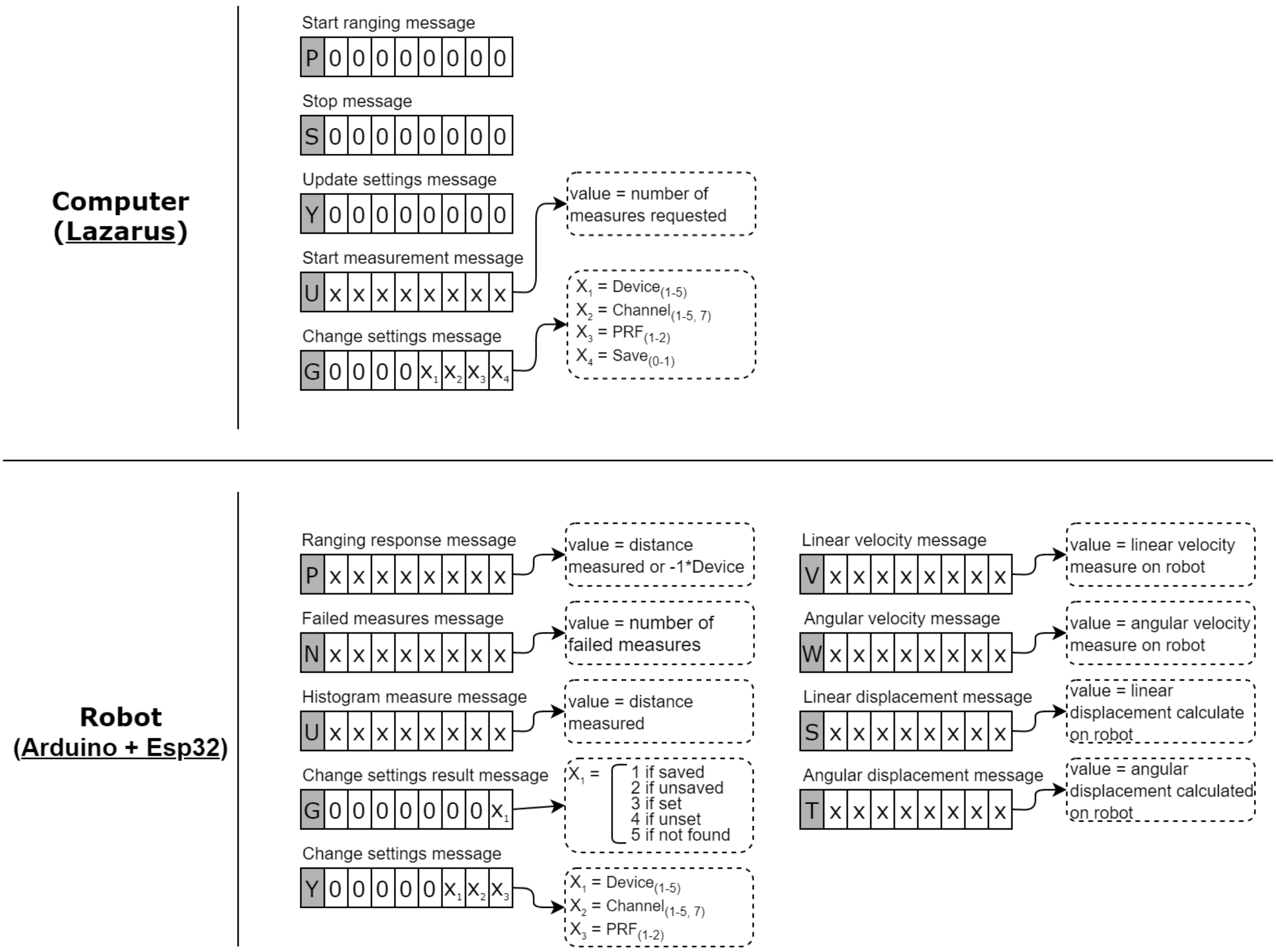


Figure 3.9: All messages exchanged between the computer and the robot

Chapter 4

Approach and Developed Algorithms

In this chapter, the algorithms implemented will be exposed along with their explanations of the theoretical foundations. Firstly, a small introduction to the problem of robot beacon-based localisation will be formulated. Then, a thorough analysis will be presented to the EKF Localisation and the adaptation done regarding the thesis goals. Finally, the approach adopted to detect outliers and the heuristics implemented in order to recover from lousy location estimates will be presented.

4.1 2D Beacon-based location

Usually, the problem of robot Beacon-Based localisation can be characterised as the estimate of the robot's pose $X = \begin{bmatrix} x_r & y_r & \theta_r \end{bmatrix}^T$ by measuring the distances and/or angles to a given number of beacons placed in $M_{B,i} = \begin{bmatrix} x_{B,i} & y_{B,i} \end{bmatrix}, i \in \{1...N_B\}$. Since both, the X and $M_{B,i}$ are defined in the global reference frame $W_X W_Y$.

However, since the problem that it is faced only deals with measurements of distances, the following assumptions were made:

- Because the robot only navigates on the ground without any inclinations, it is assumed that the robot navigates on a two-dimensional plane.

- The beacon's position is stationary and known a priori, so $M_{B,i}$ is well-defined at every moment.

- Every 40ms the odometry values are available. These values will be used to provide the system input $u(k) = \begin{bmatrix} v_k & \omega_k \end{bmatrix}^T$. These values refer to the variation of odometry between instant k and k-1. Additionally, the linear (Δd_k) and angular ($\Delta\theta_k$) displacements values will be known.

- $Z_{B,i}(k) = \begin{bmatrix} r_{B,i} \end{bmatrix}$ identifies the distance measurement between the Pozyx tag and the Pozyx anchor i at the instant k.

As a result, Figure 4.1 illustrates the 2D Beacon-based localisation model given the distances to the anchors presented in the field.

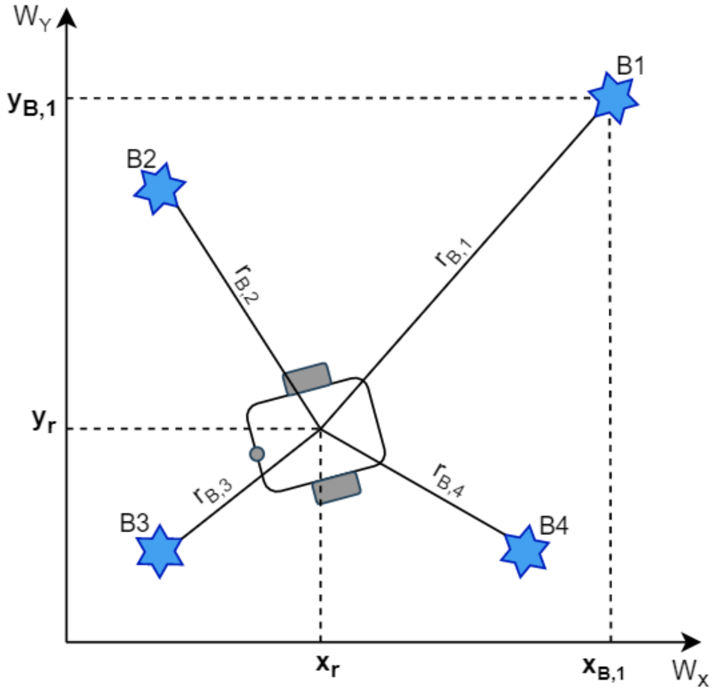


Figure 4.1: 2D location given measurements for anchors with a known position

Therefore, two algorithms and two heuristic were implemented to solve the problem of 2D Beacon-based localisation:

1. Implementation of an Extended Kalman Filter localisation algorithm for fusion the information of odometry values, distance measurements provides by Pozyx and the information of the path where the robot is navigating.

2. Implementation of an outlier detection algorithm to discard atypical measurements.

3. Application of a heuristic to allow the filter to converge to the correct solution even if it is in an incorrect solution.

4.2 Developed Algorithms

Although the Pozyx system allows to obtain an absolute location, distance measurements to anchors alone do not return a position of the robot, so a location algorithm must be chosen. Therefore, the well-known EKF localisation algorithm was deemed the right solution, given the challenges that the indoor environment presents. This is a relatively simple filter with a low computational cost, allowing us to obtain a real-time location, which is one of our requirements. Additionally, EKF is a flexible algorithm that allows for scalable sensory fusion. This is an exciting feature as it allows us to add further additional information from other sensors or technologies easily.

As a result, the odometry values were fused with the distance measurements at each anchor as well as the information of the path through which the robot navigates. On the one hand, this is a very interesting combination since odometry provides high-frequency accessible information about the robot's relative movement. On the other hand, measurements of the distances to the anchors can yield an absolute location, independent of the past and their errors are not cumulative over time (unlike odometry). Ultimately, the navigation path information improves the final estimate of the filter in order to improve its accuracy. Since these sources are not correlated, they can compensate each other very well.

Finally, and before presenting the implementation of the EKF, the kinematic model of the robot used will be presented, since it had to be implemented in the robot's control unit to extract its odometry.

4.2.1 Kinematics of differential drive robots

The robot's forward kinematics define the odometry equations that calculate the robot's relative motion. In equation 4.1, is presented the linear displacement of a differential robot of left and right wheels ($\Delta d_{L,k}$ and $\Delta d_{R,k}$, respectively). As shown in 4.1, on the one hand, these movements are directly proportional to the wheel diameters ($D_{R/L}$) and increments of the pulses ($\#i_{R/L,k}$) of the wheels measured by the respective encoder. On the other hand, it is inversely proportional to the gear reduction ratio (n) and the encoders' resolution (R_e). Then, the pair of equations in 4.2 is relative to the linear (Δd_k) and angular displacements of the robot ($\Delta\theta_k$) where the second equation depends on the robot's distance between the wheels' contact points with the ground (b). Therefore, as our system follows a velocity model the pair of equations 4.3 shows how to convert these displacements into linear and angular velocities of the robot, where the Δt corresponds to the sampling period.

$$\Delta d_{R/L,k} = \frac{\pi \cdot D_{R/L}}{n \cdot R_e} \cdot \#i_{R/L,k} \tag{4.1}$$

$$\begin{aligned} \Delta d_k &= \frac{\Delta d_{R,k} + \Delta d_{L,k}}{2} \\ \Delta\theta_k &= \frac{\Delta d_{R,k} - \Delta d_{L,k}}{b} \end{aligned} \tag{4.2}$$

$$\begin{aligned} v &= \Delta d_k \cdot \Delta t \\ \omega &= \Delta\theta_k \cdot \Delta t \end{aligned} \tag{4.3}$$

Although the forward kinematics enables the calculation of relative motion, the inverse kinematics is required to control the robot through a specific path. As illustrated in the equation pair 4.4, the linear velocity of the right ($v_{R,k}$) and left ($v_{L,k}$) wheels can be calculated from the linear (v_k) and angular (ω_k) velocities of the robot within a given instantaneous k.

$$
\begin{aligned}
v_{R,k} &= v_k + \frac{\omega_k \cdot b}{2} \\
v_{L,k} &= v_k - \frac{\omega_k \cdot b}{2}
\end{aligned}
\tag{4.4}
$$

4.2.2 Extended Kalman Filter

As mentioned earlier, EKF is an algorithm often used for locating robots and fusing sensor data. All types of Kalman Filters model the state of the robot as a Gaussian Distribution $X \sim N(\mu_{X_k}, \Sigma_{X_k})$, where μ_{X_k} represents the robot's pose mean value and Σ_{X_k} the correspondent co-variance matrix. It is important to note that in the case of mobile robotics the Kalman filter (base model) could not be applied because as it is dealing with nonlinear functions, it is necessary its extended model.

Before the algorithm implementations, it is essential to define and understand how the robot's state transition model and sensor observation model evolve.

4.2.2.1 State Transition Model

As demonstrated in the 4.5, the state transition model is a probabilistic model that describes the distribution of the state according to the inputs. In the problem of locating robots, this model is also mentioned as a kinematic model, since it defines the probability of a given state concerning the robot's relative motion.

Two main types of motion models can characterise f: Velocity Models and Odometry Models. The first describes the next state as a function of angular (ω_k) and linear (v_k) velocity, whereas the other use the linear (Δd_k) and angular ($\Delta\theta_k$) displacement instead. Thus, as mentioned above, a velocity model has been adopted (4.6), where the previous state and the linear and angular velocities values are provided as inputs to function f.

$$X_{k+1} = f(X_k, u_k) + N(0, Q(k)) \tag{4.5}$$

$$f(X_k, u_k) = X_k + \begin{bmatrix} v_k \cdot \Delta t \cdot \cos(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) \\ v_k \cdot \Delta t \cdot \sin(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) \\ \omega_k \cdot \Delta t \end{bmatrix} \tag{4.6}$$

Once defined the state transition model, EKF filter requires the linearisation of the model through the Taylor expansion. To accomplish this, the Jacobian calculation of f concerning X_k must be proceed (∇f_X 4.7) and u_k (∇f_u 4.8).

$$\nabla f_X = \frac{\partial f}{\partial X_k} = \begin{bmatrix} 1 & 0 & -v_k \cdot \Delta t \cdot \sin(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) \\ 0 & 1 & v_k \cdot \Delta t \cdot \cos(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) \\ 0 & 0 & 1 \end{bmatrix} \tag{4.7}$$

$$\nabla f_u = \frac{\partial f}{\partial u_k} = \begin{bmatrix} \Delta t \cdot \cos(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) & -\frac{1}{2} \cdot v_k \cdot \Delta t^2 \cdot \sin(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) \\ \Delta t \cdot \sin(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) & \frac{1}{2} \cdot v_k \cdot \Delta t^2 \cdot \cos(\theta_k + \frac{\omega_k \cdot \Delta t}{2}) \\ 0 & 1 \end{bmatrix} \tag{4.8}$$

Finally, to represent the uncertainty associated with the robot's dynamics, the state model also inserts a random normal distributed variable $N(0, Q(k))$. Note that each direction of movement is assumed independently of the others.

$$Q = \begin{bmatrix} \sigma_{v_k}^2 & 0 \\ 0 & \sigma_{\omega_k}^2 \end{bmatrix} \tag{4.9}$$

4.2.2.2 Observation Model

Likewise, the EKF correction phase will also require a model to handle the input measurements, also known as the Observation Model. As previously mentioned, this filter will have two types of information inputs in the filter. The first is the distance measurement made by Pozyx to the anchors, and the other is the information on the navigation path. Consequently, this filter will consist of two observation models. However, both will have in common as the estimate of the current state of the filter as the covariance matrix of the state estimate.

Starting with the model corresponding to the distance measurements to anchors, it is presented in 4.10. The observation model characterises the distance to the anchor i as the Euclidean distance between the robot position and the anchor position. Hence, $h(M_{B,i}, \widehat{X}_k)$ (4.11) represents the estimated value of the measurement given the estimate position of the robot. Once again, the process is affected by an additional Gaussian noise ($N(0,R)$). The R (covariance of measuring noise) parameter must be changed according to the error characteristics of the sensor.

$$Z_{B,i} = r_{B,i} = h(M_{B,i}, X_k) + N(0,R) \qquad R = \begin{bmatrix} \sigma_r^2 \end{bmatrix} \tag{4.10}$$

$$\widehat{Z}_{B,i} = h(M_{B,i}, \widehat{X}_k) = \sqrt{(x_{B,i} - \widehat{x}_{r,k})^2 + (y_{B,i} - \widehat{y}_{r,k})^2} \tag{4.11}$$

As in the state transition model, it is necessary to calculate the Jacobian of h in relation to $\widehat{X}_k$ (∇h_X 4.12), this is intended for the linearisation of the system.

$$\nabla h_X = \frac{\partial h}{\partial \widehat{X}_k} = \begin{bmatrix} -\frac{x_{B,i} - \widehat{x}_{r,k}}{\sqrt{(x_{B,i} - \widehat{x}_{r,k})^2 + (y_{B,i} - \widehat{y}_{r,k})^2}} & -\frac{y_{B,i} - \widehat{y}_{r,k}}{\sqrt{(x_{B,i} - \widehat{x}_{r,k})^2 + (y_{B,i} - \widehat{y}_{r,k})^2}} & 0 \end{bmatrix} \tag{4.12}$$

Finally, considering now the model related to the navigation path, it is represented in 4.13. Briefly, the idea of this model is to improve the performance of the filter. So if the position estimate of the robot is too close to a known line of the path, the idea is to provide the information to the filter that it is positioned on that line. Consequently, this model is characterised by the fixed coordinate of the line i that the robot is following and its orientation. Therefore, if the line is positioned vertically, it has a fixed x value along with it and has a fixed orientation of $\pm 90^{o}$, depending on the direction of navigation of the robot. On the other hand, if the line is positioned horizontally, it has the fixed value in y and the orientation fixed at 0 or -180°, depending again on the navigation direction of the robot. Finally, since the R_{line} corresponds to the covariance of the observation the idea is to set the value of each element very low in order to deliver to the filter the indication that there is a lot of confidence in that observation.

Moreover, $h(\widehat{X}_k)$ (4.14 and 4.16) represents the estimated value of the fixed coordinate of the line and its orientation given the estimated position of the robot.

$$Z_i = \begin{bmatrix} x_{line,i} \quad or \quad y_{line,i} \\ \theta_{line,i} \end{bmatrix} = h(X_k) + N(0,R) \qquad R_{line} = \begin{bmatrix} \sigma^2_{x/y_{line,i}} & 0 \\ 0 & \sigma^2_{\theta_{line,i}} \end{bmatrix} \tag{4.13}$$

Vertical Line:

$$\widehat{Z}_i = h(\widehat{X}_k) = \begin{bmatrix} x_{r,k} \\ \theta_{r,k} \end{bmatrix} \tag{4.14}$$

$$\nabla h_X = \frac{\partial h}{\partial \widehat{X}_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4.15}$$

Horizontal Line:

$$\widehat{Z}_i = h(\widehat{X}_k) = \begin{bmatrix} y_{r,k} \\ \theta_{r,k} \end{bmatrix} \tag{4.16}$$

$$\nabla h_X = \frac{\partial h}{\partial \widehat{X}_k} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4.17}$$

4.2.3 Outliers Detection

Generally, when taking measurements with sensors, they are prone to errors that can be generated due to hardware failures or unexpected changes in the environment. Thus, for proper use of the observations made, the process must be able to identify and deal with these unreliable data, i.e. measurements that are deviated from the typical pattern. This data processing phase is called Outlier Detection. In order to cope with this problem, several approaches have been developed. Mahalanobis' distance (MD, 4.18) is one of the most widely used approaches to handle multivariate data. MD is used as a statistical measure of the probability of some observation belonging to a given dataset. In [52, 53], it can be seen that this approach was successfully used in different applications, which consists of calculating the normalised distance between one point and the entire remaining population.

It should be noted that the Euclidean distance could be used. However, the MD takes into consideration not only the distance concerning the average but also its direction (that is, covariance). In fact, the MD is equal to the Euclidean distance only when the covariance matrix is identity (i.e., all variables are independent and with the same variation). Finally, in this approach, the outliers are removed as long as they are outside a specific ellipse which symbolises a specific probability in the distribution. Consequently, different ellipses represent different MD's and therefore, different probability thresholds.

$$Md(v) = \sqrt{(v-\mu)^T \cdot S^{-1} \cdot (v-\mu)} \tag{4.18}$$

4.3 Algorithms Implementation

After some preliminary considerations about each algorithm, the implementation adopted in this dissertation can now present. In Algorithm 1, the implementation of EKF considering Pozyx measurements is presented considering both phases of this filter and that the positions of each anchor are known a priori. In this algorithm, can also be notice in the correction phase (line 10) that the update of the position estimate is only performed if this measurement is not identified as an outlier. It is important to note that until new measurements, the covariance P_{k+1} will accumulate the odometry errors and therefore will increase gradually. However, whenever new measurements arrive (if not identified as an outlier), the localisation estimate uncertainty decrease. Besides, on lines 16:24 is where it is verified if the robot is relatively close to any of the lines that make up the path.

It should be noted that there are two types of possible lines, vertical and horizontal lines. Since with this type of lines, the intersections of the lines are perpendicular, in this verification a small margin was taken to the size of the line so that the filter can follow the curve properly. This approach occurs because, as the filter estimates always have an associated error, there is a risk of reaching the end of one line and failing to generate estimates in the next line.

In algorithm 2 is then present the correction phase of EKF considering the navigation path. Although it is not evident in the presented algorithm, the input TypeLine influences the filter estimate regarding the observation. Finally, unlike the Pozyx system, this approach can already correct the orientation of the filter estimate.

In algorithm 3 is presented the implementation of the filter that filters the outliers. It is important to note that the choice of the threshold used in this algorithm can be produced in two ways. On the one hand, this choice can be made by merely observing the data in order to eliminate the desired measures. On the other hand, a probabilistic statistical parameter can be adopted. Thus, our threshold was defined according to the probability table of the χ^2 distribution, so that distance observations with less than 2% of probability were considered as an outlier.

Algorithm 1: EKF Localisation Algorithm considering Pozyx measurements

Input : $\widehat{X}_k, Z_{B,i}, u_k, P_k, R, Q$
Output: $\widehat{X}_{k+1}, P_{k+1}$

PREDICTION
  $\widehat{X}_{k+1} = f(\widehat{X}_k, u_k)$
  $\nabla f_X = \frac{\partial f}{\partial X_k}$
  $\nabla f_u = \frac{\partial f}{\partial u_k}$
  $P_{k+1} = \nabla f_X \cdot P_k \cdot \nabla f_X^T + \nabla f_u \cdot Q \cdot \nabla f_u^T$
CORRECTION
  $\widehat{Z}_{B,i} = h(M_{B,i}, \widehat{X}_k)$
  $\nabla h_X = \frac{\partial h}{\partial X_k}$
  $S_{k,i} = \nabla h_X \cdot P_k \cdot \nabla h_X^T + R$
  $Outlier\_Detected = OutlierDetection(S_{k,i}, \widehat{Z}_{B,i}, Z_{B,i})$
  if *!Outlier_Detected* **then**
    $K_{k,i} = P_{k+1} \cdot \nabla h_X^T \cdot S_{k,i}^{-1}$
    $\widehat{X}_{k+1} = \widehat{X}_k + K_{k,i} \cdot [Z_{B,i} - \widehat{Z}_{B,i}]$
    $P_{k+1} = [I - K_{k,i} \cdot \nabla h_X] \cdot P_{k+1}$
  end
for $i = 1$ *to* $Length(Path)$ **do**
  if $\widehat{X}_{k+1}$ *near* $line_i$ **then**
    if *TypeLine is vertical* **then**
      $UpdateLines(TypeLine, Line.X, Line.\theta)$
    else
      $UpdateLines(TypeLine, Line.Y, Line.\theta)$
    end
  end
end

Algorithm 2: EKF Update phase Algorithm considering the Navigate Path

Input : $\widehat{X}_k, P_k, R_{line}, TypeLine, Line_{X/Y}, Line_\theta$
Output: $\widehat{X}_{k+1}, P_{k+1}$

UpdateLines
  $\widehat{Z}_i = h(\widehat{X}_k)$
  $\nabla h_X = \frac{\partial h}{\partial \widehat{X}_k}$
  $S_{k,i} = \nabla h_X \cdot P_k \cdot \nabla h_X^T + R_{line}$
  $K_{k,i} = P_{k+1} \cdot \nabla h_X^T \cdot S_{k,i}^{-1}$
  $\widehat{X}_{k+1} = \widehat{X}_k + K_{k,i} \cdot [Line_{X/Y} - \widehat{Z}_i]$
  $P_{k+1} = [I - K_{k,i} \cdot \nabla h_X] \cdot P_{k+1}$

Algorithm 3: Outlier Detection Algorithm

Input : $S_{k,i}, \widehat{Z}_{B,i}, Z_{B,i}$
Output: $Outlier\_Detected$
OutlierDetection
  $Md(Z_{B,i}) = \sqrt{(Z_{B,i} - \widehat{Z}_{B,i})^T \cdot S_{k,i}^{-1} \cdot (Z_{B,i} - \widehat{Z}_{B,i})}$
  if $Md(Z_{B,i}) > threshold$ **then**
    $Outlier\_Detected = TRUE$
  else
    $Outlier\_Detected = FALSE$
  end

However, it is necessary to make some brief observations concerning the algorithm 1 presented above. Although the algorithm 1 works well, it does not consider certain situations that can generate poor estimates of the robot's pose. So, it was necessary to implement a heuristic to enhance the performance of the filter and consequently, the robot pose estimate.

Firstly, it should be noted that as the filter above detects the existence of an outlier due to the current estimate of the robot's pose, there may be situations in which all measures begin to be considered outliers. This situation can happen right at the start of the filter, where the initial estimate may begin to diverge and therefore all measurements made by Pozyx start to be considered as outliers, when they may not be. However, this situation can also happen even after the filter has converged to the correct pose.

Another problem of the filter presented above is in relation to the correction phase of the path because the risk of associating the robot with a line when it is not on it can be taken. As an example, the filter start situation where the initial estimate of the filter may diverge can be reconsidered. Consequently, if an estimate is generated near a line, the filter quickly associates that it is over that line.

As a result, it is quickly possible to realise that it is still possible to improve the performance of this filter. Thus, a heuristic was developed to consider the situations mentioned above, during the entire time of execution of the filter. The idea of this heuristic is to take into account the uncertainty values of the estimate of the robot's pose both when verifying whether a measure is an outlier and when associating the robot with a line. Hence, the filter only begins to check both the outliers and associate the lines when its estimate converges (i.e. uncertainty values are low). In summary, this heuristic works as a switch that only allows checking the outliers and associating the lines when the uncertainty values of the robot's estimate current pose are below then a certain threshold. Finally, this threshold will be adjusted by observing the behaviour of the filter and the evolution of uncertainty until this heuristic meets the requirements.

Additionally, another improvement was implemented, nevertheless, this was not in the EKF. This improvement consists of taking distance measurements to the anchors randomly, but always measuring only once each anchor in each round of measurements. This improvement allows minimising the errors introduced by the measurements at each anchor. For example, suppose an anchor always has a high-error measurement. In that case, this measure is always provided to the filter in a random order, allowing the filter to converge to other results.

The algorithm 4 presents the final result of the EKF filter with the heuristics developed. As could be seen, two different thresholds have been implemented to activate this heuristic in different uncertain conditions for both situations.

Algorithm 4: EKF Localisation Algorithm considering Pozyx measurements + Heuristic implemented

---

Input : $\widehat{X}_k, Z_{B,i}, u_k, P_k, R, Q$
Output: $\widehat{X}_{k+1}, P_{k+1}$

PREDICTION
    $\widehat{X}_{k+1} = f(\widehat{X}_k, u_k)$
    $\nabla f_X = \frac{\partial f}{\partial X_k}$
    $\nabla f_u = \frac{\partial f}{\partial u_k}$
    $P_{k+1} = \nabla f_X \cdot P_k \cdot \nabla f_X^T + \nabla f_u \cdot Q \cdot \nabla f_u^T$

CORRECTION
    $\widehat{Z}_{B,i} = h(M_{B,i}, \widehat{X}_k)$
    $\nabla h_X = \frac{\partial h}{\partial X_k}$
    $S_{k,i} = \nabla h_X \cdot P_k \cdot \nabla h_X^T + R$
    $K_{k,i} = P_{k+1} \cdot \nabla h_X^T \cdot S_{k,i}^{-1}$
    if *($K_{k,i} < threshold\_Outlier$) or ($K_{k,i} > -threshold\_Outlier$)* **then**
        $Outlier\_Detected = OutlierDetection(S_{k,i}, \widehat{Z}_{B,i}, Z_{B,i})$
    else
        $Outlier\_Detected = FLASE$
    end
    if *!Outlier_Detected* **then**
        $\widehat{X}_{k+1} = \widehat{X}_k + K_{k,i} \cdot [Z_{B,i} - \widehat{Z}_{B,i}]$
        $P_{k+1} = [I - K_{k,i} \cdot \nabla h_X] \cdot P_{k+1}$
    end
if *($K_{k,i} < threshold\_Path$) or ($K_{k,i} > -threshold\_Path$)* **then**
    for $i = 1$ *to* $Length(Path)$ **do**
        if $\widehat{X}_{k+1}$ *near* $line_i$ **then**
            if *TypeLine is vertical* **then**
                $UpdateLines(TypeLine, Line.X, Line.\theta)$
            else
                $UpdateLines(TypeLine, Line.Y, Line.\theta)$
            end
        end
    end
end

Chapter 5

Experimental Methodology

In this chapter, different types of tests conducted will be presented along with a description of each test performed in this work. First, a description and presentation of the robot used will be exposed, as well as a presentation of the Pozyx system and the types of UWB configurations available. Then, the two performance tests and the sequence of tests performed on each one will be presented, counting with a description of each test. Finally, the sequence of location tests executed will be presented, also with a description of each test.

5.1 Research Platforms Description

5.1.1 Modified Robot@Factory Lite robot

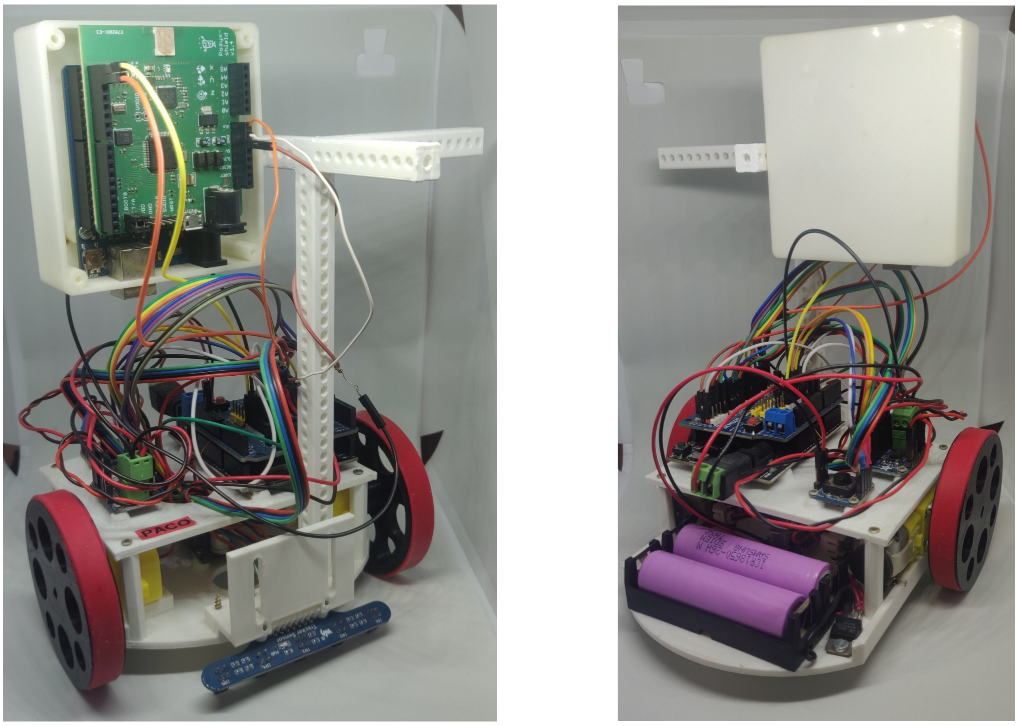
As mentioned above, this robot is just an update to an existing old version of the Robot@Factory Lite competition. In general, the most significant improvements were the introduction of wheel encoders, a microcontroller with wireless communication and the Pozyx system to obtain an absolute location. Additionally, the wheels were changed to have more ground grip, because the previous version skidded the wheels a lot, which introduces errors in the odometry readings. Moreover, it remains the same follows line robot developed for the competition.

Figure 5.8 is present two pictures of the final assembly of the robot. Note in this image that the Pozyx tag has been placed vertically and facing forward, with the antenna on top. The primary purpose of this position is to improve the received signal and obtain the best performance in the measurements.

Following is a list of the components that are present in the robot.

- Track Sensor (Waveshare):
  - 5 infrared sensors (ITR20001/T).
  - Detection range: 1cm - 5cm.
- 2 DC motors with encoders:
  - Encoder maximum output: 1920 pulses within one round.

- Driver (TB6612 - Adafruit).
- StepDown (LM25965).
- MOSFET (BUZ10).
- Switch Adafruit.
- Wemos Esp32 D1 R32 (similar to an Arduino UNO with Esp32).
- Sensor shield (YFRobot).
- 2 batteries for power (ICR1850-26H SAMSUNG).
- Arduino UNO + Pozyx tag (Creator system)



(a) Final assembly of the robot seen from the front (b) Final assembly of the robot seen from behind

Figure 5.1: Final assembly of the robot

5.1.2 Pozyx System

For the UWB ranging context implementation, was selected the Pozyx [54]. It is a hardware and software RTLS solution that provides a robust and accurate positioning, easy to use and easy to integrate.

The company offers two product families:

1. The "Creator system", which is targeted at the prototyping market. It is the perfect solution for small hobby projects, a quick technology validation or a straightforward proof of concept.

2. The "Enterprise system", which is designed specifically for large projects with very demanding requirements around performance or to be built in large industrial environments.

Therefore, it was selected the "creator system". The choice was due to being cheaper and because it was made for small scale setups and and it is a proof of concept project.

Thereby, this system can reach a maximum area size of 20mx20m, with a maximum of 8 anchors (beacons) and five tags (tracked devices). Each module has an embedded DecaWave chip, a chip that was presented as a possible solution in the literature review. The Creator product is tag centric, which implies that the tag itself performs the positioning through communication among the available anchors. The anchors merely respond to the tag(s). Besides, at least with four anchors within range, the tag can compute its position once ranging with each anchor. In addition, an anchor can be configured as a master tag, increasing the system and providing multi-tag support. However, there is a strict limit on how many anchors can be positioned reliably using this technique.

The “creator System” consists of 5 modules, one tag working with an Arduino UNO and four anchors. That together can provide raw range measurements, position estimations (2D or 3D, depending on the places of the anchors) and orientation. The orientation is achieved by an embedded IMU chip that collects additional data using other sensors, like an accelerometer, a gyroscope, a magnetometer (all sensors within the IMU) and a pressure sensor. The fundamental architecture of a Pozyx tag is shown in Figure 5.2.

Regarding the range procedure, it is based on the two-way TOF technique, even though the system can also output the RSS of the signals received by the tag. Through this system is expected accuracy in Line-of-Sight conditions around 10 cm.

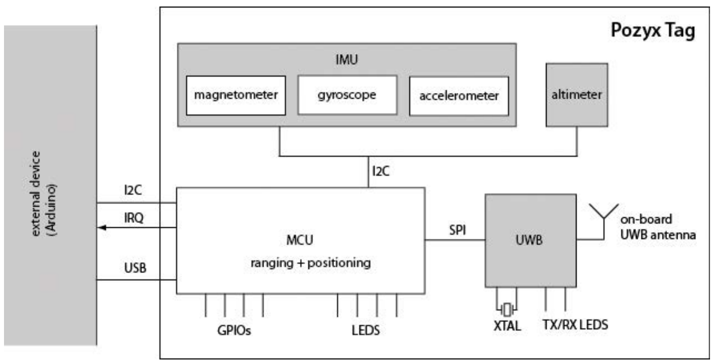


Figure 5.2: Architecture of a Pozyx Tag. Adapted from [54]

5.1.2.1 UWB configurations

The UWB communication between the devices can have different configurations that may impact the system performance, not just in terms of accuracy but also in terms of maximum range distance, energy consumption or update rates. These settings can be adjusted according to four different parameters:

- **Channel:** The communication between devices has six independent UWB channels, presented in Table 5.1. Usually, lower channel numbers have lower centre frequencies which increase the communication range. Finally, devices on different UWB channels cannot communicate and do not interfere with each other.
- **Bitrate:** That corresponds to the velocity of data transmission. For this parameter three possible options are available: 110kbit/sec, 850kbit/sec or 6.81Mbit/sec. Consequently, a higher value will result in smaller messages and faster communication. However, it will decrease the maximum operating range and receiver sensitivity.
- **Pulse Repetition Frequency (PRF):** Here, there are two usable options: 16MHz or 64MHz. This parameter can be seen as a possibility of having distinct groups communicating on the same channel without interfering. However, if the first option is chosen, it may reduce the maximum operating range.
- **Preamble Length:** Which is the number of symbols sent in the UWB packet's preamble. This setting has 8 different options: 4096, 2048, 1536, 1024, 512, 256, 128, or 64 symbols. Shorter preamble length that results in shorter messages will commonly decrease the operating range but will reduce the transmission and receiving times.

Table 5.1: Characteristics of Pozyx's UWB Channels

Channel	Center Frequency (MHz)	Bandwidth (MHz)
1	3494.4	499.2
2	3993.6	499.2
3	4492.8	499.2
4	3993.6	1331.2
5	6489.6	499.2
7	6489.6	1331.2

For the implementation tests, firmware v2.0 was used, which provides maximum data rates of 350Hz for ranging.

5.2 Experimental Tests

As previously mentioned, the experimental tests were divided into two phases. Firstly, some experiments were performed to completely characterise the system and the measurement noise involved, to assess the approach to the next stage. Then, the localisation tests were performed, using the results obtained in the previous testing phase.

As a result, to achieve the final proposal, the following order of tasks was followed:

1. IMU performance test.

2. Characterisation of the UWB's range error.

3. Different Location tests to verify EKF performance.

It should be noted that although information from the IMU was not used in EKF (the second stage tests), some performance tests were carried out for future implementation in the filter.

Furthermore, to study the performance of Pozyx modules, some examples of the *Pozyx Arduino Library* [55] were adapted: *Ready_to_Range* (to perform a Single communication between the tag and an anchor), *Pozyx_anchor_configurator*, *Pozyx_doDiscovery*, *Pozyx_gainConfigurator*, *Pozyx_savechannel* and *Pozyx_UWB_configurator*. These examples were adapted to study the influence of the different settings on the performance tests of the first stage.

Finally, to visualise the results obtained, the GUI developed and previously presented in 3.1 has been used.

5.2.1 IMU Performance Test

Although the IMU was not used in the development of this thesis, it is essential for the purpose of the project. If the project is analysed as it is now, the only sources of information that update the robot's orientation are the navigation path and odometry. However, both sources have disadvantages. On the one hand, as indicated in the literature, odometry introduces significant errors over long periods and is, therefore, a source that only estimates the orientation (Prediction phase of EKF). On the other hand, the navigation path, despite being an update source (Correction phase of EKF), only allows us to update the orientation of the robot when it navigates in a straight line and knowing the line it is following. Hence, it is required a sensor to provide information about the robot's orientation. Thus, the source of information could be the IMU, which despite also introducing errors over long periods, it is easy to re-calibrate. For example, when the robot is navigating in a straight line with high certainty, the IMU can be re-calibrated.

As a result, a preliminary performance study for an IMU (MPU6050) was developed. The study consists of leaving the IMU immobile to perform the measurements over twenty-four hours. Ultimately, the goal is to verify how the offsets of each sensor fluctuate over time, how the chip temperature varies and finally prove if there is any correlation between each sensor and the temperature. Thus, to reduce the amount of information stored over the twenty-four hours, an average of the readings will be made every ten seconds.

5.2.2 Pozyx Error Characterisation

Due to the current situation (Covid-19), all the tests took place in a house, an indoor environment with a complex configuration. Figure 5.3 represents, the space where the tests took place has two types of configuration. The first is an open space (symbolised in a red box), and the second is similar to a hallway (symbolised in a blue box). The purpose of these two different space configurations was to verify that different configurations produce different results.

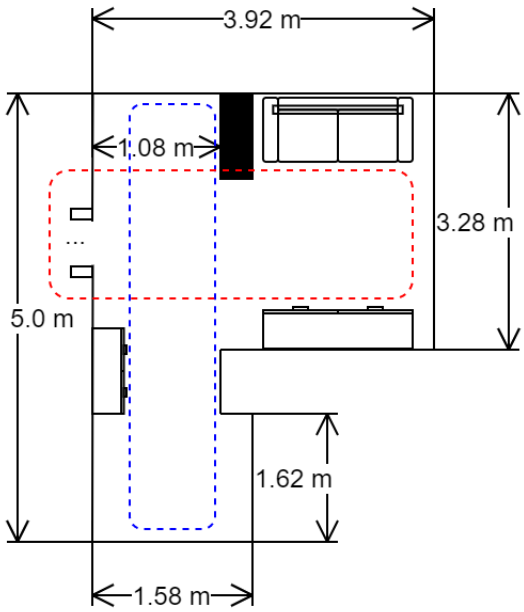


Figure 5.3: Indoor space where tests took place

Consequently, the second part of these tests was to observe whether different UWB settings lead to an improvement in ranging performance and the impact of the UWB settings on the result of ranging measurement histogram. Therefore, pre-tests were conducted to select the best four channels to proceed to the actual tests. Finally, due to the literature review is expected that the different combinations of UWB settings will have an impact on the ranging range and communication time.

Additionally, owing to the limitation of the available indoor space, an outside test was performed to verify the maximum operating range of each channel. Although the outdoor environment has a different impact on UWB ranging, the road where the test took place is narrow, has buildings on both sides and parked cars on the road. Hence, it is also a challenging environment to perform a ranging measurement.

Furthermore, the ground-truth of the actual distance of each measurement was achieved with a laser sensor (illustrated in Figure 5.4) with a maximum range of 30 meters and with an uncertainty of 1 millimetre.

Figure 5.4: Laser used as a ground truth to measure the actual distance

Finally, both the tag and the anchor are positioned 16 centimetres from the ground, supported by an aluminium profile holder. Later, to verify the influence of these supports, these will be exchanged for PLA holders, and all these tests will be repeated to verify what performance improvements can be achieved. Figure 5.5 shows the two different supports used in these tests.

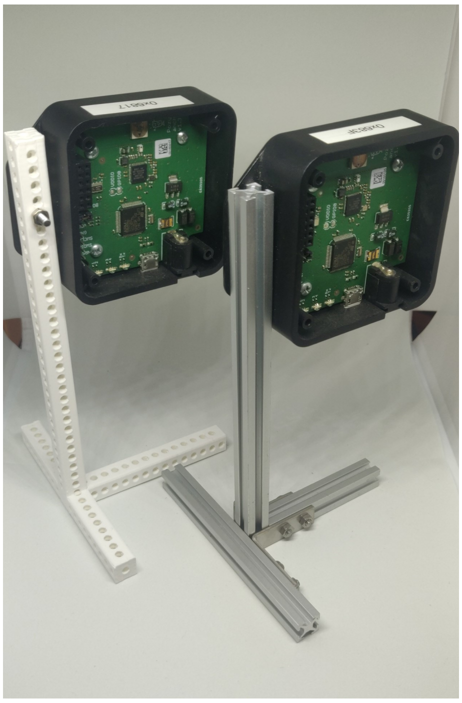


Figure 5.5: Two different supports used in tests

Therefore, two types of tests were performed, one with a fixed distance between the tag and the anchor and other with an increasing distance between both. The first aims to test the interferences of obstacles between the tag and the anchor (creating a NLOS scenario), as well as the impact of this when placed at different distances. Besides, without any obstacle, the influence of tag rotation on measurement performance was also tested. The second type of tests aims to verify the variation of offsets and standard deviations as a function of the measurement distance.

To sum up, the tests took place in two types of environment, indoor and outdoor. In the outdoor environment, only one type of test was performed, measuring in LOS conditions to detect the maximum range of each channel. In an indoor environment, the nine tests explained below were carried out in two types of configurations, open-space and hallway. These were performed twice, the first with aluminium profile holders and the other with PLA holders.

First type of Pozyx performance test

Figure 5.6 illustrates the different tests performed for a better perception of them.

Test 1: This test seeks to understand the performance of the measurements in the best conditions (LOS), for future comparison of results with the other tests. Besides, this test was used to choose which channels to use in future tests because if any channel reveals terrible results in these conditions, these results were expected to worsen.

Test 2-4: With these three tests, the idea is to understand what is the interference of a person when positioned in the middle of communication. Thus, to better simulate the structure of the human body (70% of water), a bucket of water was placed at 1 meter, 2 meters and 3 meters from the tag.

Test 5-6: These two tests are intended to understand whether the total obstruction of both the anchor and the tag influences the measurement performance. It must be noted that the most important result is the total obstruction of the tag as it will be the most common situation in an industrial environment.

Test 7-8: The last two tests aim to verify if the rotation on the Z-axis compromises the measurement performance. This test is crucial because it is a recurring scenario when the robot is navigating through the map.

Second type of Pozyx performance test

This last type of test, as already mentioned before, helps to verify the evolution of offset and standard deviation as a function of measurement distance. For this reason, it was performed between 0.5 meters and 4 meters (maximum range available on indoor space with LOS), with a step of 0.5 meters. Figure 5.7 illustrate this test.

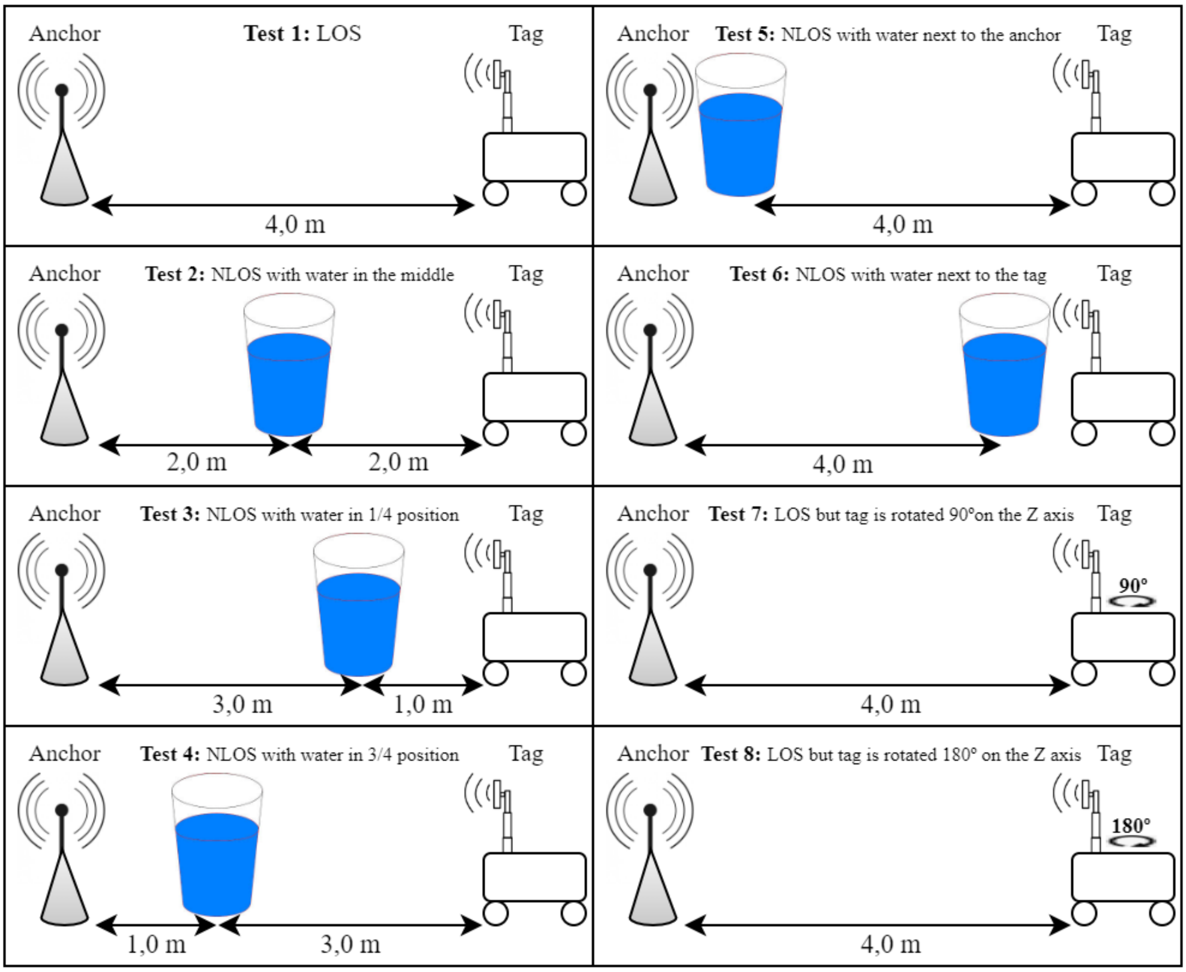


Figure 5.6: Representation of all first type tests

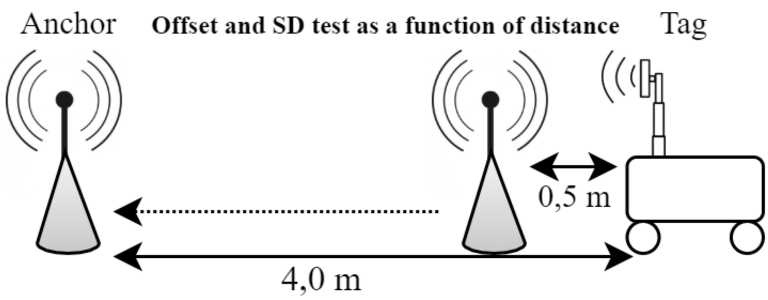
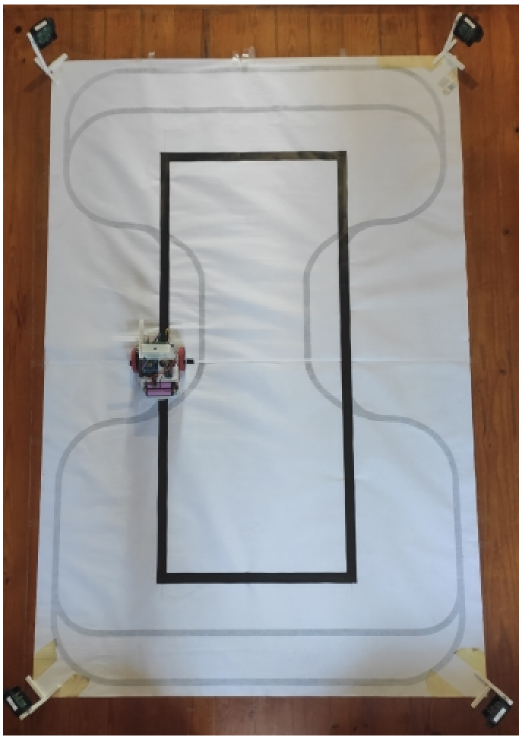


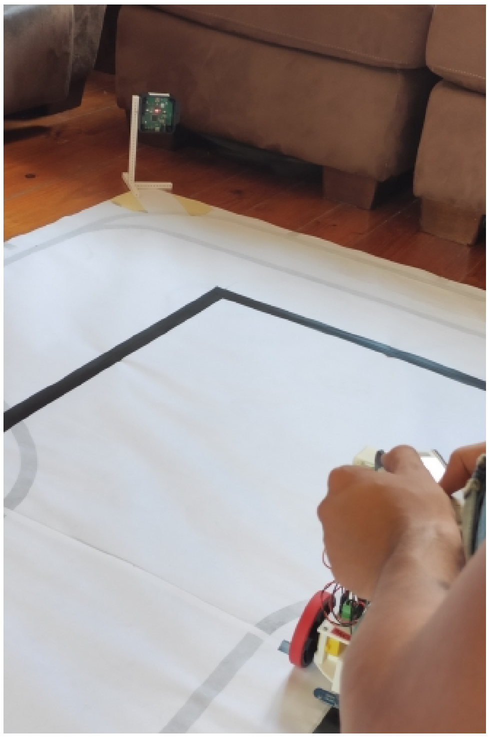
Figure 5.7: Representation of the second type test

5.2.3 Location Tests

After the Pozyx noise was characterised, a sequence of tests was carried out to verify the behaviour and results obtained by the developed EKF filter. Thus, the tests took place in an area of $1.2m$x$1.8m$, with the Pozyx anchors positioned in the corners of this area. Concerning the ground truth used for the tests that will be performed, it will be the same laser used in previous tests. For robot navigation, a simple rectangular path (4 lines) was constructed for proof of concept, where the positioning of each line was obtained with the laser. Later, these lines will be inserted into the GUI to compare the filter estimates against the actual path. Figure 5.8a demonstrates the final result of the test area with the anchors positioned at the corners and the path placed in the centre. As can be seen in the figure, the place considered as the departure of any test carried out is represented. Additionally, it was only considered in these tests a single navigation direction on this path, being clockwise.



(a) Test area used in Location tests



(b) Illustration of measuring the actual distance

Figure 5.8: Location tests

Consequently, the following sequence of tests was taken:

1. EKF test with robot stopped, Pozyx system off and real distances measured:
    - The idea of this test is to test whether the filter was well designed by inserting the filter the actual values of the distances at each anchor. Thus, with the robot in the starting position and with the laser, the distance from the robot to each anchor was measured, for later use in the filter (situation represented in Figure 5.8b).

2. EKF test with robot stopped, Pozyx system off and real distances measured plus some noise:

   - The idea of this test is to verify if with the same conditions as the previous test the filter can converge to the correct position when the actual distances plus some Gaussian noise is entered with zero mean and the standard deviation calculated on the previous tests of Pozyx characterisation. With this test, a measurement made with the Pozyx system is already being simulated.

3. EKF test with robot stopped and Pozyx system on:

   - This test is quite the same as the previous one. However, it allows us to know if the Pozyx system is working well and if the standard deviation used fits the system.

4. EKF test with the robot in movement and Pozyx system off:

   - In this test, the goal is to test now only the prediction phase of the EKF filter and see what results can be obtained only with the odometry. Here there will not be any injection of measures. The objective is not to happen the correction phase of the filter.

5. EKF test with the robot in movement and Pozyx system on:

   - After testing the filter by parts and making sure it is working well, the idea is now to see how the filter behaves as a whole and compare the results when only odometry or only Pozyx system is used. Here different types of tests can be performed, making combinations with the outlier detection filter and the heuristic.

6. EKF test with the robot in movement, Pozyx system on and considering the navigation Path:

   - Finally, in this final test, the goal is to use all the information from all existing sources to see if an estimate of the robot pose with high accuracy ($< 10cm$) can be reached. Since there is no other location system that serves as ground truth, at the end of a few seconds the robot will stop for further measurement of its position with the laser, in order to see the accuracy of the filter estimate. Here different types of tests can be performed, making combinations with the outlier detection filter and the heuristics.

Note that the combination of odometry and navigation path does not make sense to be tested. In fact, odometry only returns the relative motion of the robot so the result would always be dependent on the initial position introduced in the filter. In addition to this combination, two other combinations make no sense to be tested. The first is to test the system with Pozyx on and robot in motion but without sending the data from the odometry. Moreover, the other is to test the Pozyx system with the navigation path information and with the robot in motion but without sending the data from the odometry. These tests do not make sense to be tested because it lacks the information of the movement of the robot that comes from odometry. Thus, although the filter generates pose estimations, these can even correspond to reality at the beginning, however then will no longer be able to follow the robot, generating uninteresting results.

Chapter 6

Results and Discussion

In this chapter, the results obtained in each test mentioned in the previous chapter will be presented, complemented by a discussion of them when necessary. Thus, the results will be shown in the same order as they were described previously. First, the results obtained in the IMU performance test will be presented, accompanied by a discussion regarding the existing correlations. Then, the results of the characterisation of the Pozyx error will be displayed. Where will be exhibited a summary of the tests carried out with the old supports followed by a demonstration and discussion of the results with the new supports. Finally, the results of each location test will be presented, which will be complemented by several observations and comparisons between tests.

6.1 Results of IMU Performance test

As already mentioned above, although the IMU has not been used in this project, this test is still impressive. This study allows us to understand the internal offsets that exist in this IMU and how it evolved over time. Additionally, it allowed verifying if there is any correlation between the values read by each sensor with the chip temperature. This result is especially interesting because, as is known, the temperature of any electronic equipment rises over the operation time, and this increase in temperature may lead to variations in sensors measurements.

Consequently, the IMU would be to use as another source of information to use in the filter. However, it would be an essential source because it would allow updating the orientation of the robot when it navigates either by an unknown line of the path or at the intersections of the lines. Thus, as it is known in the literature, IMUs tend to require dynamic calibration because, due to the accumulation of errors, their measurements start to degrade over time. Hence, this calibration could be done in several ways. In the case of this dissertation, the IMU could be calibrated when the robot navigates in a known straight line, with high certainty.

As a result, figure 6.1 shows the results obtained in each of the sensors present in this IMU over the twenty-four hours test.

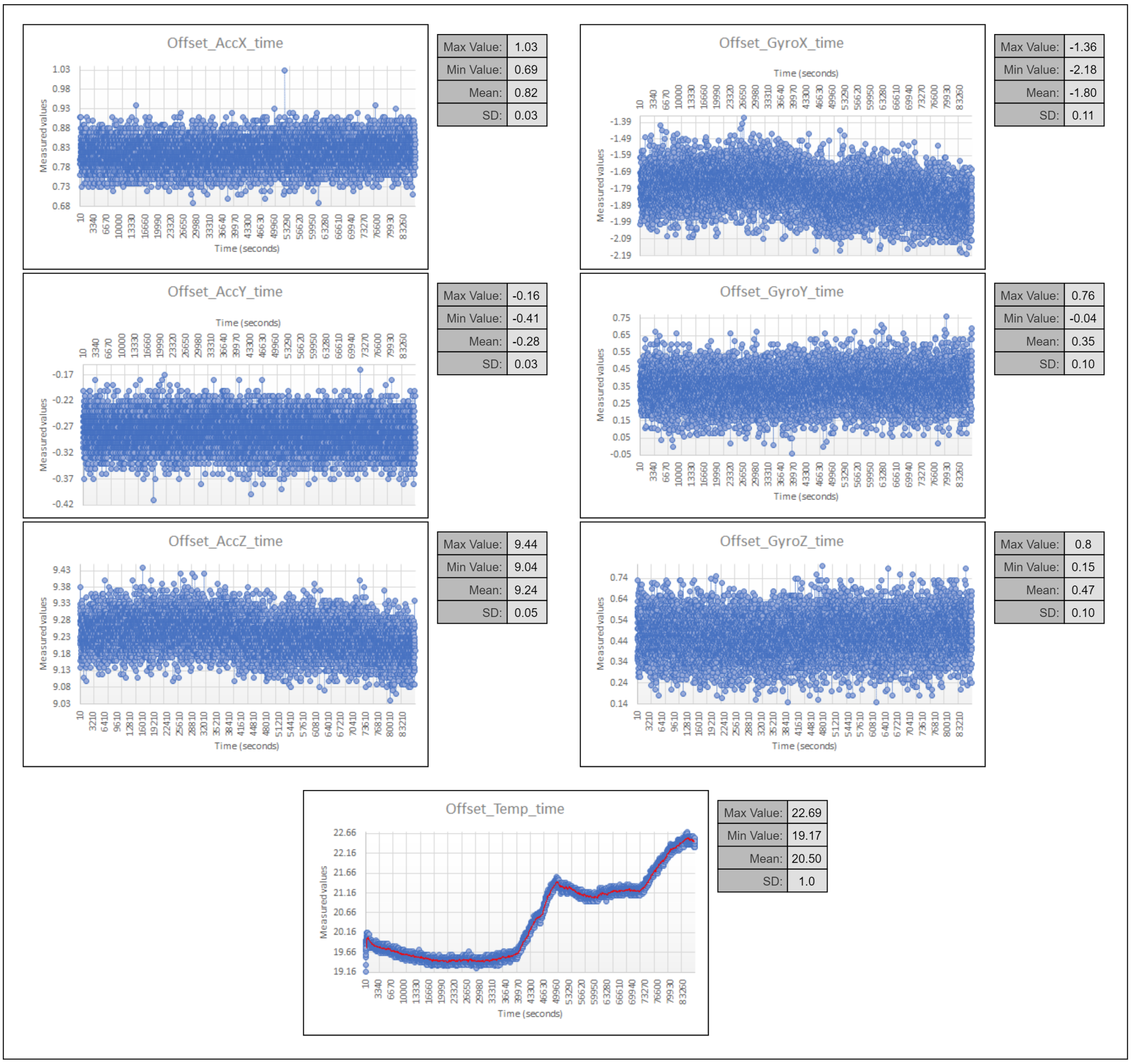


Figure 6.1: Results obtained from the readings of each of the sensors present in the IMU (MPU6050) after twenty-four hours

From the results obtained with this test, present in Figure 6.1, it is interesting to mention that the standard deviations remain quite constant along each axis of each sensor. However, it is essential to note that although all values have as their base reference the “0”, the acceleration according to the Z-axis axis is based on the value of gravitational acceleration ($\approx 9.8m/s^2$). Additionally, it is important to mention that the test started at the end of the night (23:55), which justifies the initial decrease in temperature because the night cooled.

Finally, Table 6.1 shows the results of the correlation between each of the IMU sensors and temperature. It is relevant to mention that Pearson’s correlation was used for this purpose. Moreover, according to the literature, values of correlation coefficient below 0.2 are considered almost uncorrelation, between 0.2 and 0.5 are considered with an average correlation and above 0.5 with a strong correlation. Besides, negative correlation coefficient values indicate a negative correlation.

Table 6.1: Table with correlation coefficients between two variables (IMU sensors and temperature)

Variable X	Variable Y	Correlation coefficient
Acceleration X-axis	Temperature	0.13
Acceleration Y-axis	Temperature	-0.10
Acceleration Z-axis	Temperature	-0.37
Gyroscope X-axis	Temperature	-0.43
Gyroscope Y-axis	Temperature	0.12
Gyroscope Z-axis	Temperature	0.12

Consequently, it is possible to mention two important facts about the result obtained. Firstly, for the case study of this thesis, only the linear acceleration in Y-axis (movement direction) and angular velocity in Z-axis, that are represented in cyan blue lines in the table, are relevant and these data are not correlated with temperature. Secondly, it is noticed that the linear acceleration in Z-axis and the angular velocity in X-axis, represented in grey lines in the table, have a negative average correlation with temperature. In fact, this is detected in Figure 6.1, where, when the temperature rises, the values measured by these sensors tend to drop slightly.

6.2 Results of Pozyx Error Characterisation tests

When characterising the performance of a system, it is crucial to be aware that an error may have multiple sources and be of different types. The following tests will focus essentially on accuracy and precision analysis, which are typically associated with systematic and random errors, respectively. Although both are important, in the specific case of this thesis, characterising the precision of the sensor is particularly important since it will be used in the EKF to characterise the measurement noise of the Pozyx system. Besides, accuracy measures the proximity of observations to actual distance values, thus characterising the existing offset.

Consequently, some performance tests were conducted. As already mentioned in the previous chapter, these tests took place in two environments. Firstly, the results obtained with the maximum range test performed outdoor will be presented, followed by the results obtained indoor. Where the results obtained with the aluminium holders will be presented first and then the results with the PLA holders. In order to synthesise the information and minimise the number of figures with the results, the results of the tests performed with aluminium holders were synthesised in tables.

6.2.1 Outdoor Maximum Range test

As has been mentioned before, this test has only one purpose, which is to measure the maximum range of each channel. Therefore, Figure 6.2 shows the results obtained in this test. It is important to note that almost all channels had the same maximum range, apart from channel 2, which obtained a much higher range. Hence, to minimise the number of images presented, Figure 6.2 displays only the results of one of the channels with a smaller range and channel 2.

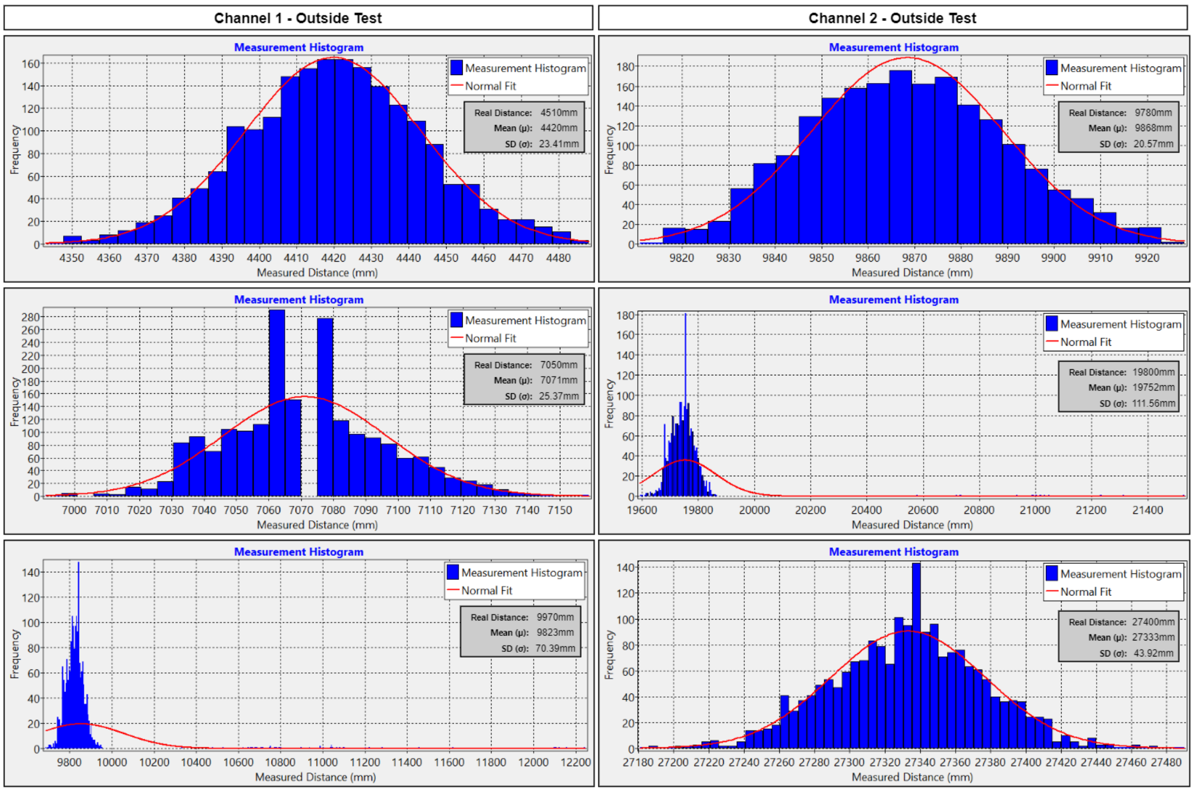


Figure 6.2: Results of two channels in outdoor maximum range test

Through this test, it was possible to conclude that in the conditions of a narrow street, all channels except channel 2 have a maximum range of 10 meters. Wherefrom this distance the Pozyx tag (emitter) stops detecting the Pozyx anchor (receiver). Additionally, it is possible to conclude that although the last measurement with channel 2 was made close to 30 meters, this should not be the maximum range. Because it was not possible to make measurements at higher distances due to limitations of the street and since it is the maximum range of the laser. However, this channel begins to exhibit higher standard deviations, which is not desirable. Finally, it must be mentioned that the high standard deviations presented in the third and second tests of channel 1 and 2, respectively, might be minimised with the usage of an outlier detector filter.

6.2.2 Indoor Performance tests

As already mentioned before, these tests aim to verify whether different space configurations generate different results and the impact of changes in the configurations available in the pozyx system. Therefore, after consulting the documentation provided by Pozyx, it was decided that only the impact of changing the communication channel, the PRF and the antenna gain (both the tag and the anchor) would be tested. The impact of changing the bitrate and the preamble length was not tested, since it was already known that it would decrease the maximum measurement range.

Results obtain with the aluminium holders

When performing the sequence of tests proposed above, two events were noticed that were influencing the measurements. Despite not being part of the test sequence, it was decided to register as they prove that the conditions under which the measurements are being conducted influence its result. The first event occurs when the anchor is against the wall. Thus, table 6.2 shows the results of when the anchor positioned against the wall and when it is 20cm away from it (minimal distance advised by Pozyx). The second event happens when measuring with the tag positioned immediately after a door and with the anchor 20cm from the wall. Consequently, table 6.3 presents the result of this test, where it is possible to notice the influence of the door on the measurement accuracy.

Table 6.2: Influence of a wall on a measurement

	Channel 1	**Channel 2**	**Channel 5**
Anchor against the wall	$\varepsilon = 10.3cm$ $\sigma = 2.15cm$	$\varepsilon = 22.7cm$ $\sigma = 3.68cm$	$\varepsilon = -1.0cm$ $\sigma = 3.07cm$
Anchor 20cm away from wall	$\varepsilon = -2.9cm$ $\sigma = 8.84cm$	$\varepsilon = 8.80cm$ $\sigma = 2.67cm$	$\varepsilon = 10.1cm$ $\sigma = 2.90cm$

Table 6.3: Influence of a door in the middle of communication

	Channel 2
No door in the middle of communication	$\varepsilon = 9.80cm$ $\sigma = 1.18cm$
Door in the middle of communication	$\varepsilon = 18.3cm$ $\sigma = 2.89cm$

Following is presented the table 6.4, which presents the results of Test 1, in open space configuration, for all channels and PRF combinations. It should be noted that channel 7 is not in the table because it was not possible to get any results with this channel. This test allowed to choose the three best combinations of channels with the PRF to proceed to the following tests.

Table 6.4: Test 1 performed with all channel and PRF combinations

	Channel 1	**Channel 2**	**Channel 3**	**Channel 4**	**Channel 5**
$PRF \leftarrow 16MHz$	$\varepsilon = 45.98cm$ $\sigma = 2.83cm$	$\varepsilon = 19.20cm$ $\sigma = 2.57cm$	Does not work	Does not work	Does not work
$PRF \leftarrow 64MHz$	$\varepsilon = 13.11cm$ $\sigma = 6.44cm$	$\varepsilon = 12.29cm$ $\sigma = 2.91cm$	$\varepsilon = 3.22cm$ $\sigma = 2.82cm$	$\varepsilon = 15.09cm$ $\sigma = 3.42cm$	$\varepsilon = 34.23cm$ $\sigma = 2.89cm$

As a result, the three combinations with the best performance were channels 1, 2 and 3 both with the PRF at 64MHz. Additionally, this test allows verifying that the 16MHz PRF decreases the maximum measurement range.

Then, tables 6.5 and 6.6 presents the results for the sequence of tests previously proposed, with the combinations selected in the previous test, considering the open space and hallway configurations, respectively. Additionally, the impact of amplification of antenna gain, both on the tag and anchor, was tested when compared to the default gain.

Table 6.5: Sequence of tests performed in the open space configuration with aluminium holders

	Channel 1		**Channel 2**		**Channel 3**	
	Default Gain	Amplified Gain	Default Gain	Amplified Gain	Default Gain	Amplified Gain
Test 1	$\varepsilon = 13.11cm$ $\sigma = 6.44cm$	$\varepsilon = 25.86cm$ $\sigma = 4.67cm$	$\varepsilon = 12.29cm$ $\sigma = 2.91cm$	$\varepsilon = 11.34cm$ $\sigma = 2.54cm$	$\varepsilon = 3.22cm$ $\sigma = 2.82cm$	$\varepsilon = -5.71cm$ $\sigma = 2.12cm$
Test 2	$\varepsilon = 8.58cm$ $\sigma = 3.39cm$	$\varepsilon = 15.12cm$ $\sigma = 2.88cm$	$\varepsilon = 19.12cm$ $\sigma = 17.16^{*}cm$	$\varepsilon = 24.85cm$ $\sigma = 17.93^{*}cm$	$\varepsilon = 1.81cm$ $\sigma = 2.26cm$	$\varepsilon = 3.35cm$ $\sigma = 2.92cm$
Test 3	$\varepsilon = 12.85cm$ $\sigma = 3.40cm$	$\varepsilon = 17.57cm$ $\sigma = 3.22cm$	$\varepsilon = 40.84cm$ $\sigma = 3.63cm$	$\varepsilon = -28.35cm$ $\sigma = 17.44^{*}cm$	$\varepsilon = 9.95cm$ $\sigma = 2.18cm$	$\varepsilon = 19.08cm$ $\sigma = 2.46cm$
Test 4	$\varepsilon = 8.08cm$ $\sigma = 3.20cm$	$\varepsilon = 15.94cm$ $\sigma = 3.32cm$	$\varepsilon = 15.94cm$ $\sigma = 3.61cm$	$\varepsilon = -29.96cm$ $\sigma = 1.86cm$	$\varepsilon = 22.41cm$ $\sigma = 3.61cm$	$\varepsilon = 25.87cm$ $\sigma = 3.71cm$
Test 5	Does not work	$\varepsilon = -1.64cm$ $\sigma = 5.99cm$	$\varepsilon = 13.94cm$ $\sigma = 2.54cm$	$\varepsilon = 18.85cm$ $\sigma = 1.69cm$	Does not work	$\varepsilon = 39.74cm$ $\sigma = 8.61cm$
Test 6	Does not work	$\varepsilon = 45.01cm$ $\sigma = 3.63cm$	$\varepsilon = 41.76cm$ $\sigma = 11.40^{*}cm$	$\varepsilon = 24.92cm$ $\sigma = 2.20cm$	$\varepsilon = 26.98cm$ $\sigma = 4.30cm$	$\varepsilon = 22.21cm$ $\sigma = 22.59^{*}cm$
Test 7	$\varepsilon = 11.48cm$ $\sigma = 17.24^{*}cm$	$\varepsilon = -10.04cm$ $\sigma = 19.29^{*}cm$	$\varepsilon = 7.01cm$ $\sigma = 2.11cm$	$\varepsilon = 4.96cm$ $\sigma = 2.16cm$	$\varepsilon = -0.89cm$ $\sigma = 1.74cm$	$\varepsilon = 0.07cm$ $\sigma = 1.73cm$
Test 8	Does not work	$\varepsilon = -17.43cm$ $\sigma = 2.42cm$	$\varepsilon = 22.74cm$ $\sigma = 5.34cm$	$\varepsilon = 44.37cm$ $\sigma = 5.67cm$	$\varepsilon = -0.15cm$ $\sigma = 2.13cm$	$\varepsilon = 19.22cm$ $\sigma = 4.14cm$

*Note: The standard deviation is high in this test due to the presence of several outliers.

Table 6.6: Sequence of tests performed in the Hallway configuration with aluminium holders

	Channel 1		**Channel 2**		**Channel 3**	
	Default Gain	Amplified Gain	Default Gain	Amplified Gain	Default Gain	Amplified Gain
Test 1	Does not work	$\varepsilon = -14.31cm$ $\sigma = 2.49cm$	$\varepsilon = -9.26cm$ $\sigma = 2.36cm$	$\varepsilon = -9.16cm$ $\sigma = 1.79cm$	$\varepsilon = 14.54cm$ $\sigma = 2.24cm$	$\varepsilon = 7.73cm$ $\sigma = 1.92cm$
Test 2	Does not work	$\varepsilon = -9.75cm$ $\sigma = 6.34cm$	$\varepsilon = 13.37cm$ $\sigma = 2.09cm$	$\varepsilon = 12.29cm$ $\sigma = 1.25cm$	$\varepsilon = 1.43cm$ $\sigma = 2.04cm$	$\varepsilon = 3.53cm$ $\sigma = 2.04cm$
Test 3	Does not work	$\varepsilon = 36.47cm$ $\sigma = 5.26cm$	$\varepsilon = 12.32cm$ $\sigma = 2.03cm$	$\varepsilon = 12.46cm$ $\sigma = 1.60cm$	$\varepsilon = 9.63cm$ $\sigma = 2.17cm$	$\varepsilon = 1.26cm$ $\sigma = 1.99cm$
Test 4	Does not work	$\varepsilon = 14.64cm$ $\sigma = 4.75cm$	$\varepsilon = 12.48cm$ $\sigma = 1.96cm$	$\varepsilon = 11.44cm$ $\sigma = 1.61cm$	$\varepsilon = 7.70cm$ $\sigma = 1.60cm$	$\varepsilon = 3.58cm$ $\sigma = 1.51cm$
Test 5	Does not work	$\varepsilon = 2.65cm$ $\sigma = 3.14cm$	Does not work	$\varepsilon = 12.54cm$ $\sigma = 1.80cm$	$\varepsilon = 20.13cm$ $\sigma = 5.16cm$	$\varepsilon = 19.00cm$ $\sigma = 3.02cm$
Test 6	Does not work	$\varepsilon = 26.39cm$ $\sigma = 21.59^{*}cm$	Does not work	$\varepsilon = 64.93cm$ $\sigma = 1.96cm$	$\varepsilon = 16.33cm$ $\sigma = 15.66^{*}cm$	$\varepsilon = -1.48cm$ $\sigma = 20.50^{*}cm$
Test 7	Does not work	$\varepsilon = -38.28cm$ $\sigma = 1.82cm$	$\varepsilon = 5.40cm$ $\sigma = 1.94cm$	$\varepsilon = -2.45cm$ $\sigma = 3.51cm$	$\varepsilon = 4.08cm$ $\sigma = 1.78cm$	$\varepsilon = -2.45cm$ $\sigma = 1.69cm$
Test 8	Does not work	$\varepsilon = 5.72cm$ $\sigma = 2.63cm$	$\varepsilon = 33.59cm$ $\sigma = 6.59cm$	$\varepsilon = 6.92cm$ $\sigma = 5.71cm$	$\varepsilon = 47.51cm$ $\sigma = 4.55cm$	$\varepsilon = 45.17cm$ $\sigma = 2.25cm$

*Note: The standard deviation is high in this test due to the presence of several outliers.

Through the results observed in the tables 6.5 and 6.6, it is possible to draw four main conclusions. The first is that increasing the gain enable communications that were not possible with the default gain, improving the penetration in the obstacles. The second is that the configuration of the space where the measurements are performed influences the test results. Note, for example, in the case of the hallway configuration where the errors have decreased slightly in all channels. This result can be verified since radio waves are more directed due to the restrictions of the walls rather than having more space to navigate, as is the case of open space. The third conclusion is that channel 1 is the one with the weakest results, as it is the one that most often cannot perform a measurement and has slightly higher errors in several tests. As a result, this channel will no longer be considered in the following tests. Finally, the last conclusion and probably one of the most important is that the Pozyx's antenna cannot perform measurements equally in every orientation. For instance, it can be noticed in the results of test 7, where it is realised that the errors are much lower. Actually, the antenna radiates omnidirectionally on the X-Y plane but not on the Y-Z plane. Thus, different orientations between the tag and the anchor would produce different variations in the measurement performance, as can be observed in the results of test 1 for test 7 and for test 8.

Finally, the results of the last type of test, considering only the hallway configuration, are demonstrated in table 6.7.

Table 6.7: Offset and SD as a function of measurement distance with aluminium holders

Measurement Distance	**Channel 2** Default Gain	**Channel 2** Amplified Gain	**Channel 3** Default Gain	**Channel 3** Amplified Gain
$50cm$	$\varepsilon = -3.60cm$ $\sigma = 1.76cm$	$\varepsilon = -8.28cm$ $\sigma = 1.76cm$	$\varepsilon = 0.68cm$ $\sigma = 1.99cm$	$\varepsilon = -7.57cm$ $\sigma = 1.79cm$
$100cm$	$\varepsilon = -1.07cm$ $\sigma = 2.06cm$	$\varepsilon = -2.98cm$ $\sigma = 1.90cm$	$\varepsilon = 3.97cm$ $\sigma = 1.97cm$	$\varepsilon = -4.78cm$ $\sigma = 1.78cm$
$150cm$	$\varepsilon = -3.10cm$ $\sigma = 2.15cm$	$\varepsilon = -3.95cm$ $\sigma = 1.87cm$	$\varepsilon = 2.12cm$ $\sigma = 1.45cm$	$\varepsilon = 1.32cm$ $\sigma = 1.93cm$
$200cm$	$\varepsilon = -0.76cm$ $\sigma = 1.81cm$	$\varepsilon = 2.52cm$ $\sigma = 2.71cm$	$\varepsilon = 4.96cm$ $\sigma = 1.55cm$	$\varepsilon = 9.84cm$ $\sigma = 2.37cm$
$250cm$	$\varepsilon = 5.42cm$ $\sigma = 2.45cm$	$\varepsilon = -7.18cm$ $\sigma = 1.23cm$	$\varepsilon = 11.43cm$ $\sigma = 2.88cm$	$\varepsilon = 9.13cm$ $\sigma = 2.20cm$
$300cm$	$\varepsilon = -2.06cm$ $\sigma = 1.75cm$	$\varepsilon = 6.39cm$ $\sigma = 2.17cm$	$\varepsilon = 9.47cm$ $\sigma = 2.35cm$	$\varepsilon = 9.88cm$ $\sigma = 1.83cm$
$350cm$	$\varepsilon = 10.29cm$ $\sigma = 4.56cm$	$\varepsilon = 1.54cm$ $\sigma = 1.59cm$	$\varepsilon = -5.40cm$ $\sigma = 3.22cm$	$\varepsilon = -14.83cm$ $\sigma = 1.41cm$
$400cm$	$\varepsilon = -12.00cm$ $\sigma = 1.82cm$	$\varepsilon = -4.78cm$ $\sigma = 2.07cm$	$\varepsilon = 15.74cm$ $\sigma = 2.70cm$	$\varepsilon = 12.62cm$ $\sigma = 2.43cm$

Results obtain with the PLA holders

Considering now the change, both tag and anchor, to the PLA holders, the same tests were performed. However, now the results will not be presented in tables but histograms, for the first type of tests, and in chart bars, for the second type of test. Therefore, the tests were performed with default gain because it is already known what impact the amplified gain has on the measurements.

As a result, figure 6.3 and 6.4 demonstrate the results obtained for the first type of tests performed in the open space and hallway configuration, respectively.

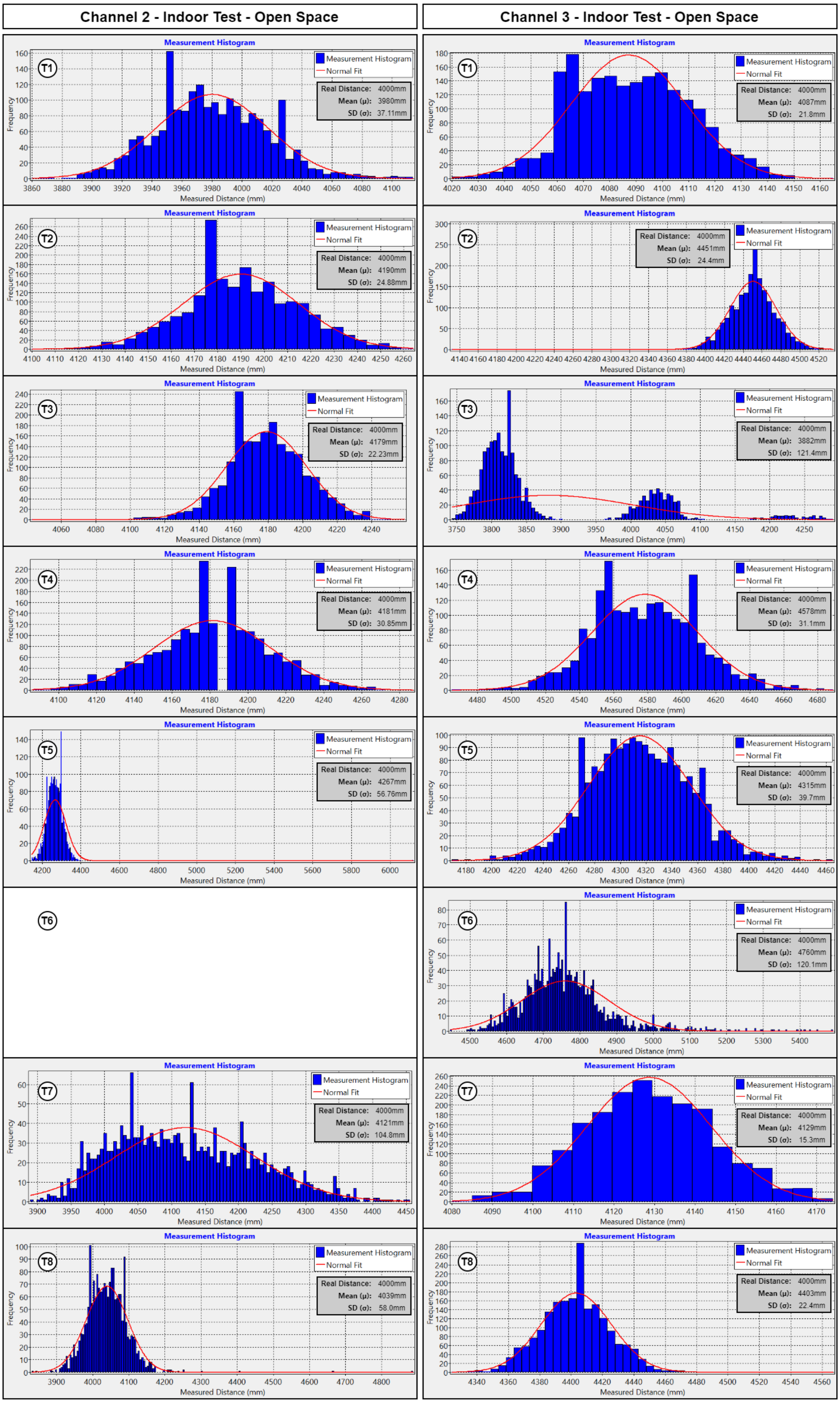


Figure 6.3: Sequence of tests performed in the open space configuration with PLA holders

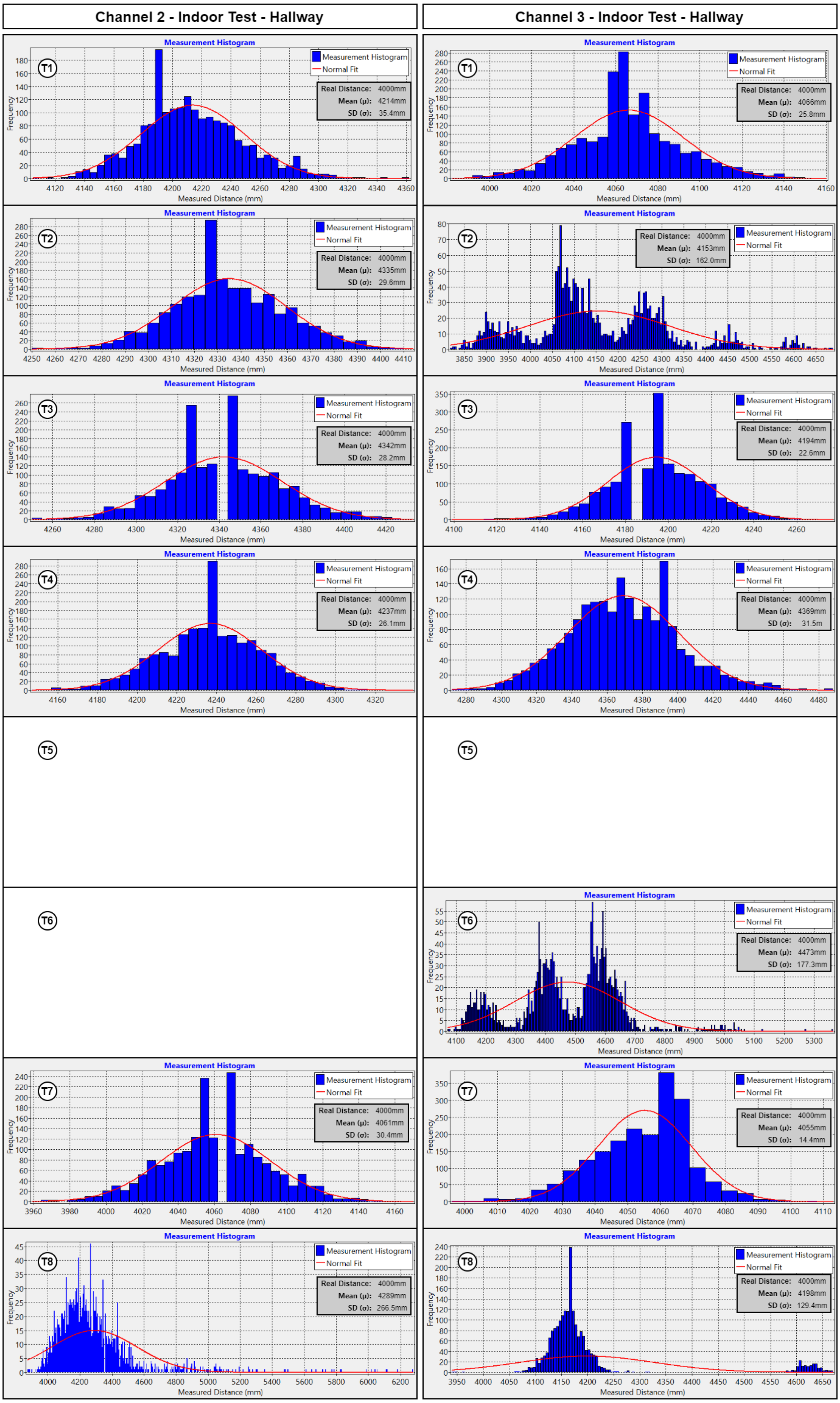
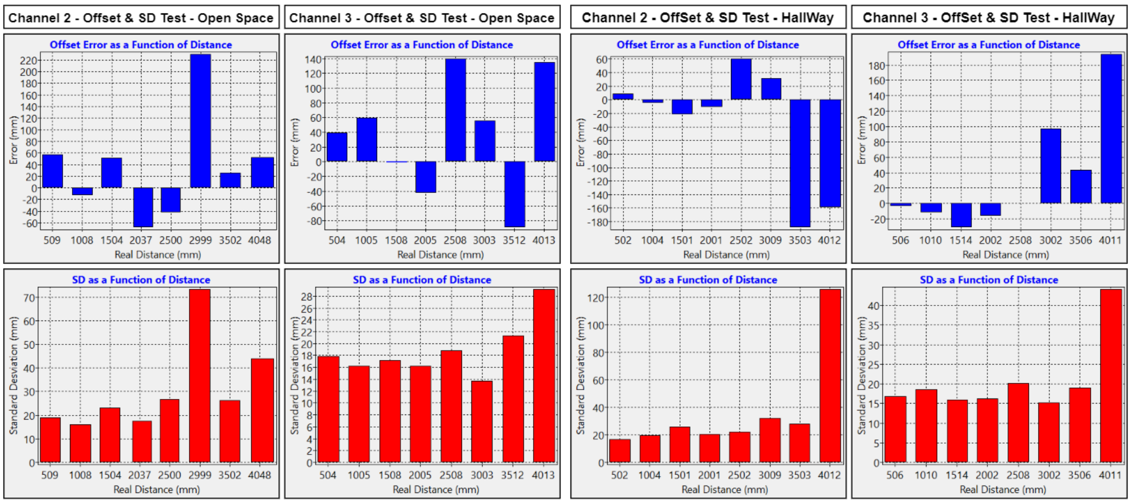


Figure 6.4: Sequence of tests performed in the hallway configuration with PLA holders

It should be noted that the white blocks represented in Figures 6.3 and 6.4 symbolise that it was not possible to perform the measurement.

Ultimately, figure 6.5 shows the results of the second type of tests in both configurations considered.



(a) Open Space Results (b) Hallway Results

Figure 6.5: Offset and SD as a function of measurement distance with PLA holders

Through these results, it was not possible to conclude whether the aluminium holders influenced the measurement performance. In fact, the results obtained with PLA holders sometimes get better results. However, they also have worse results in some tests. Thus, it would be necessary to repeat the tests again and on the same day, so that the measurements are performed under the same conditions, to verify if these results are maintained.

6.3 Results of Location tests

Moving now to the robot's current location system, data processing and analysis was done with two primary purposes. These being the EKF tuning accompanied by a step-by-step test, following the order of the previously proposed tests, in order to achieve a real-time location with high accuracy. For the following tests, PLA holders were used, as well as the use of channel 2 with the default gain, since although the amplified gain generated good results sometimes included some fluctuations in the errors demonstrated.

EKF Tuning

An essential step about these filters is the tuning of the EKF parameters. Changing its parameters affects both the convergence of the algorithm as well as the smoothness of the resultant trajectory estimate. Considering the previous measuring noise characterisation, R and Q were adjusted in such a way that the results of the robot pose estimate presented were neither noise-sensitive nor too slow. Thus, the adopted implementation relates the dynamics noise (Q) with the measuring noise (R).

After some tests, Q was adjusted to $0.001 \cdot R$. The R value was defined following the mean, standard deviation obtained in the Pozyx Error Characterisation. Regarding the initial state estimates, P_0 is a $3x3$ identity matrix.

EKF test with robot stopped, pozyx system off and real distances measured

Figure 6.6 demonstrates the result of the filter when the actual distances from the robot to the anchors is introduced into EKF. The bottom image represents an approximation of the image from above, and the blue lines represent the navigation path mentioned before. Thus, it is essential to mention that in the image of the lower right corner is presented the last estimate of the filter and the initial pose of the robot, where it can be seen that the orientation remained unchanged. In fact, the measurements taken by Pozyx do not enter information about the orientation of the robot. Consequently, there is a $9.2mm$ estimate error which is quite acceptable.

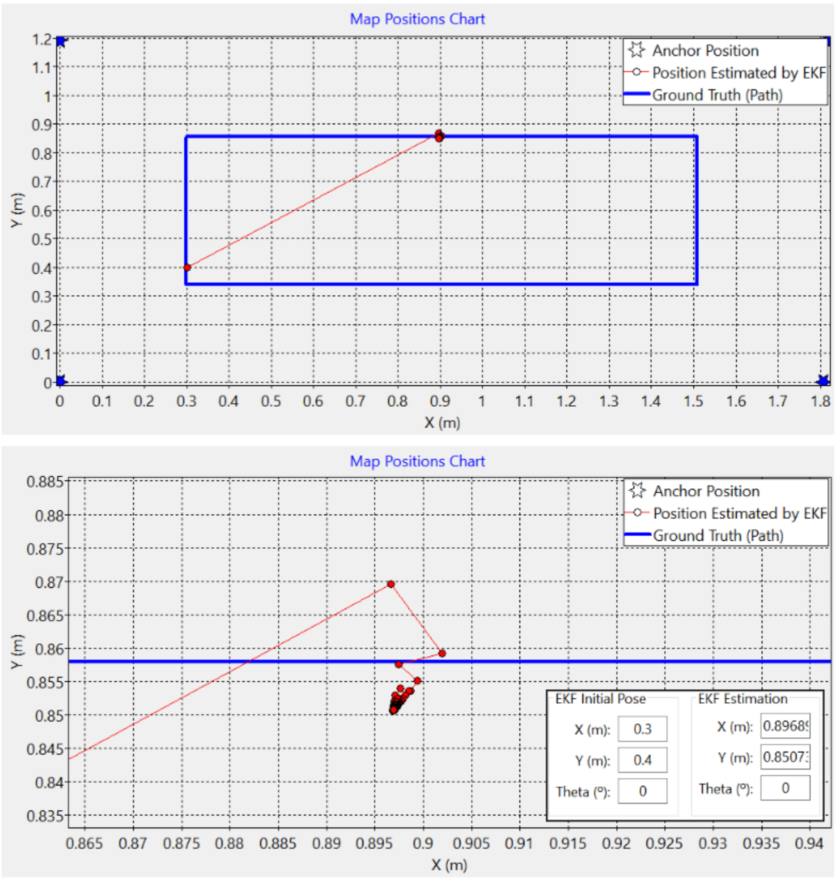


Figure 6.6: EKF Estimate Result in Test 1

EKF test with robot stopped, pozyx system off and real distances measured plus some noise

Figure 6.7 shows the result obtained for the second proposed test, which only differs from the addition of noise to the actual measurements introduced in the filter. As it is possible to verify even though the filter needs to estimate more states, the final accuracy remained at $9.2mm$.

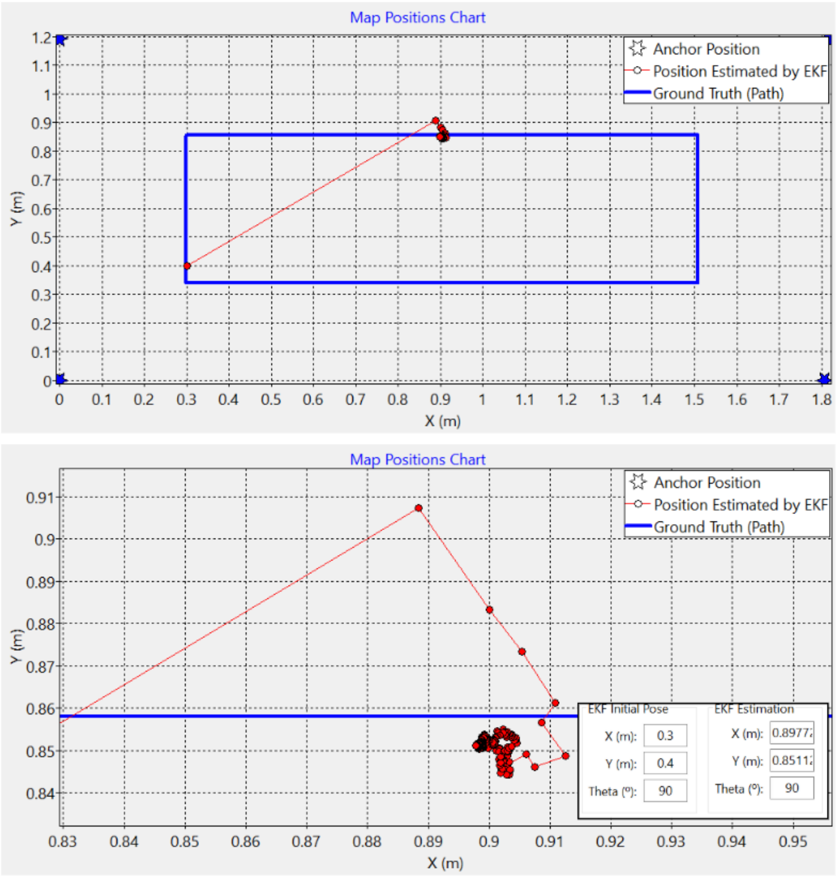


Figure 6.7: EKF Estimate Result in Test 2

EKF test with robot stopped and pozyx system on

Figure 6.8 shows the result of EKF estimates when the outlier's detection filter is not being applied. Thus, it is simple to realise that outliers have a huge impact on filter performance and that therefore it is necessary to sense them and remove them. Consequently, considering the MD filter previously demonstrated, assuming it follows a chi-square distribution with 1 degree of freedom, the threshold was set so that measurements outside the 98% confidence were removed. As a result, figure 6.9 presents EKF estimates using this filter where it is possible to notice that an accuracy of $3.0cm$ has been obtained, which is also an excellent result.

Finally, it is important to note that the test with heuristics does not make sense to be tested here, because all outliers would be inserted into the filter until it stabilises, which would worsen the EKF estimate. The use of heuristics only makes sense when the robot is in motion.

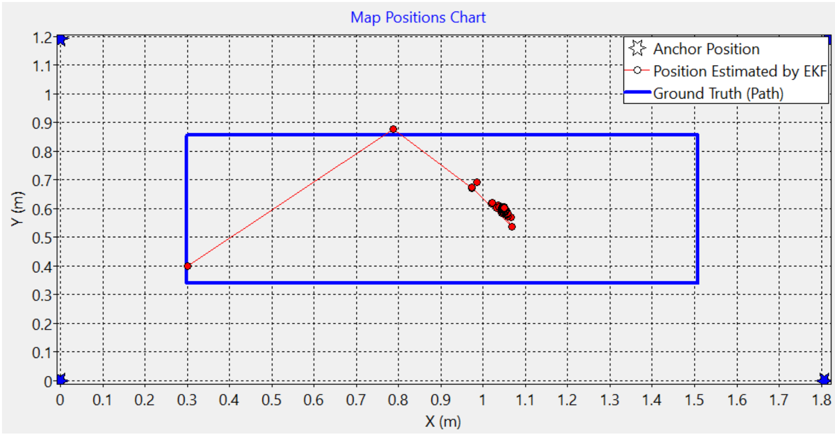


Figure 6.8: EKF Estimate Result in Test 3 without Outliers Detection

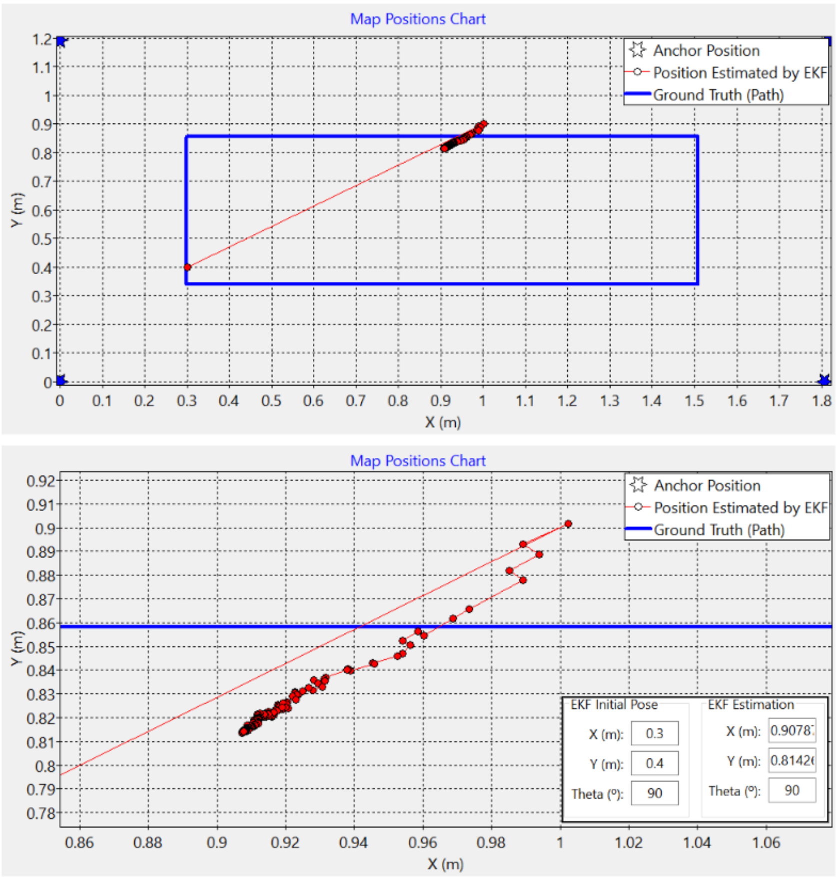


Figure 6.9: EKF Estimate Result in Test 3 with Outliers Detection

EKF test with robot stopped and pozyx system on

Figure 6.10 illustrates the result of EKF execution when it is only considered the odometry readings, after 1.5 laps. As expected, the result of this test presents errors, because as it is possible to check the odometry location is clearly affected by some wheel slippage in the curves. Besides, it is necessary to clarify that in this test, it was necessary to provide the EKF with the actual initial pose, since the odometry only provides a relative location. Finally, it must also be mentioned that the initial position of the robot is offset from the line by about $1cm$ because in reality the antenna is displaced $1cm$ in relation to the centre of the robot.

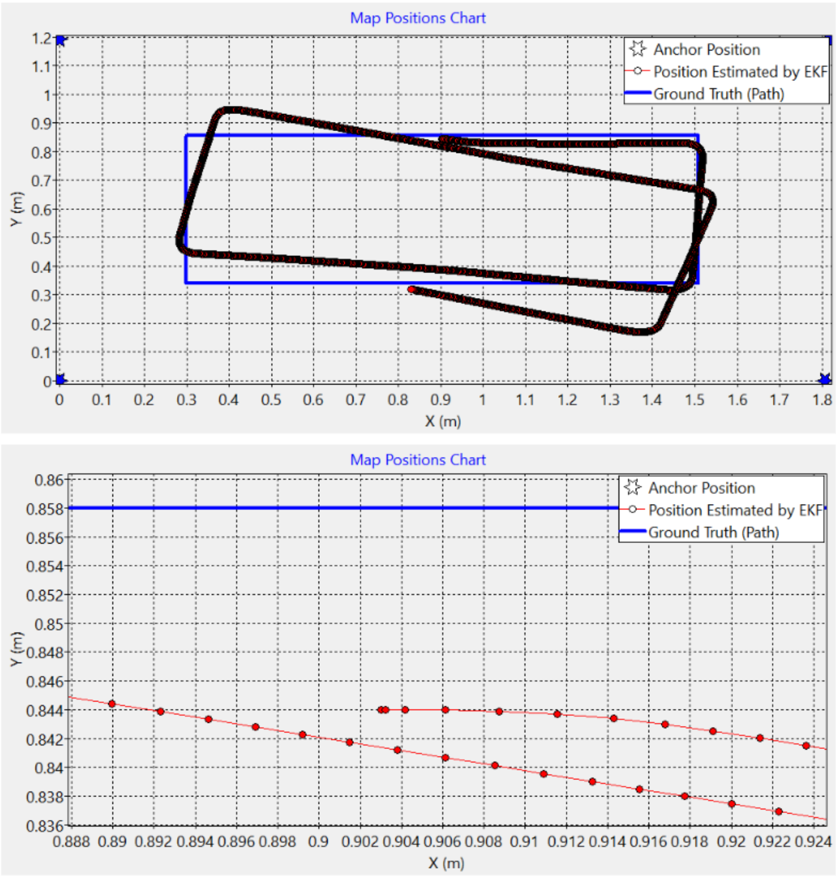


Figure 6.10: EKF Estimate Result in Test 4

EKF test with the robot in movement and pozyx system on

Figure 6.11 presents the different results obtained in this test, where the test result without the outliers detection and heuristic (first image) can be verified. The test result with the outliers detection but without the heuristic (middle image). And finally, the result of the test both with the outliers detection and with the heuristic (last image). At first, the results seem disappointing. However, it is possible to draw useful conclusions from this test. First, it is possible to realise that the noise characterisation in the path is not well defined. Hence, it is necessary to adjust the R as a function of the distance to the robot and its' possible rotation. Then, it is also necessary to realise that the test conditions are not the best as the anchors are very close to the robot and are positioned very close to several objects that may be interfering with the measurement.

Moreover, the middle image is an excellent example of why heuristics are necessary because, in this situation, the outlier detection filter began to remove all measurements, thus not allowing the convergence to the correct pose. The same is no longer the case in the last image that in several situations the filter began to diverge, but the heuristic acted, allowing the filter to converge to the correct pose. It can also be verified that, although it took too long, in the end, the filter ended up converging to the correct pose, ending with a position error of $4.6cm$ and an orientation error of 5.1^{o}.

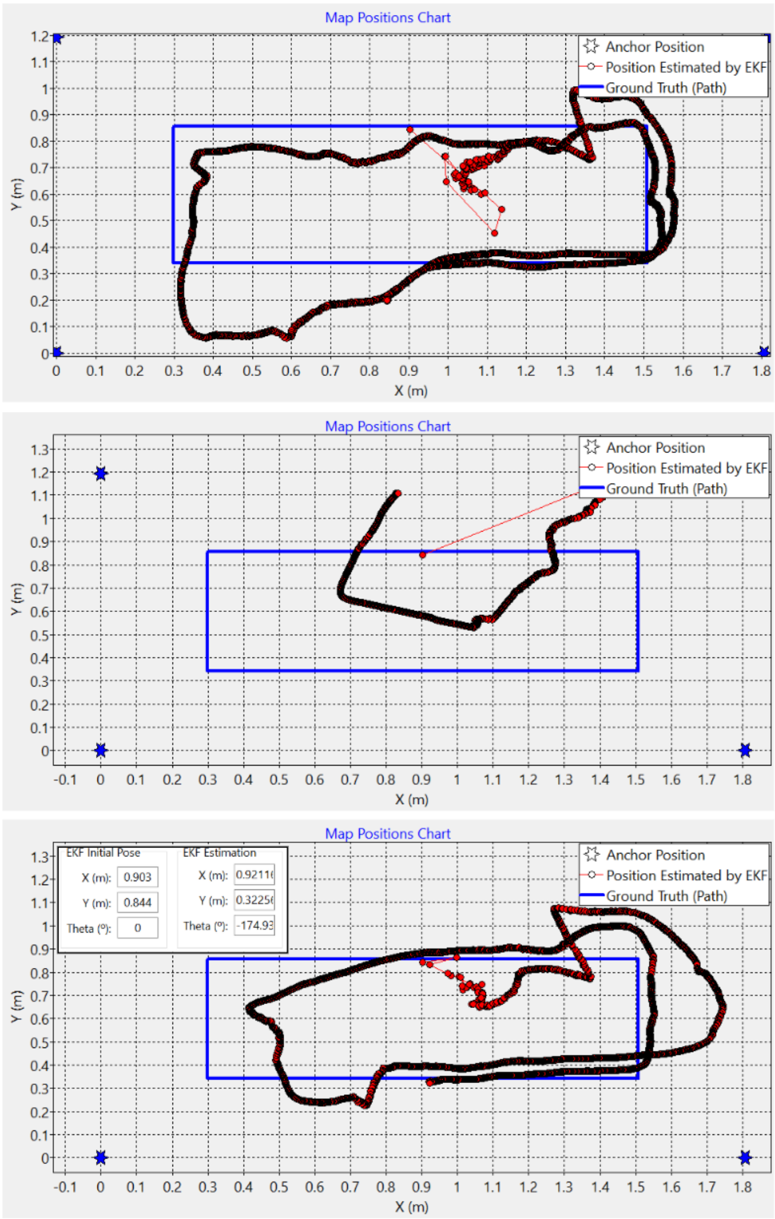


Figure 6.11: EKF Estimate Result in Test 5

EKF test with the robot in movement, pozyx system on and considering the navigation Path

Figure 6.12 illustrates the results for this final test, where the first image corresponds to the test result without outliers detection and heuristics. The middle image represents the test result without outliers detection but with the heuristic related to the path. The final image shows the test result considering both the outliers detection and both heuristics. Apparently, it seems that the initial result without considering any heuristics and without considering the outliers detection, is better however when considering the heuristics, the EKF after stabilising their estimates, produces results with better accuracy. Thus, when the robot stop at the end of 1.5 laps, a position error of 2.1*cm* and an orientation error of 0^{o} were observed.

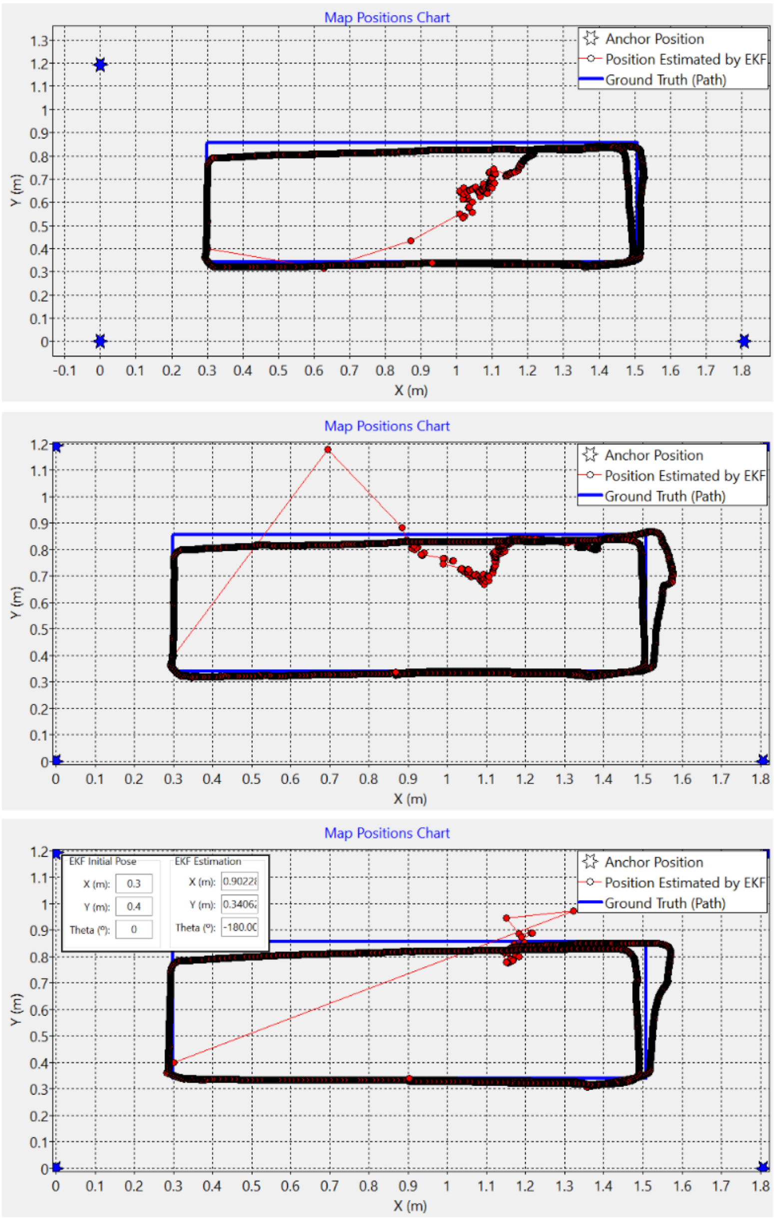


Figure 6.12: EKF Estimate Result in Test 6

Additionally, this test lacks any further observations. Figure 6.13 illustrates three images to exemplify three different situations. The first image presented at the top demonstrates the importance of heuristic about the path. In fact, the robot departed from the top of the path, as in all tests. However, it was enough for the filter to generate an estimate relatively close to a line to the position of the robot be immediately associated with that line.

The second image represents an approximation of the last image in Figure 6.12 and serves to prove what was already mentioned above. Moreover, it is also possible to confirm that the filter estimates are offset from the line for the reason explained above.

The last image serves to prove that the filter does not always have bad starts and that sometimes it is possible to have a good result right on the first corner. In this case, the starting point of the robot was not the same. However, it all depends on the uncertainty of the filter in its estimates to take more or less time to converge to the right pose.

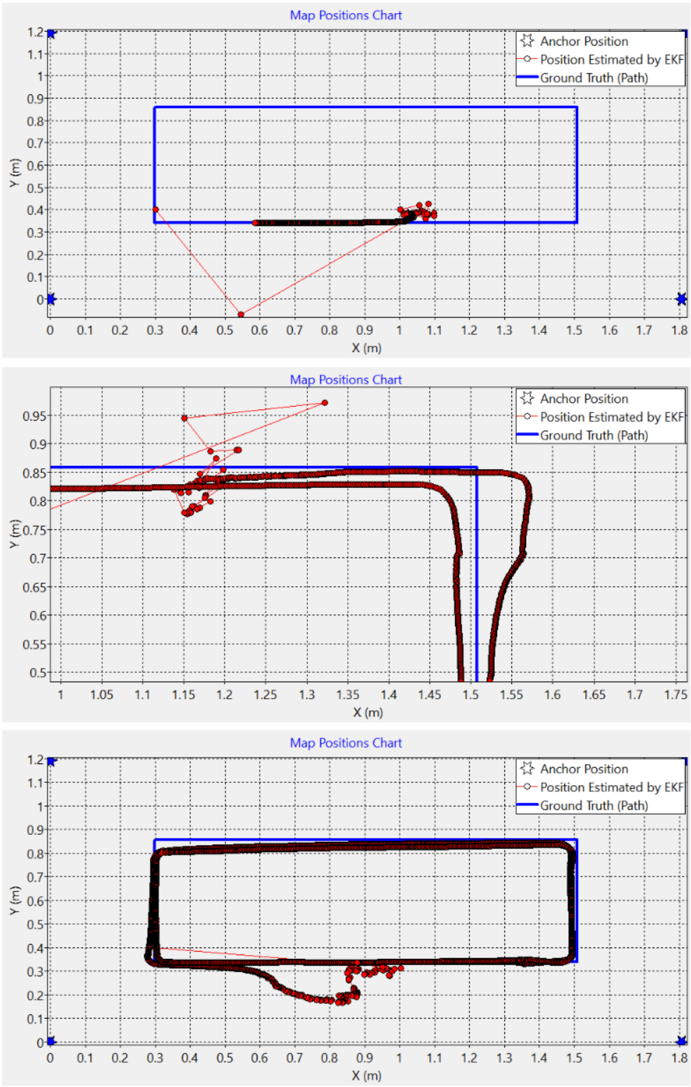


Figure 6.13: Some observations regarding Test 6

Chapter 7

Conclusions and Future Work

During this thesis, the main objective was to develop a real-time location system, using UWB-TOF technology, capable of estimating the pose of a mobile robot with high accuracy ($< 10cm$). Therefore, a beacon-based location system has been implemented using an EKF.

First, a performance study was conducted on the Pozyx system in order to understand the impact of both the different UWB configurations available and the surrounding environment and test conditions in a measurement. Consequently, it was possible to realise that this technology is highly affected both by the environment in which it is inserted and the configuration of the test space. Moreover, through several performance tests, it was possible to realise that in general, the different UWB configurations available tend to decrease the maximum measurement range. Unlike the antenna gain that in addition to increasing the maximum measurement range obtained outstanding results. Finally, it was also possible to observe that the Pozyx antenna does not radiate omnidirectionally in all planes, leading to different variations in the measurement performance with different orientations between the tag and the anchor.

Then the proposed and implemented EKF proved to be an exciting approach and with extremely positive outcomes. Thus, the EKF proved to be a filter that requires careful tuning, to balance between the convergence speed and the smoothness of the resultant trajectory estimate. Besides, the heuristics implemented in the proposed EKF proved to be a decent approach to free the filter and allow it to converge to the correct pose. Finally, it was noticed that the sensory fusion of the readings of the odometry with the measurements of the distance by Pozyx and with the navigation path is a great approach and results in very promissory results.

Future work regarding the UWB-TOF location system must include more intensively studies on the impact of the different UWB configurations as well as the antenna orientation and environment limitations (LOS vs NLOS). This better error and noise characterisation would enable to expand the location to broader and more challenging environments. Moreover, it would be essential to conduct further studies concerning the measurement performance with the amplified antennas gain as well as performing further tests to verify that the aluminium holders about PLA holders have an impact on measurement performance.

Furthermore, regarding the EKF location system, some considerations could be part of a possible future implementation:

- The fusion of IMU information into the current EKF. IMU can serve as another reference for better accuracy about the robot orientation.
- Test different outlier detection and removal techniques because the MD technique sometimes fails in outliers detection.
- Implement a variable measurement noise (R) according to the measured distance and tag orientation concerning the anchor.
- Compare the EKF implemented with another high-precision location system to identify the filter's accuracy along the path and not only at the end.

Overall, this work with Pozyx system showed that it is a proper and effective tool to improve the robot location in a challenging indoor environment given its good cost/accuracy trade-off.

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