Indoor Location Systems using Ultra Wide-band

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Abstract

Ultra-Wide Band (UWB) technology has emerged as a promising solution for indoor location systems due to its high precision and robustness in challenging environments. This study delves into the specific challenges associated with non-line-of-sight (NLoS) conditions and varying infrastructure within indoor settings. UWB performs well in challenging environments with its robustness to multipath interference, providing consistent and accurate positioning, making UWB a preferable alternative to other technologies. We investigate the performance and reliability of UWB technology under controlled and public environments, focusing on how obstacles, walls, affect its accuracy. Through a series of experiments in diverse indoor scenarios, we aim to highlight the strengths and limitations of UWB in overcoming NLoS challenges and adapting to different infrastructure conditions. This research aims to enhance the deployment of UWB-based indoor location systems, ensuring more reliable and accurate positioning for various real-world applications.

Resumo

A tecnologia Ultra-Wide Band (UWB) emergiu como uma solução promissora para sistemas de localização indoor devido à sua alta precisão e robustez em ambientes desafiadores. Este estudo investiga os desafios específicos associados a condições de não linha de visão (NLoS) e a diferentes infraestruturas em ambientes internos. A UWB apresenta um bom desempenho em ambientes desafiantes devido à sua robustez contra interferências de múltiplos caminhos, fornecendo uma localização consistente e precisa, o que faz da UWB uma alternativa preferível a outras tecnologias. Investigamos o desempenho e a fiabilidade da tecnologia UWB em ambientes controlados e públicos, focando-nos em como obstáculos, paredes e interferências afetam a propagação do sinal e a precisão. Através de uma série de experiências em diversos cenários internos, pretendemos destacar os pontos fortes e as limitações do UWB na superação de desafios NLoS e na adaptação a diferentes condições de infraestrutura. Esta pesquisa visa melhorar a implementação de sistemas de localização indoor baseados em UWB, garantindo uma localização mais fiável e precisa para várias aplicações do mundo real.

Acknowledgments

I would like to thank my family and friends for all the support throughout the years, as well as my dissertation advisors Professor Eduardo Marques and Professor Sérgio Crisóstomo for the guidance, involvement and dedication provided along this challenging process.

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Acronyms

AoA Angle of Arrival

BLE Bluetooth Low Energy

DCC Departamento de Ciência de Computadores

DR Dead Reckoning

ECC Electronic Communications Committee

ERDF European Regional Development Fund

FCUP Faculdade de Ciências da Universidade do Porto

GNSS Global Navigation Satellite Systems

IMU Inertial Measurement Unit

IoT Internet of Things

LoS Line of Sight

NLoS Non-Line of Sight

QoS Quality of Service

RSS Received Signal Strength

RSSI Received Signal Strength Indication

RTLS Real-Time Location System

RTT Round Trip Time

TDoA Time Difference of Arrival

ToA Time of Arrival

ToF Time of Flight

TWR Two-Way Ranging

UWB Ultra-Wide Band

VLC Visual Light Communication

WLAN Wireless Local Area Network

Chapter 1

Introduction

1.1 Motivation

Indoor location systems face challenges similar to GNSS, such as signal interference and multipath propagation in WiFi or UWB and the accumulation of errors in position estimates that rely solely on inertial sensor measurements, which can lead to poor accuracy.

The ability to accurately locate people and objects has become increasingly important in recent years, as it makes daily lives more convenient in many ways such as allowing the user to view their location in real time, discovering the fastest path to reach a certain point of interest , tracking of packages inside warehouses or art pieces in an art museum, and many more cases, leading to the development of numerous location-based services.

Outdoors, where there is a clear view of the sky, Global Navigation Satellite Systems (GNSS) provide accurate location estimates, however, in indoor environments, this signal reception is severely compromised, resulting in poor accuracy of position estimates. To address this, an indoor location system infrastructure is required.

Various technologies can be employed, sometimes simultaneously, to improve indoor location accuracy. These include receive signal strength (RSS) from WiFi access points (APs) or Bluetooth beacons, range estimates from WiFi-RTT compliant APs or Ultra-Wide Band (UWB) beacons, and inertial sensors found in devices like smartphones.

With this in mind , we aimed to study and observe specifically the UWB technology and evaluate its accuracy and how it behaves in different type of settings.

1.2 Contributions

To achieve the previously stated objectives, we began by conducting experiments in a laboratory setting using the MDEK1001 kit, which includes the DWM1001 UWB module, to generate distance estimates between two modules. After verifying the accuracy of these distance estimates, we proceeded to test the position estimates provided by the Decawave algorithm. Additionally, we developed a Least Squares (LS) based algorithm and compared its accuracy with the Decawave algorithm. We extended these experiments to a larger scale in the hallways of our department. By analyzing and comparing the results from both algorithms, we refined our LS algorithm and gained deeper insights into how different environments impact UWB-based position estimation.

To further summarize, our contributions were:

- The development of a software architecture that allows indoor location using UWB.
- Experimental data gathering in a laboratory with clear LoS and in a public area setting with varying LoS / NLoS conditions.
- Analysis of the accuracy levels and the value dispersion of the positioning estimates recorded by the DWM1001 during our experiments.
- Comparison of the Decawave algorithm and a developed Least Squares based algorithm.
- Study of the impact of NLoS caused by infrastructures in UWB communications.
- Findings on the constraints of the DWM1001.

1.3 Structure

This thesis is divided as followed:

Chapter 2 - **Background**: This chapter aims to explain the related concepts and technologies used in indoor location, as well as the software and hardware employed in this thesis.

Chapter 3 - **State of Art**: This chapter discusses several articles relevant to the proposed work. These articles were selected due to their similarities to this study in the context of indoor location.

Chapter 4 - **Development**: This chapter shows the architecture and planning behind the experiments and talks about the contributions of this thesis.

Chapter 5 - **Experiments and Results**: This chapter presents two experiments conducted in the context of indoor location services, using UWB technology in both controlled and public environments.

Chapter 6 - **Conclusion** This chapter concludes the dissertation.

Chapter 2

Background

In this chapter we talk about the existing technologies and solutions for indoor location systems, looking into the diverse ways to estimate a position and tracking an object indoors. A brief summary of the contents of this chapter:

- **Section 2.1** - introduces the key concepts associated with estimating a position indoors.
- **Section 2.2** - explains the various available methods for distance estimation.
- **Section 2.3** - discusses the most important algorithms used in this dissertation.
- **Section 2.4** - presents the available technologies to estimate a position.
- **Section 2.5** - discusses the most common challenges when working with this type of technologies.

2.1 Key concepts

When we talk about indoor location there are a myriad of different factors that need to be considered. Here we explain the most important ones.

Indoor location systems are technologies designed to locate people or objects inside buildings where GPS signals are weak or unavailable. These systems are increasingly important for a variety of applications, including navigation, asset tracking, security, and customer engagement in sectors such as retail, healthcare, manufacturing, and logistics. While GPS is the most known and common technology for tracking, it falls short on its capabilities to estimate a position indoors due to the signal being unable to penetrate constructions well enough. For many purposes it has become paramount to track certain objects indoors, and this has led to the development of different, capable applications and algorithms along the years. The key technologies used are Wi-Fi-RTT, Ultra-Wide Band, WLAN, Bluetooth, inertial sensors, RFID-based solutions, light-based communication and computer vision. Each technology comes with its unique strengths and limitations, and often, a combination of multiple technologies provides the best solution for specific use cases.

While indoor location systems offer significant benefits, they also face a range of challenges that can affect their performance:

- **Accuracy:** Crucial metric that shows how far the estimate measurement is from the measured ground truth. Signals can be disrupted by walls, floors, furniture, and other obstacles, leading to inaccurate location data. Interference from other electronic devices can also degrade signal quality. They may also reflect off surfaces such as walls, ceilings, and floors, causing multiple signals to reach the receiver at different times. This can confuse the system and reduce accuracy.
- **Deployment and Maintenance**: Setting up an indoor location system often requires significant infrastructure, this can be costly and time-consuming. Accurate location systems often require extensive calibration and mapping of the indoor environment, which can be labor-intensive and needs to be updated regularly as the environment changes.
- **Scalability:** More infrastructure is needed to maintain accuracy over larger spaces. In environments with a high density of people or objects, such as shopping malls or warehouses, managing and maintaining accurate tracking can become complex.
- **Privacy and Security:** Collecting and processing location data raises privacy concerns. Users must be informed about what data is being collected and how it is used, and systems must comply with privacy regulations such as GDPR. Location systems can be vulnerable to hacking and unauthorized access. Ensuring the security of the system to protect sensitive location data is critical. Ensuring that users understand and are comfortable with the technology is crucial for its success. This includes addressing any privacy concerns they may have.
- **Accessibility:** Systems must be designed to be user-friendly and require minimal training for effective use.
- **Compatibility:** Integrating indoor location systems with existing IT infrastructure, enterprise resource planning systems, or other software can be challenging. Different systems and technologies may use different data formats and protocols, making integration and data standardization a complex task.

2.2 Distance estimation

This section describes different methods used to estimate the distance between reference points and the target.

2.2.1 Time of Arrival (ToA)

It is the simplest time-based distance estimation method. It relies on one-way communication, where units are either dedicated transmitters or receivers, thereby reducing their individual complexity. In a ranging operation, the transmitter sends a timestamp to the receiver. The receiver then compares this timestamp to the time of arrival. Since the speed of light is a known constant, the distance between the transmitter and receiver can be calculated. However, the accuracy of ToA is highly dependent on the accuracy of the clocks in the transmitters and receivers. These clocks must be synchronized and exhibit very low drift. A clock error of just 1 ns can result in an error of approximately 30 centimeters, making ToA systems challenging to implement in practice [2].

2.2.2 Time Difference of Arrival (TDoA)

It is similar to Time of Arrival (ToA), but instead of calculating the time for each signal to travel from the transmitter to the receiver, it measures the difference in arrival times from multiple known reference points. This method calculates the relative distances to each reference point.

TDoA requires strict synchronization among the reference points to ensure the measuring signal is sent simultaneously. Unlike ToA, the receiver does not need to be synchronized because it measures the relative difference in arrival times rather than the absolute time. This simplifies the system since the reference points are usually fixed and can be connected via wires, eliminating the need for complex wireless clock synchronization algorithms. However, if the master point responsible for synchronization fails, the entire system's reliability quickly degrades [2].

2.2.3 Time of Flight (ToF)

This method extends TDoA by eliminating the need for synchronization between reference points in the system.

It works by sending a measuring signal from a reference point to the target, which then responds after a known delay as illustrated in Figure 2.1. This allows the reference point to calculate the total time of flight and thus determine the distance using the formula:

$$\text{Distance} = \frac{C \cdot (t_{\text{Rx}} - t_{\text{Tx}}) - t_{\text{reply}}}{2}$$

Where C is the speed of light (approximately 3×10^8 m/s or 299,792,458 m/s), t_{Tx} is the transmission time of the initial message, and t_{Rx} is the reception time of the response. The difference between these two times represents the total round-trip time. This method allows for distance calculation without being affected by clock offsets between the involved nodes. The clock error is reduced to the drift that occurs between t_{Tx} and t_{Rx} [2].

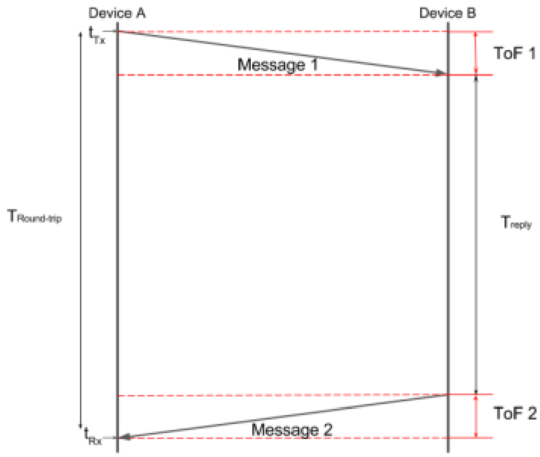


Figure 2.1: How ToF works illustrated.[2]

2.2.4 Two-way Ranging (TWR)

This is another technique used in wireless communication systems to measure the distance between two devices, such as a transmitter (anchor) and a receiver (tag). The largest error source in these messages is the random drift of the clock frequency between sending the first and receiving the second message. This drift causes errors in the time difference used to calculate the distance, impacting the overall accuracy. To reduce this error, we could use higher precision crystal oscillators as a clock reference, but this significantly increases system cost [2].

To mitigate some of the issues, especially clock drift, a variant called Double-Sided Two Way Ranging (DS-TWR) is used. In DS-TWR, an additional message is exchanged, allowing for the correction of clock drift errors and improving the accuracy of the distance measurement. This involves sending three messages instead of two: an initial poll message, a response message, and a final message to acknowledge the response. The average of the times measured helps in reducing the impact of clock drift.

Assuming the clock drift error is uniformly distributed, this will eliminate most of the error, thus increasing accuracy significantly at the cost of additional messages per ranging exchange. The following equation is used to calculate ToF by this method:

$$T_{\text{prop}} = \frac{T_{\text{round1}} \cdot T_{\text{round2}} - T_{\text{reply1}} \cdot T_{\text{reply2}}}{T_{\text{round1}} \cdot T_{\text{round2}} + T_{\text{reply1}} \cdot T_{\text{reply2}}} \tag{2.1}$$

where T_{prop} is ToF and the others are the times represented in TWR between the Poll-Response and Response-Final messages. With this theres also a power consumption advantage since this message structure allows the tag to initiate the ranging exchange, enabling it to stay in a low-power mode until it decides to send a poll message. This saves power and simplifies adding more tags to the system, making it optimal for indoor location systems .

2.2.5 Angle of Arrival (AoA)

This method uses the angles of two incoming signals to the receiver to determine its position relative to two fixed reference points. It allows for position estimation using one less fixed point than time-based methods, thereby significantly reducing the required system hardware and minimizing error sources. However, accurately determining the angle of an incoming signal is significantly more complex than time stamping. Additionally, reflected signals greatly impact accuracy in NLoS situations, making this method less commonly used than time-based counterparts [2].

2.2.6 Received Signal Strength (RSS)

This method uses reference points or target objects as transmitters, with the other side acting as receivers. The receivers measure the signal strength in decibels received from the transmitters. Many transceivers using various RF techniques for communication can generate a Received Signal Strength Indication (RSSI). This normalized value uses a reference value at a distance of one meter from the transmitter as a baseline, ensuring that the RSS can be easily read and used by a system.

RSS is straightforward because it relies on simple signal strength measurements. However, a major issue arises when the reference points and target objects are in a Non-Line of Sight (NLoS) configuration, as the signal can be absorbed by various materials. RSS is typically used in low-cost applications with lower accuracy demands, as the results are often inconsistent, lacking precision or range, and are difficult to handle under mixed conditions. To achieve better estimations, additional algorithms or hardware are required [2].

2.3 Location Algorithms

2.3.1 Multi-Lateration

One of the most known methods of acquiring an estimate position is by using multi-lateration. Tri-lateration, represented in Figure 2.2, is a method that uses geometry to estimate the target position of targets. Using this technique we can estimate a 2D position, but for this to work at least three anchors are necessary. In case of estimating a 3D position we would require an additional anchor.

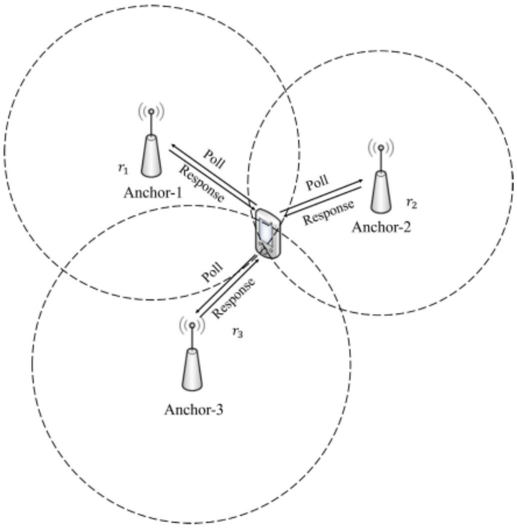


Figure 2.2: Trilateration example in TWR UWB communications [10].

2.3.2 Least Squares

This is an algorithm that aims to estimate and minimize error in positioning using multi-lateration. Providing ranges and coordinates between an anchor and a tag for example, we can estimate a position by using the following equation:

$$\begin{cases} (X_1 - x)^2 + (Y_1 - y)^2 + (Z_1 - z)^2 = d_1^2 \\ (X_2 - x)^2 + (Y_2 - y)^2 + (Z_2 - z)^2 = d_2^2 \\ \vdots \\ (X_n - x)^2 + (Y_n - y)^2 + (Z_n - z)^2 = d_n^2 \end{cases}$$

2.4 Technologies

2.4.1 GNSS

The term Global Navigation Satellite System (GNSS) refers to any satellite constellation that provides positioning, navigation, and timing (PNT) services on a global or regional scale. GNSS can achieve high-precision positioning in outdoor environments, enabling location-based services such as user positioning and navigation. However, GNSS signals often fail to penetrate indoor environments effectively, and the signals that do arrive are typically too weak to achieve high-precision positioning.

With the widespread use of smartphones, positioning technologies have become accessible to a large user base. GNSS is the most well-known and widely used technology for outdoor localization, offering sufficient position accuracy in open sky conditions for most mass-market applications. However, GNSS accuracy can be significantly compromised inside buildings or in urban canyons. In such cases, GNSS signals may be affected by multipath effects, received at low power, or even blocked [3]

2.4.2 Bluetooth

Bluetooth can be used to estimate a target's location by measuring the Received Signal Strength Indicator (RSSI). This method allows for phone tracking without requiring additional hardware on the tracked device, although a network of reference points must be installed. The introduction of Bluetooth Low Energy (BLE) has facilitated the development of compact, energy-efficient hardware [3].

2.4.3 Wi-Fi RTT

WiFi Round Trip Time (WiFi-RTT) is a two-way ranging method that offers a significant advantage by not requiring clock synchronization. It enables computing devices to determine their indoor location and measure the distance to nearby WiFi access points with a precision of 1 meter using round-trip delay. In other words, the technology operates based on the time delays between signal reception and transmission. Essentially, the WiFi-RTT protocol allows for estimating the distance between two WiFi devices [3].

2.4.4 UWB

Ultra-Wide Band (UWB) technology is notable for its precision and robustness. It employs a wide range of frequency bands to transmit high-energy pulses while minimizing interference with other RF equipment operating at the same frequencies. UWB-based systems typically use time-based methods to determine target positions.

UWB offers high accuracy due to its precise measurement of travel time and supports Non-Line of Sight (NLoS) conditions. The wide frequency band resists interference from reflected signals, and the high energy content of the signal can penetrate many softer materials. Given the common occurrence of obstructions in typical indoor environments, UWB is an excellent choice for general-purpose systems rather than specialized systems where Line of Sight (LoS) can be guaranteed. Its long-range, high-energy signal implies excellent scalability and reduces the need for complex processing of the results. This precision is primarily due to the dispersion of signal energy over a wide frequency range, allowing for very accurate time-stamping of incoming messages.

However, the main disadvantage of UWB is that it is not as mature as other technologies, leading to higher costs for specific hardware and limited support availability. The Federal Communications Commission (FCC) has allocated 7.5 GHz of spectrum for unlicensed use of

UWB devices in the 3.1 to 10.6 GHz frequency band. UWB is emerging as a solution for the IEEE 802.15.3a (TG3a) standard, which aims to provide a specification for low-complexity, low-cost, low-power, and high-data-rate wireless connectivity among devices within or entering a personal operating space. The data rate must exceed 110 Mb/s to meet consumer multimedia industry needs for wireless personal-area networks (WPAN) communications. The standard also addresses the quality of service (QoS) capabilities required to support multimedia data types. Since the signal period of UWB is less than a nanosecond, these short impulses allow multiple transmitters to operate in parallel while mitigating the multipath effect [3]

2.4.5 Visual Light Communication

Visual Light Communication (VLC) employs various light emitters and detectors to determine the target's position within an area. Indoor positioning systems based on VLC can be categorized into two types.

The first type uses a grid of basic photo diodes to receive light from the tracking target. The position is computed based on which detectors receive the emitted light. This system consists of inexpensive hardware but does not allow the target to know its position without additional communication and does not support more complex setups with multiple targets.

The second type uses a camera as a detector on the target, paired with stationary emitters that each send a unique ID by blinking a binary sequence. The target can compute its position based on the angle to each individual emitter. This method is highly accurate and supports an almost unlimited number of targets. However, cameras are relatively expensive and require Line of Sight (LoS), making them unsuitable for dynamic environments [3].

2.4.6 Inertial Sensors

By acquiring information about the movement of the target in different ways we can assess its position using tools like the Accelerometer, which provides the acceleration of the moving object and the Gyroscope giving us the angular velocity, used to determine the direction of the movement. These units together are called an Inertial Measurement Unit (IMU), we could also reinforce this with a Magnetometer to improve gyroscope's measurements and a Barometer to get altitude in a 3D space, by measuring pressure.

2.5 Common Challenges

2.5.1 Spectral interference

Any wireless system that uses electromagnetic waves for information transmission must follow specific regulations regarding frequency usage to prevent devices from interfering with each other. In Europe, these frequency bands are regulated by the Electronic Communications Committee (ECC), which specifies which bands can be used for various applications to avoid critical interference between devices operating within these bands. As a result, unlicensed bands tend to be crowded, leading to performance degradations from spectral interference. This issue is particularly prevalent in indoor environments, where the density of such systems is generally higher than outdoors.

This congestion poses a significant challenge for location estimation systems, which are sensitive to deviations from ideal conditions and require accurate results. Therefore, it is crucial to ensure that these systems do not interfere with other devices in the area [2].

2.5.2 Line of Sight

Line of Sight (LoS) is the most important factor that highly impacts ranging in these systems. While GPS almost always has a clear LoS outside, the same cannot be said about tracking inside buildings using Indoor Location technologies.

- **LoS** refers to a direct, unobstructed path between the transmitter and the receiver, it is crucial for achieving the highest levels of accuracy and performance.
- **Non-Line of Sight (NLoS)** refers to the contrary of LoS, which would be an obstructed path between the transmitter and the receiver.

In a LoS scenario, signal intensity fluctuations and electromagnetic wave propagation periods are well-characterized, allowing location estimation methods to perform effectively, provided there is no spectrum interference. In contrast, Non-Line of Sight scenarios are much more challenging due to additional unknowns that depend heavily on the specific environment and technology used.

Electromagnetic waves can penetrate various objects depending on the wave frequency and the material of the obstruction, but they experience significant attenuation and longer propagation times compared to traveling through air. In some cases, the direct signal path is completely blocked, resulting in the target being detected only through reflections or not at all [2].

This can be easily comprehended by observing the NLoS scenario portrayed in Figure 2.3.

2.5.3 Multipath fading

Another issue in complex indoor environments is multipath fading, which occurs when signal reflections from various surfaces interfere with the original signal. These reflections, often differing in phase, can cause the original signal to lose strength or become distorted. Additionally, distinguishing the original signal from its reflected components can be challenging, leading to inaccuracies in time of flight or signal strength measurements since the reflected paths are longer

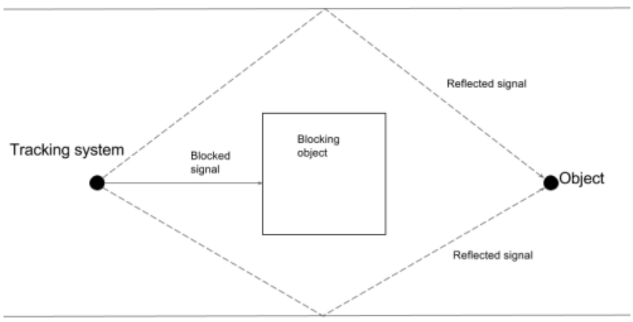


Figure 2.3: Communication attempt in a NLoS scenario.[2]

than the direct path. Such effects are difficult to predict in complex indoor settings and can cause inaccuracies in all types of position estimation methods. Advanced algorithms can mitigate some of the effects of multipath fading, which can be beneficial depending on the technology used and the complexity of the environment [2].

Chapter 3

State of the art

In this chapter a review of the literature was done and we have chosen to include the most relevant ones for our work.

3.1 AugBot

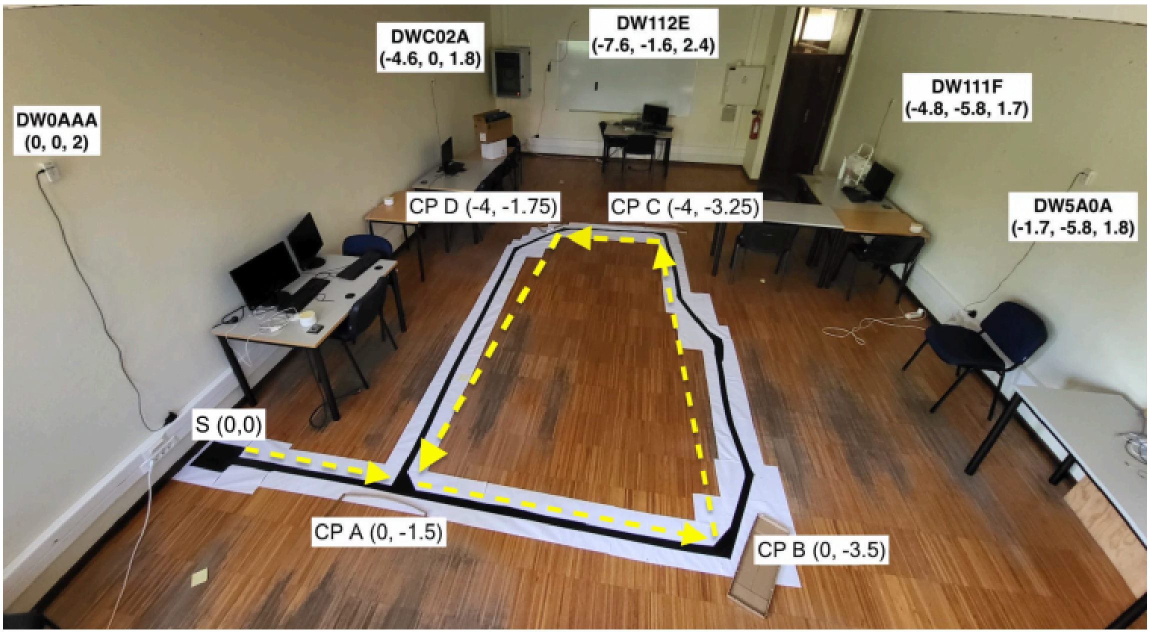


Figure 3.1: The Augbot route for the conducted experiments [3].

Carvalho's thesis [3] focuses on the development of AugBot, a framework designed to test and develop indoor location algorithms. AugBot is implemented using the Robot Operating System (ROS), which allows for modular separation of concerns such as sensor readings, communication, and location algorithms. This is the previous work that this dissertation is based on. It supports both physical and simulated environments, utilizing the AlphaBot2 robot, UWB beacons, and the Gazebo simulation engine. MDEK1001 devices were used as the UWB devices to enable estimating the robot position along its path. The robot was placed at a starting point S, as seen in Figure 3.1, following the yellow marked path, passing along setup sensor control points with the help of micro:bit, while data was being recorded. The experiments use various algorithms, such as LS and Dead Reckoning as well as some variants of each. The results from both environments, physical and virtual, showed that the developed algorithms performed adequately.

3.2 Silvia et al.

Silvia et al. [9] provide a comprehensive analysis and testing of an UWB location system. The study aims to address the inefficiencies present in logistics processes by leveraging UWB technology to enhance the accuracy and reliability of indoor positioning systems.

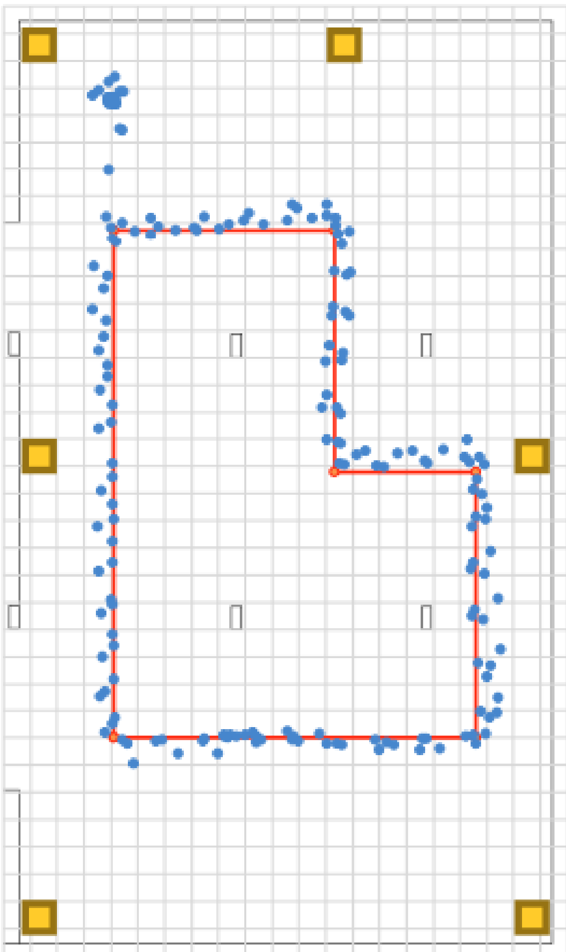


Figure 3.2: Tracking of one target moving at an average speed of 2.0 m/s [9]

The main objective of the experiment was to evaluate the effectiveness and accuracy of the

UWB in a logistics environment. The system was configured to track the positions of various objects within an indoor environment, as seen in Figure 3.2. The test was conducted in both a controlled environment, which allowed for a systematic analysis of the system's performance under ideal conditions and an industrial setting, which provided insights into the system's practical applicability and robustness in real-world logistics operations.

Accuracy was measured by comparing the actual positions of the objects with the positions reported by the UWB system. Precision was assessed based on the consistency of the reported positions over multiple measurements.

The results from the controlled environment indicated that the UWB system could achieve high accuracy, with positioning errors typically within a few centimeters. In the industrial setting, while the accuracy was slightly reduced due to environmental factors such as multipath effects and signal attenuation, the system still performed well enough to be considered viable for practical use. This approach is very similar to the one discussed in our work.

The experiment demonstrated that this technology could be effectively used for various logistics applications, such as tracking the movement of forklifts, estimating the movement of pallets and cartons, and measuring the distances traveled by operators. These applications can significantly improve the efficiency of warehouse operations by providing real-time location data and reducing the time spent on locating items.

One of the areas identified for improvement is the scalability of the UWB. As the size of the tracking area increases, the number of anchors required also increases, which can lead to higher costs and complexity. Future research could focus on developing algorithms to mitigate the effects of multipath propagation and signal attenuation, particularly in complex industrial environments.

3.3 Zhuang et al.

Zhuang et al. [12] explored the use of an UWB indoor positioning system to track the movement and behavior of sows in a barn environment. The study was conducted in a barn with group-housed sows at the Flanders Research Institute for Agriculture, Fisheries and Food. The barn was equipped with seven UWB base stations (anchors) and multiple tracker tags. Using DWM1001, two types of tests were performed:

- In the stationary tests, sixteen test points were set up in each pen, with measurements taken at two heights (0.3 m and 1.0 m) to simulate lying and standing sows respectively.
- In the in-motion tests tags were moved along predefined paths within the pens to mimic the movement of walking sows.

For locating stationary tags the system achieved 0.37 m accuracy at 1 m height and 0.50 m accuracy at 0.3 m height. While tracking moving tags at 1 m height 0.38 m accuracy was achieved. Three filters were tested to further improve the positioning performance. The median filter had the highest improvement on locating stationary and moving tags. The bilateral filter had a balanced capability of uncovering complex moving trajectories. The double exponential moving average filter was more suited when real-time updates were required. The overall results showed that tracking group housed sows inside a pig barn was feasible using the UWB positioning system.

3.4 Jiménez et al.

Jimenez et al. [6] discussed the importance of accurate location systems for people, robots, and IoT devices, focusing on UWB technology due to its centimeter-level accuracy.

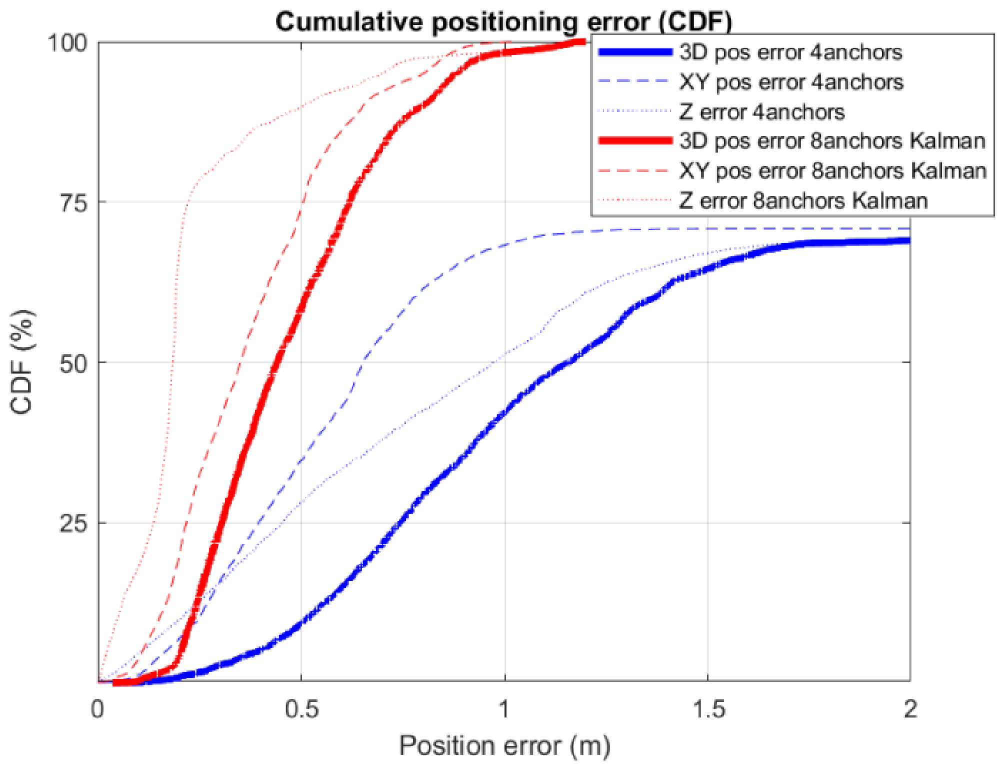


Figure 3.3: Cumulative distribution funcion of the apartment (NLOS conditions present) experiment position errors. 4 anchor ranges in red, and 8 anchor ranges in blue [6].

It addresses the challenge of signal degradation in indoor environments caused by obstacles, proposing robust estimation algorithms that use measurement redundancy to mitigate outliers. The study evaluates the same Decawave UWB system we use, which is easy to deploy but limited to four anchor measurements per tag, and proposes a solution to extend this to eight ranges using a double interleaved network. This is achieved by creating pairs of anchors and pairs of tags in different networks. After evaluating what kind of methods would be more effective to further improve the accuracy of the data, the chosen option was an adapted and robustified Extended Kalman Filter.

Experiments were conducted in two scenarios, a laboratory and an apartment and the results showed significant improvements in accuracy with the multi-range approach compared to the original four-range system. The most significant improvement was in the apartment scenario, where NLOS conditions were present making the error fairly higher in the default 4 range setup, as seen in Figure 3.3. An important contribution of the paper is that it demonstrates with two very different deployments how the same approach (same sensors, EKF parameters, and NLOS models) can be applied in totally different scenarios with the same rate of performance improvement.

The results in the 4 anchors setup and NLOS conditions are much in line with the ones we obtained in this work.

3.5 Volpi et al.

Volpi et al. [11] present extensive testing on the MDEK1001 development kits used in this thesis, and as the authors say, it is to be intended practical in nature, acting as a guideline for those practitioners who are interested in a solution of this kind and could benefit from the "lessons learned" or get inspired from the tests carried out. It focuses on key aspects as investigating the effect of different anchor arrangements and orientations on system performance, evaluating the performance of the RTLS when tracking multiple tags simultaneously and assessing the battery life of the tags to ensure sustainability for industrial applications. The authors also evaluate the system's accuracy in both stationary and moving conditions, determine the impact of tag-anchor antenna orientation on tracking accuracy and assess how quickly the system can accurately locate tags after being reset.

The study concludes there is:

- Optimal anchor placement and robust performance in various tag orientations.
- High accuracy in both static and dynamic conditions.
- Effective multi-tag tracking without significant accuracy loss.
- Sufficient battery life and efficient power consumption.
- Quick start-up times and strong performance in harsh industrial conditions.

However, the authors leave some feedback on what could be improved, such as the further optimization of anchor placements by continued experimentation with different anchor configurations, which could further enhance system accuracy, developing tags with even better power efficiency and environmental resilience possibly improving the system's practicality, implementing more sophisticated algorithms for error correction and data fusion reducing the impact of any residual orientation sensitivity and further enhance tracking precision, as well as combining the RTLS with other tracking technologies or industrial systems providing a more comprehensive solution for various industrial applications.

3.6 Musa et al.

Musa et al. [8] discuss a novel method to improve indoor location tracking accuracy by addressing the challenges posed by NLOS conditions. The authors propose a machine learning approach using a decision tree algorithm to detect NLOS conditions based on UWB channel quality indicators. The decision tree model was trained and tested using data collected from seven different indoor environments, which provided diverse NLOS and LOS scenarios.

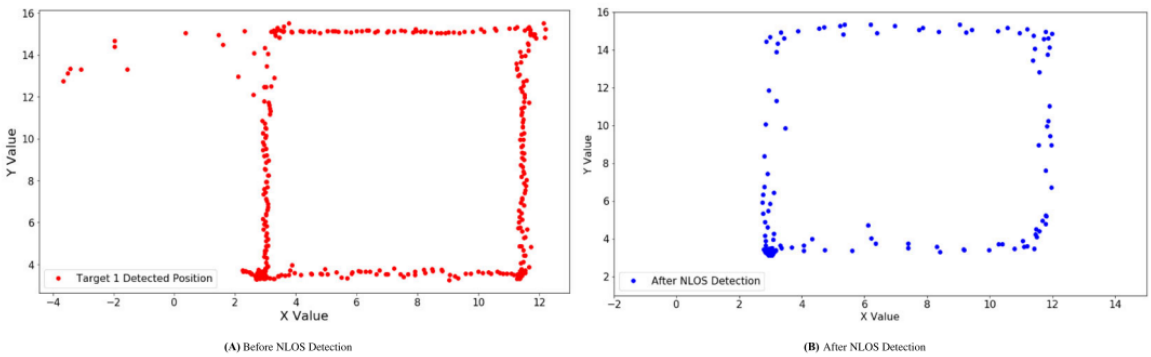


Figure 3.4: Indoor location tracking results: before vs after NLOS detection [8]

The decision tree model achieved a 90% accuracy in correctly identifying LOS and NLOS conditions across the seven different indoor environments. This high detection rate demonstrates the effectiveness of the decision tree in discerning between both scenarios.

By incorporating the NLOS detection model, the overall accuracy of the UWB-based indoor location tracking system was significantly improved. The model allowed for more accurate distance estimations by correcting for NLOS-induced errors, leading to better positioning results.

The decision tree-based NLOS detection method provides a substantial enhancement to UWB-based indoor location tracking systems. By accurately detecting NLOS conditions and compensating for the associated errors, this approach ensures more reliable and precise location tracking in complex indoor environments.

This research helps in identifying potential ways to reinforce UWB accuracy , by minimizing errors in NLOS scenarios.

3.7 Albaidhani and Alsudani

Albaidhani and Alsudani [1] present a algorithm uses UWB technology without relying on NLOS identification or mitigation techniques. The system randomly distributes anchor nodes (reference points) and clusters them into groups. Each group estimates the position of a mobile station using the Linearized Least Square (LLS) method.

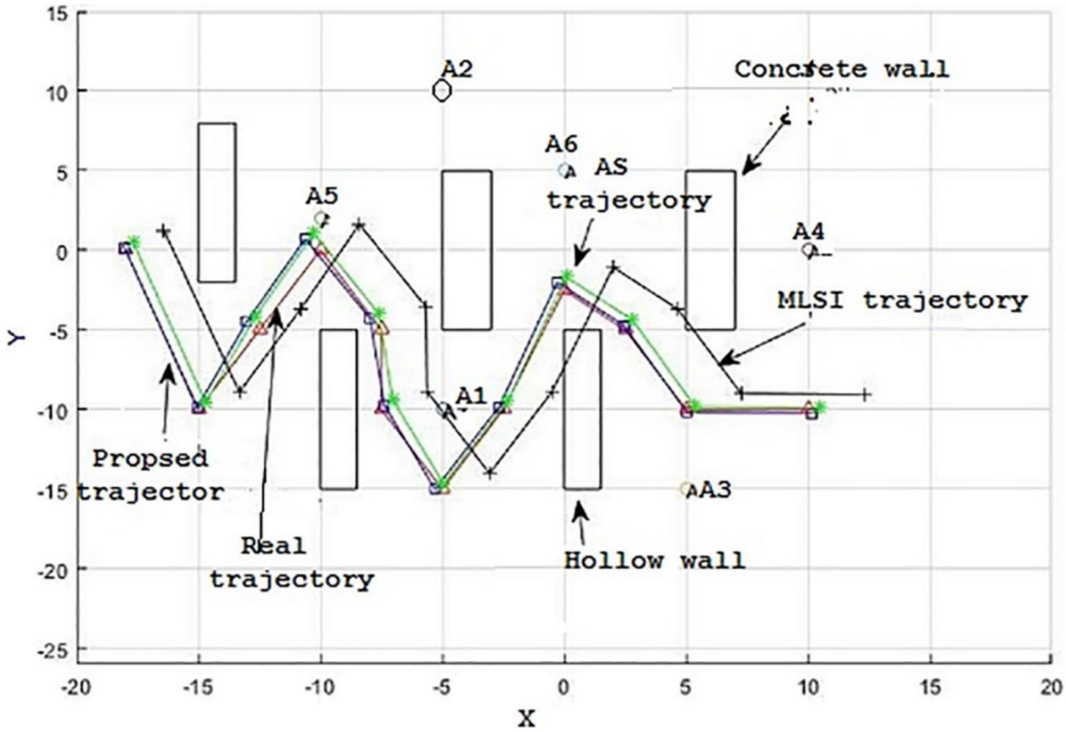


Figure 3.5: The real trajectory, the estimated (proposed) trajectory and the previous developed algorithm trajectory [1].

A weighted GDOP metric is used to evaluate the positioning accuracy of each group, and the one with the lowest positioning error is selected to refine the position estimate using a modified LLS method. This system achieves a mean square error of approximately 25 cm^2 in challenging environments, outperforming other systems in terms of time, complexity, and accuracy.

Anchor nodes are installed randomly in an indoor environment with specific dimensions and wall types (concrete and hollow). These nodes communicate with a mobile station using UWB technology.

The algorithm clusters the anchor nodes into different groups, each containing 4 to n-1 nodes (where n is the total number of nodes). Each group independently calculates the mobile station's position using the conventional LLS method. The system computes the GDOP for each group, which quantifies the precision of the position estimates and the group with the lowest result is selected for the final position estimation.

The results are noticeable in Figure 3.5, where the real and proposed path diverge only slightly.

Chapter 4

Development

In this chapter, we present the materials used in Section 4.1, the planned architectures and software in Section 4.2, the experimental planning in Section 4.3, and our contributions in Section 4.4.

4.1 DWM1001 UWB Modules

The MDEK1001 ultra-wideband (UWB) development kit from Decawave is a piece of hardware that includes the embedded DWM1001 module. This was the used hardware for all experiences that involve UWB communications in this dissertation.

Figure 4.1: MDEK1001 Device [4]

4.1.1 Configurations and Definitions

The module can be configured by precisely measuring the position of their antenna and then inserting the x, y, and z coordinates in relation to the selected source point. This operation allows to identify each antenna in a precise space. The devices may be configured to behave as an “anchor”, one of the fixed nodes in the system, “bridge”, a fixed node that routes the data between the UWB network and IP network, or a “tag”, one of the mobile located nodes in the system. We can configure any number of modules in anchor mode, but a tag will only receive four distance estimates at any given moment. Only tags are capable of receiving and reporting distance estimates from anchors, and one anchor must act as the network initiator.

Each module designated to function as an anchor is configured through Minicom with its position on the grid and the network it belongs to. It must also be set to anchor mode, with one module designated as the network initiator.

An example of the commands for the anchor setup:

- **nma** - enter anchor mode.
- **aps x y z** - set the position of the anchor in the grid.
- **nis 0x1234** - join the network 0x1234.
- **nmi** - required if we want to make that node the initiator, only one is needed in the network.

The module intended to function as a tag must be configured in tag mode and assigned to the same network as the anchors from which it will receive distance estimates.

The tag setup:

- **nmt** - to enter tag mode.
- **nis 0x1234** - same as anchor mode, join the same network.
- **les** - to display the distance estimate and the position estimate, though the position estimate is only available if there are at least three distance estimates.

According to the manual [5], the module defines the position estimate accuracy and precision parameters as follows:

Accuracy - is the error between the position reported by the nodes and the real position. Currently the DW1000 used in this design provides approximately 10 cm accuracy.

Precision - is the value a least-significant bit (LSB) represents. In the on-board firmware of this system, the precision is 1 mm, i.e. 0.001 meter. The positions are presented in 3-dimension coordinates (X, Y, Z), where X, Y, and Z each is a 32-bit integer (4 bytes). Each LSB represents 1 mm. This is for easier interpretation of the value as well as easier mathematics over the reported values.

When deciding the precision, it is important to choose it with respect to accuracy to get a meaningful result. It is useless to show the user precise values if accuracy is low. The 1mm precision is too fine-grained with respect to the current 10 cm accuracy. Therefore, in presenting the location, precision of 1 cm, i.e. 0.01 meter, is used. Only when the coordinate/distance has changed over 1 cm will the updated value be presented. It is similar as rounding float/double values to meaningful number of decimal places.

4.1.2 Distance Estimation

Few details are documented for the indoor location algorithm used, but we know from the system user manual of the DWM1001 [4] that the internal TWR location engine is used in tag mode to calculate an estimate of the tag's position using the two-way ranging results and known positions of the anchors selected for the ranging and we also know:

- A location estimate can be calculated with either 3 or 4 range results, i.e. can tolerate missing a response from any one of the four anchors selected for ranging and still calculate a new estimate of the tags location.
- The location engine uses maximum likelihood estimation. When it has four ranging results the location engine creates sets of data (4 sets of 3 ranges). The sets are then used to calculate possible tag positions.
- The implementation uses cache to speed up the estimation of the positions. If the anchors which are used for calculation have not been changed, the cached value will be used and there is no need to recalculate the initial matrices.

The location engine then uses different criteria to choose or to combine them to calculate the estimation of position. The estimated position is verified by using measured distances. The positions which result in shorter distances than the measured are considered less accurate (multipath will result only in longer distances). The location engine calculates the errors between the estimated positions and the real distance and removes the positions which have high errors. The final position is calculated using the selected estimated positions. The location engine will also report a quality factor (0-100) based on all of these criteria and the calculated errors. A fixed moving average of the last 3 location results is used for the estimation of the final position.

We will refer to this as the **Decawave** algorithm throughout the rest of this dissertation.

4.2 Software and Architecture

We used Minicom as a serial communication tool to connect devices through the serial ports of a GNU/Linux PC. We also experimented with MQTT, which is a messaging protocol designed specifically for the IoT and provides a lightweight publish/subscribe messaging transport, making it ideal for connecting remote devices that require minimal code and low network bandwidth.

By combining Minicom with python scripting, we were able to capture and save all the data being displayed on the screen to a text file. This allowed us to store and process all the data transmitted by the MDEK1001. The Python scripts we developed had several functions, including parsing and saving data, estimating positions both in real-time and after the experiments using the LS method, implementing MQTT publish/subscribe services, and generating easily readable CSV files for further data analysis.

Using the tools mentioned earlier, we developed a software architecture for indoor positioning that enabled the estimation of a device's location under various conditions. We began by analyzing the spaces where the experiments would take place and planned the initial setup accordingly.

The earliest experiment was simple, involving just one tag and one anchor, to assess the equipment's performance in its simplest configuration. We tested its ranging capability at distances of 2, 4, and 8 meters, achieving the expected values according to its definition of accuracy. Following that success, the first setup we experimented on was straightforward, designed to test the module's position estimate capabilities. It involved three anchors and one tag, with a laptop connected to the tag for data recording, as shown in in Figure 4.2.

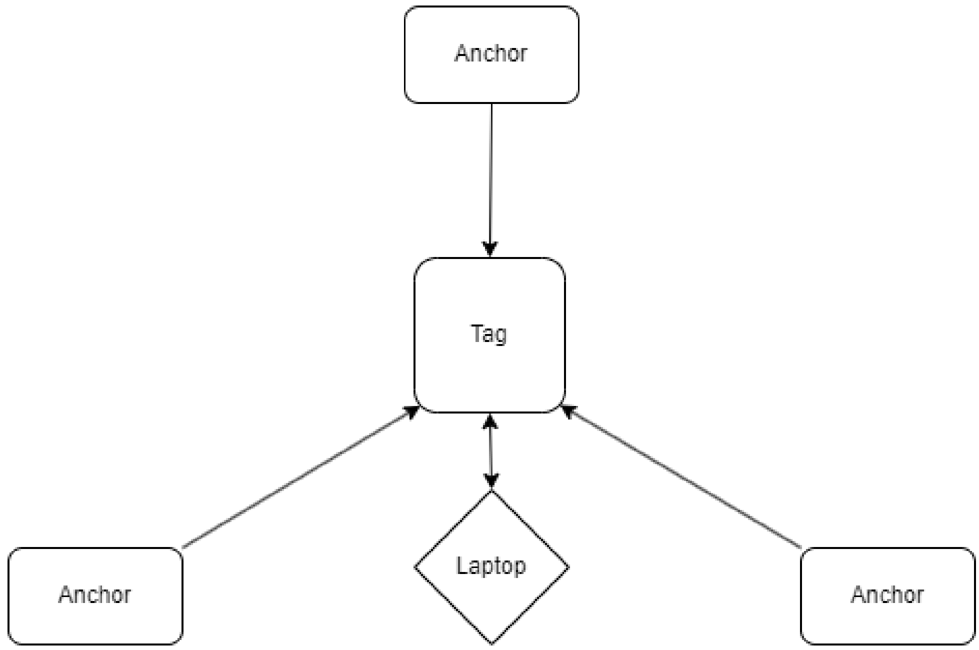


Figure 4.2: Setup with 3 anchors and 1 tag. The tag is connected to a laptop to save the data being outputted to a text file.

In the second setup, depicted in Figure 4.3, we planned a different scenario by having three different tags estimating their distance to the anchor. Each tag was connected to a Raspberry Pi to individually record the ranges reported by the tags. In the final stage, we set up MQTT to publish the three ranges and retrieve them on a laptop subscribed to the ranges topic, allowing it to estimate the anchor's position using the LS method.

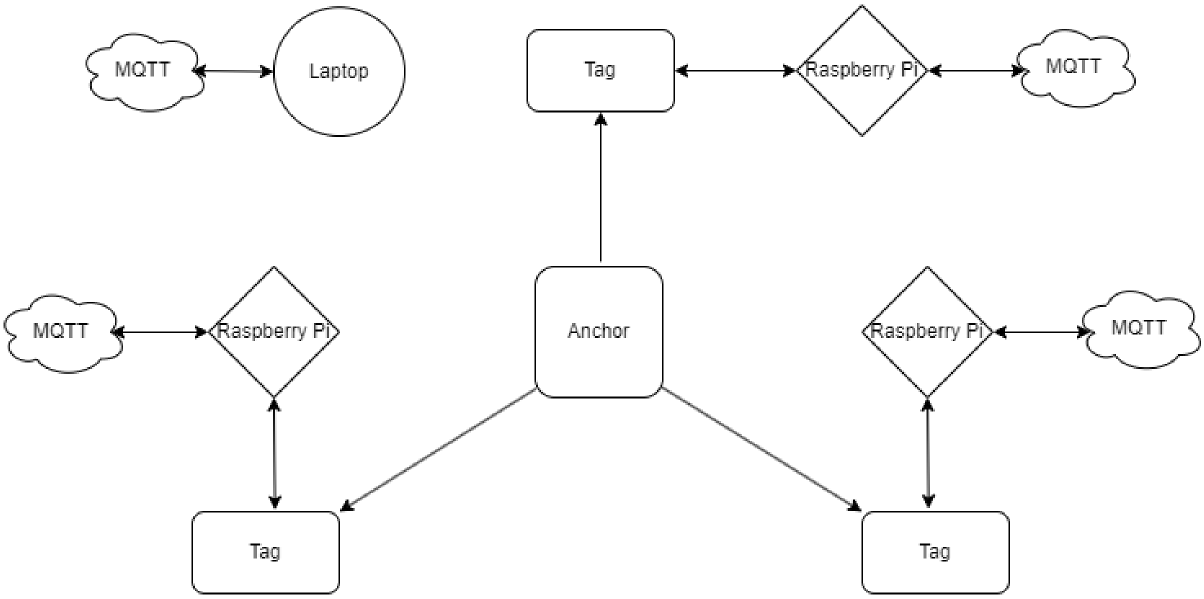


Figure 4.3: 3 tags and 1 anchor. Each tag is connected to a raspberry pi.

A challenge with this scenario is that the DWM1001 module is designed to operate with the configuration of a minimum of three anchors reporting their positioning to a tag, so it wouldn't produce any position estimates, only the individual distance ranges could be acquired in this setup. This meant that there was no way to directly compare the LS estimate with the results from the Decawave algorithm in this scenario.

4.3 Experiments Planning

We aimed to use the materials and architectures we developed to experiment with and test the capabilities of the DWM1001, focusing on the impact of LoS/NLoS conditions and the accuracy of an indoor positioning system using UWB.

Two experiments were planned, both designed to evaluate the accuracy of this technology and equipment, as well as our own developed algorithm, using two different architectures.

The first experiment aimed to be straightforward, with an unobstructed line of sight, minimal equipment, and as few external factors as possible that might affect the results. The second experiment was intended to test the same architectures in a more realistic and demanding environment, such as the hallways of our department. This setting introduced frequent foot traffic, a variety of objects, and NLoS conditions. Additionally, the amount of equipment would be scaled up to cover a much larger area.

In our first experiment, conducted in a laboratory room, we implemented both architectures and carried out the tests. However, we concluded that a direct comparison between the two sets of results was not feasible because the three tags in this architecture each received only one distance estimate from the single anchor, making them unable to produce position estimates on their own. This limitation made it impossible to analyze the Decawave results in relation to our LS results.

On our second experiment, a public area, we had been presented with presented several challenges, one of which was the uneven surface of the area. This required us to measure and account for the Z-axis to eliminate its influence on the results. We manually measured the entire area, including the control points and anchor locations and implemented our first architecture in a larger scale.

4.4 Contributions

Our contribution to this thesis involved the study of indoor position estimation in real-life scenarios. We conducted an experimental evaluation in two distinct settings. First, we tested the capabilities and limitations of the DWM1001 in a controlled laboratory environment with no obstacles, ensuring perfect conditions to assess the system's potential. Secondly, we extended the evaluation to a public area on university grounds, introducing more realistic challenges.

We had rather significant insights on how LoS and NLoS conditions can affect the outcome of the distance estimation, even finding a specific case where NLoS was affecting severely the readings in our algorithm. It also led to understand how the DWM1001 restricts the use of 3 or 4 anchors, being unable to exceed that number of reported ranges to a single tag at a given time.

Additionally, we planned to test a system we developed for both scenarios. This system involved using all the anchors as tags, with the mobile device acting as the anchor. In this setup, the tags, connected to Raspberry Pi units, would report their ranges via UART interface. Utilizing python scripts, the Raspberry Pi would then publish these ranges via MQTT, creating a network that streams data to a single device responsible for performing LS calculations, estimating the anchor's position, and publishing it to a topic that could be subscribed by a client device. This approach allowed the person or object to only need to have the lightweight DWM1001 module attached to it. By subscribing to the MQTT topic, the position estimates could be viewed from anywhere.

We implemented and tested this system in a laboratory setting. However, due to a shortage of Raspberry Pi units needed to replicate the setup for the hallway experiment, we opted to include results from the laboratory tests to illustrate the different architectures, as using both setups in both scenarios was not feasible.

Chapter 5

Experiments and Results

In this chapter we discuss the conducted experiments, their setup and the respective results. The first experience is set in a laboratory room, discussed in Section 5.1, and the second one, in a public area on university grounds, discussed in Section 5.2, portraying a more realistic scenario where line of sight and walls play a role in interfering with UWB communications, comparing these results and errors. Every value and measurement in the text, tables and figures is to be considered in meters unless otherwise stated.

5.1 Laboratory room experiment

The first experiment took place in the Embedded Systems room of the Computer Science Department of the Faculty of Sciences of the University of Porto. The floor already has markings which formed 1x1 meters long squares as portrayed in Figure 5.1. The experience consisted in measuring ranges individually from each tag, labeled from Pub(1-3), to an anchor (Mobile Device) placed in different places, for each experience in the grid and measuring how accurate the Decawave algorithm estimated ranges were from the ground truth, to explore the accuracy and capabilities of the DWM1001 UWB modules.

An experiment was conducted where the nodes hosting the tags were connected to a local network and transmitted data via MQTT to a node that calculated the LS. This setup did not influence the data and so it was not considered.

5.1.1 Setup

In all experiments conducted, the software **Minicom** was used to read from the serial port of the MDEK1001 and collect its data. The following algorithms were considered:

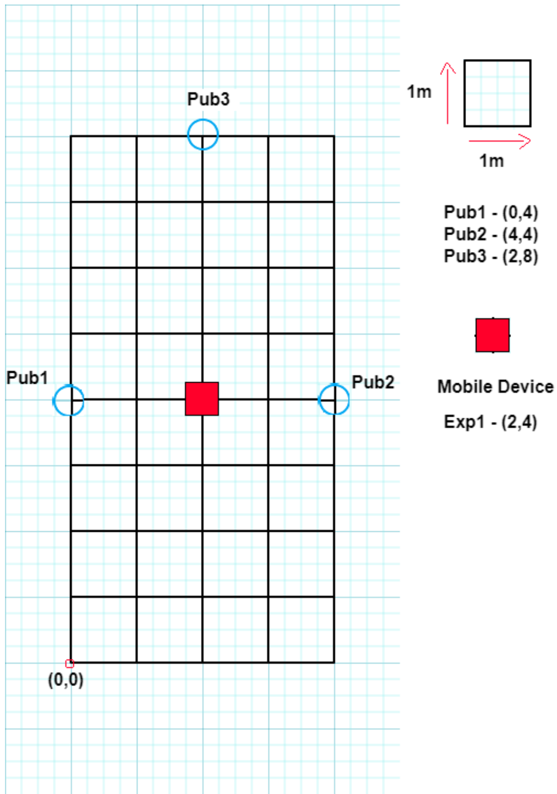
- **Decawave**, the built-in localisation firmware of MDEK1001.

Figure 5.1: Laboratory room.

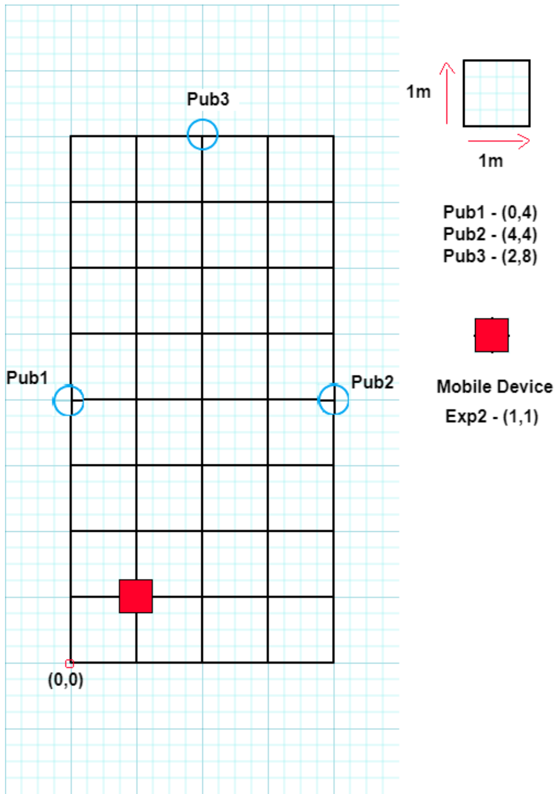
- **Least Squares**, the estimation of where the tag position is, using multi-lateration with the positions of the UWB anchors and the respective ranges to the tag.

The floor markings, seen in Figure 5.1, made it possible to form a 4x8 meters grid. By placing three MDEK1001 UWB devices setup as tags and another one as an anchor, we would record the individual range values on each tag continuously for 2 minutes for each of the scenarios shown in Figure 5.2. All coordinates shown are in meters. The devices were put on the floor standing upright as to allow for the most optimal transmission of the electromagnetic waves between them. In the different scenarios considered, we placed the anchor in different places of our grid, to see if there is any significant disturbance even in a good LoS condition. The following device placements were used:

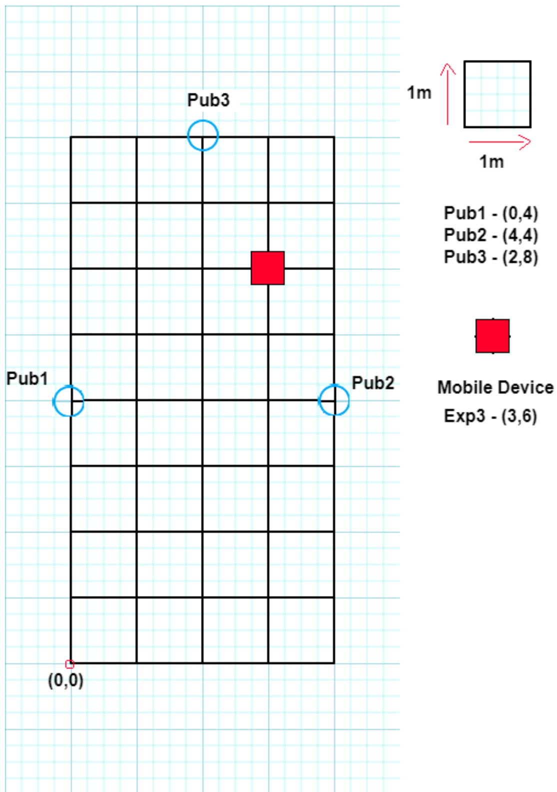
1. The device was centered in the grid (2,4).
2. The device was left and close to the origin (1,1).
3. The device was slightly to the right of the center of the triangulation (3,6).
4. The device was mirrored in the Y axis to the second experience (3,1).



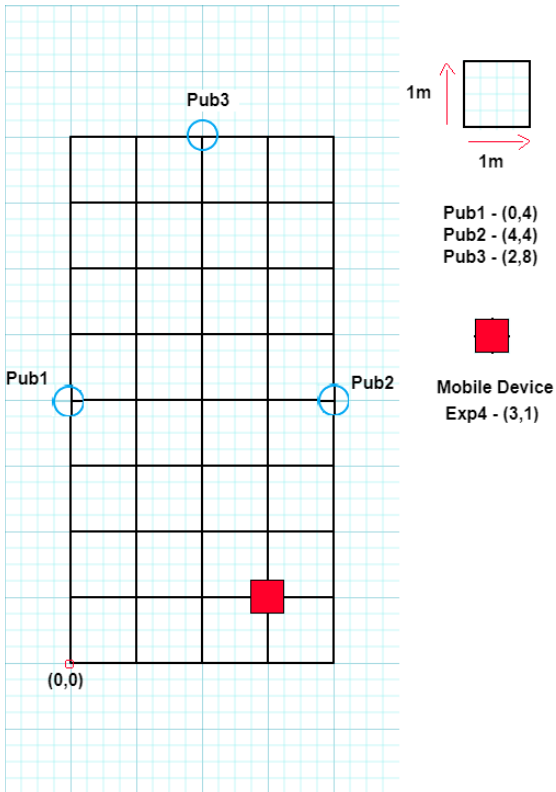
Exp 1



Exp 2



Exp 3

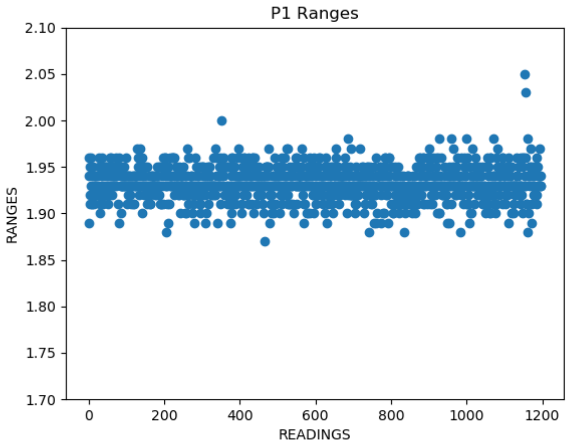


Exp 4

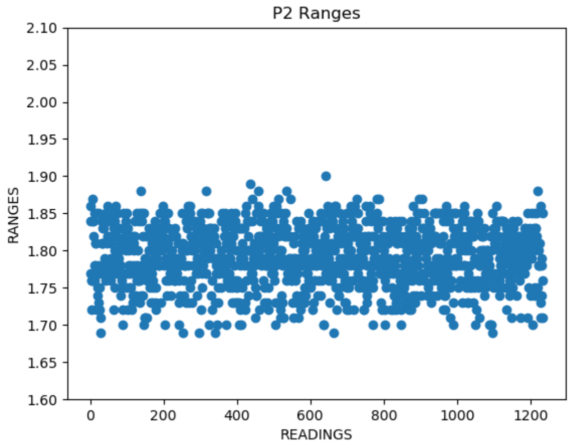
Figure 5.2: A view of 4 different scenarios considered in the experiments.

5.1.2 Analysis and Results

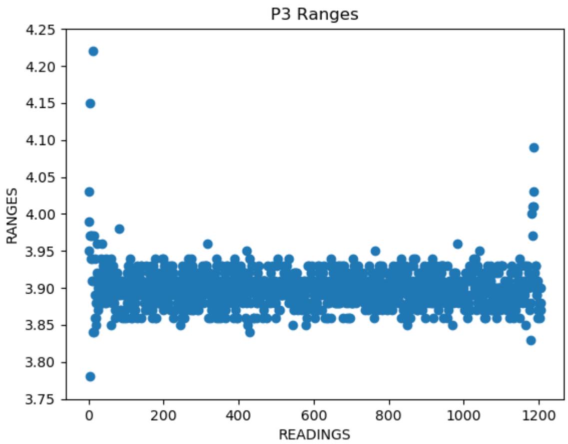
The reported ranges average error was low, which meant a relatively accurate reading from the ground truth if we consider the equipment value of accuracy which is 0.10 meters [5]. This can be seen in Figure 5.3 for Experiment 1, which shows a graphical view of the reported ranges in a 2 minute time frame, X axis represents the lines of data registered and Y shows the reported range to the anchor in meters.



Pub1



Pub2



Pub3

Figure 5.3: A graphical view of the result of each range reported during Exp 1.

All the other experiments had similar results, which can be observed in the average error in ranging for each of the tags to the mobile device in each experiment, as portrayed in Table 5.1. After applying LS for each experiment and calculating its average error and standard deviation, we solidify this further, observing in Table 5.1 the estimates for the mobile device position were fairly accurate.

Table 5.1: Average of error in ranging and standard deviation for each tag, in each experiment and average of LS error and Standard Deviation in all experiences.

Exp	Pub1 μ	Pub1 σ	Pub2 μ	Pub2 σ	Pub3 μ	Pub3 σ	LS μ	LS σ
1	0.07	0.02	0.21	0.04	0.10	0.03	0.12	0.02
2	0.08	0.02	0.11	0.03	0.09	0.10	0.13	0.05
3	0.09	0.02	0.07	0.02	0.05	0.02	0.09	0.02
4	0.04	0.03	0.10	0.12	0.14	0.03	0.16	0.06

5.2 Hallways Experiment

In the halls of the Computer Science Department of the Faculty of Sciences of the University of Porto, we designed an experiment which consisted in placing various MDEK1001 devices configured as anchors, in order to track a tag in different control points.

5.2.1 Setup

Figure 5.4 depicts the layout of the experiment. Anchor locations are identified as P1 to P9, and control points that are part of the tag's course are identified as PC1 to PC11. Starting on PC5, data (ranges and position estimates) was recorded for 30 seconds before moving on to the next control point, following the direction of the arrows. This process was repeated until we registered data on all control points and got back to the starting point.

Note that P1 is the origin of the coordinate frame, with coordinates (0,0). The anchor at P1 was also configured as the initiator for the UWB network. The length of the corridor was 13 meters long from P1 to P3, making it the X max coordinate and from P3 to P5 the corridor was 24 meters long making it our Y max coordinate. We spread out 9 MDEK1001 devices, configured in anchor mode and labeled P1 to P9, all strategically placed to minimize dead zones as much as possible in the corridors, while always trying to maintain triangulation between them in the different zones. The devices were setup on the same height relative to each other and the moving tag was held approximately at the same height, so the Z coordinate could be disregarded.

All 9 anchor devices were stuck onto the wall in a 90 degrees angle relative to the wall to assure the best propagation of the electromagnetic waves, while the tag device was attached to a laptop recording the ranges it received from up to 4 anchors at an instant in time, along with the position estimate provided by the Decawave algorithm. The data was registered in intervals of 30 seconds, only producing estimates when a quality factor above 90 was obtained, according to Decawave algorithm standards.

All data was captured exactly as generated by the algorithm and later processed, using python scripts, to discard any entries that did not produce a position estimate for the tag. This was done in order to obtain an accurate comparison between the Decawave algorithm and LS.

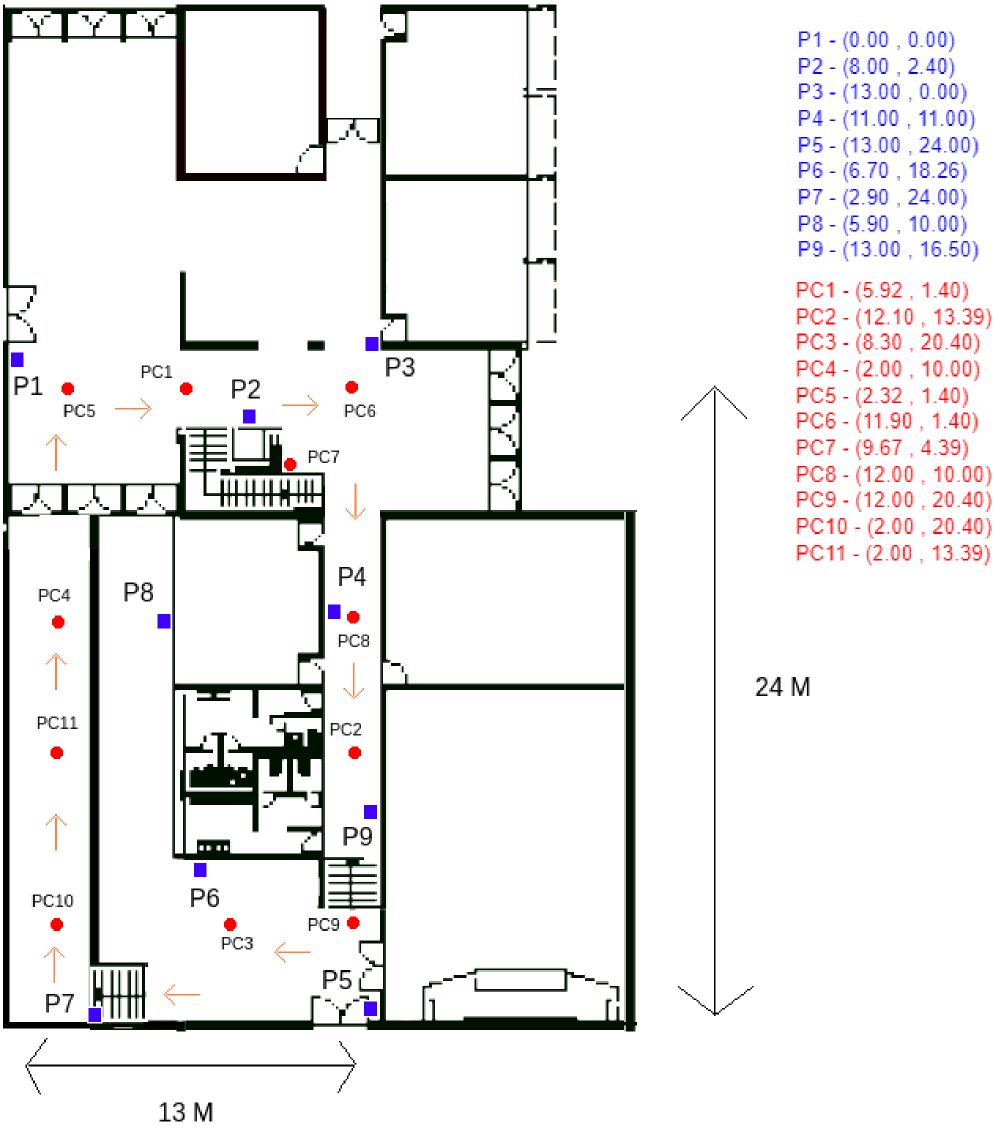


Figure 5.4: Experience layout with UWB anchors P(1-9) and control points PC(1-11). The path begins in PC5 following the arrows direction, stopping in every control point, and finally returning to its starting point.

The estimates were then compared using the average error and standard deviation relative to the measured ground truth for both algorithms.

5.2.2 Analysis and Results

When analysing the results we could see that PC7, as expected beforehand due to NLoS from most of its nearby anchors, did not produce any position estimate. It would only register a ranging from P3 and sometimes P2 due to some reflected transmissions, this point was created to show exactly how important an unobstructed LoS is.

Looking at the DWM results shown in Table 5.2, we can observe that the corridor with PC2, PC6, PC8 and PC9 produced the worst results in terms of how high the error was comparatively. This is because the corridor is narrower and the devices P3,P4,P9 and P5 are relatively almost co-linear which is known to cause precision issues in estimating a position in UWB as discussed by Martalò et al. [7].

Comparing the DWM and LS position estimates, the difference between the two is mostly negligible, except the readings from PC3 where the error is more noticeable on our algorithm. We analyse the results for PC3 in more detail next.

Table 5.2: Average Error of LeastSquares and Decawave recorded on each control point.

Control Point	LS μ	LS σ	DWM μ	DWM σ
PC1	0.25	0.08	0.38	0.06
PC2	1.07	0.18	1.17	0.19
PC3	0.74	0.78	0.09	0.16
PC4	0.08	0.04	0.06	0.03
PC5	0.28	0.11	0.16	0.08
PC6	0.91	0.07	0.81	0.05
PC7	no data	no data	no data	no data
PC8	0.71	0.16	0.6	0.25
PC9	1.26	0.15	1.06	0.07
PC10	0.21	0.09	0.21	0.09
PC11	0.19	0.2	0.12	0.1

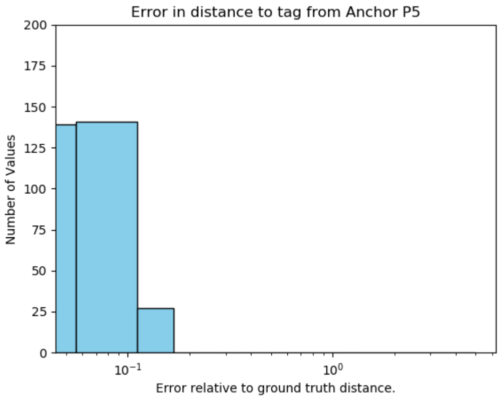
5.2.2.1 Detailed Analysis on PC3

By further investigating on this specific case, singling out the different reported ranges from the anchors, calculating the distance between the two points and the associated error in the ranging, presented in Figure 5.5, it is observable in that P9 has a much higher error than the other anchors, which led to the increase in its error in **LeastSquares** while using these ranging values.

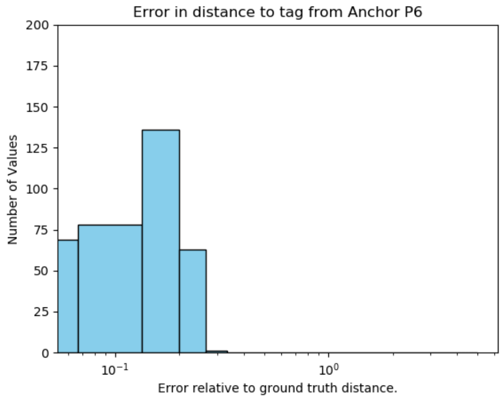
Table 5.3: LS error in all combinations of 3 anchors available in PC3.

Using	LS μ	LS σ
P5/P6/P7	0.09	0.04
P5/P6/P9	1.09	0.73
P6/P7/P9	1.48	1.71
P5/P7/P9	1.15	1.29

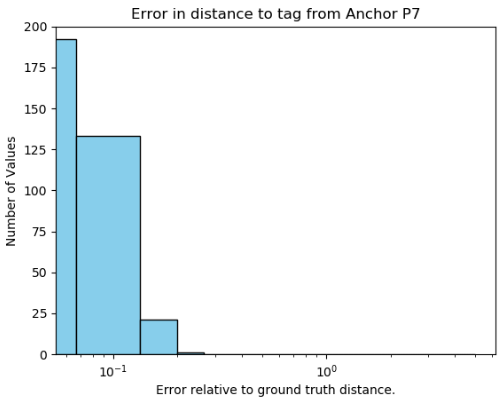
If we look at Figure 5.4 we can see that P9 is in a position where LoS is not totally present, making the signal carrying the data reach the tag with poor fidelity. To be certain of this , we



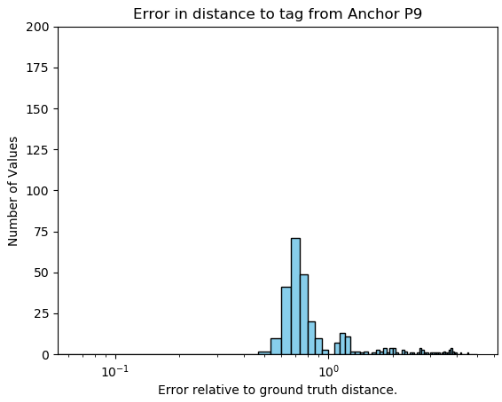
P5 Ranging Error



P6 Ranging Error



P7 Ranging Error



P9 Ranging Error

Figure 5.5: Error in the distance measured by every anchor in range while in PC3 in the Hallways Experiment.

started by trying all the possible combinations of 3 anchors. In Table 5.3, we can see that the only case where the error in our algorithm is low is when P9 is not present.

Not using this anchor for this particular study case confirms the results are similar, seen in Table 5.4, and closer to the DWM estimate.

Table 5.4: PC3 new LS best estimates using anchors P5/P6/P7 ranges.

Control Point	LS μ	LS σ	DWM μ	DWM σ
PC3	0.09	0.04	0.09	0.16

In a final comparison, Figure 5.6, represents the errors from all control points combined. We can observe that the Decawave algorithm and the corrected LS produced similar results.

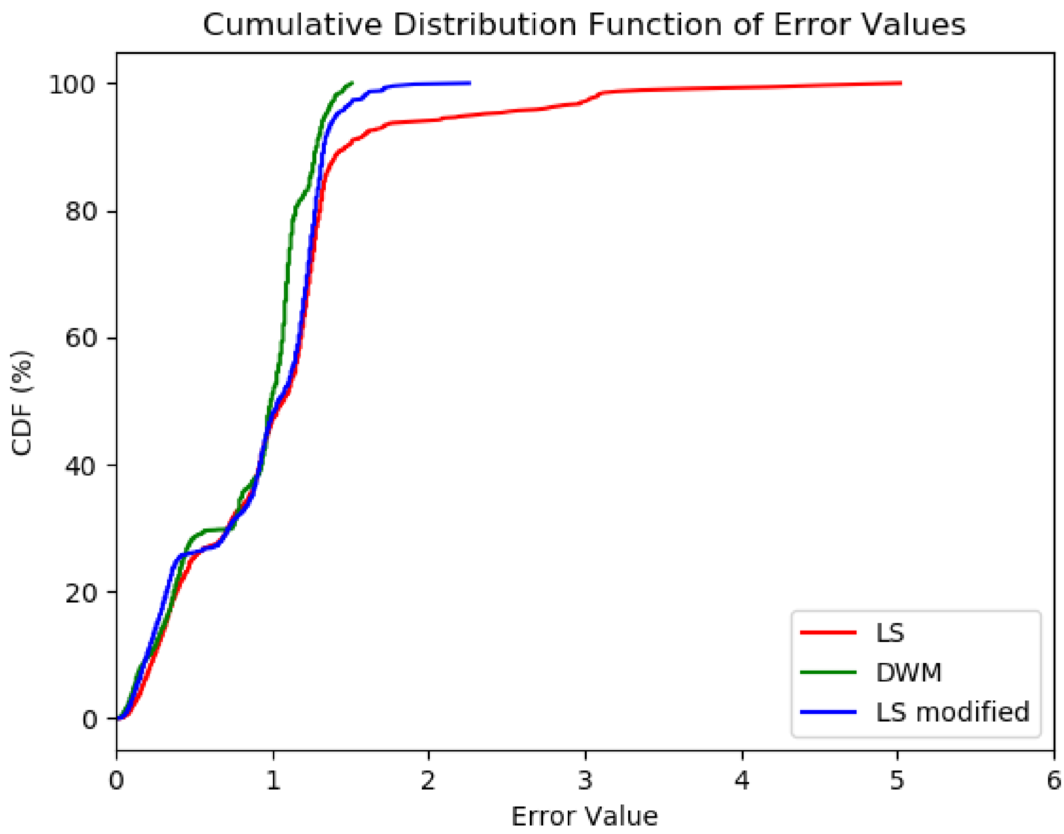


Figure 5.6: CDF of the error values in all control points. The red line indicates the LS errors, the green line shows the DWM errors, and the blue line represents the LS errors with the best error results from PC3.

5.3 Results Discussion

In both presented experimental scenarios, the Decawave proved to be fairly accurate and robust enough to allow for distance estimation indoors. Specifically in the last experiment, showing a good adaptation to rough conditions such as obstacles like metal bars, stairs, narrow hallways and different types of materials like wood, granite, metals and glass. However it still shows some restrictions and room for improvement regarding the number of anchors it can accept ranges from in an instance of time. The narrow corridors, still wide enough for at least two rows of students to pass by, also proved to be a challenge for the equipment distance estimation, as we can see in the results, the control points where the error in estimation increased was precisely in that corridor (PC2, PC6, PC8, PC9). Our final algorithm, the modified LS, proved to be of similar effectiveness, using the data provided from the DWM1001 readings, but could also be tweaked and further improved with other algorithms that could minimize the NLoS impact on the data. For the narrow corridors, as Jiménez et al. [6] demonstrated in their work more tags and anchors could help mitigate this problem and increase the accuracy.

Chapter 6

Conclusions

This thesis explored the challenges and solutions associated with indoor positioning systems using UWB technologies, more specifically the DWM1001 module, focusing on both controlled and public environments. Through a series of experiments, we tested the module's capabilities in a laboratory setting with ideal conditions, as well as in more complex environments, such as university hallways with varying levels and potential obstacles.

The laboratory experiments demonstrated that the DWM1001 can effectively estimate positions under optimal conditions, delivering satisfactory ranging results. These findings validate the module's baseline performance in a controlled environment.

In contrast, the hallway experiments revealed additional challenges. By meticulously measuring the space and adjusting for these challenges, we were able to set up a robust system that could still provide reliable positioning estimates, despite the complexities of the environment.

Our research further highlighted the limitations of the DWM1001 in scenarios where the traditional setup of three anchors and one tag is altered, such as in the reversed scenario with three tags and one anchor. This experiment underscored the module's dependency on its default configuration.

Overall, this thesis contributes to the understanding of indoor positioning system performance in varying conditions and offers insights into the practical implementation challenges that arise in real-world applications.

Future work could build on these findings by exploring alternative configurations and improving the system's adaptability to more complex environments, and experimenting with different algorithms and hardware.

Bibliography

[1] Abbas Albaidhani and Ahlam Alsudani. Anchor selection by geometric dilution of precision for an indoor positioning system using ultra-wide band technology. *IET Wireless Sensor Systems*, 11(1):22–31, 2021.

[2] Sebastian Dädeby and Joakim Hesselgren. A system for indoor positioning using ultra-wideband technology. *Master's thesis*, 2017.

[3] João Paulo de Melo Carvalho. Augbot: indoor location system using ros. *Master's thesis*, 2022.

[4] Decawave. *DWM1001 System Overview And Performance*. Qorvo, 950-A Lawrence Dr. Thousand Oaks, CA 91320. United States of America., 2018. Version 2.1.

[5] Decawave. *DWM1001 Firmware API Guide*. Qorvo, 950-A Lawrence Dr. Thousand Oaks, CA 91320. United States of America., 2019. Version 2.3.

[6] Antonio R Jiménez and Fernando Seco. Improving the accuracy of decawave's uwb mdek1001 location system by gaining access to multiple ranges. *Sensors*, 21(5):1787, 2021.

[7] Marco Martalò, Simone Perri, Gianmichele Verdano, Francesco De Mola, Francesco Monica, and Gianluigi Ferrari. Improved uwb tdoa-based positioning using a single hotspot for industrial iot applications. *IEEE Transactions on Industrial Informatics*, 18(6):3915–3925, 2021.

[8] Ardiansyah Musa, Gde Dharma Nugraha, Hyojeong Han, Deokjai Choi, Seongho Seo, and Juseok Kim. A decision tree-based nlos detection method for the uwb indoor location tracking accuracy improvement. *International Journal of Communication Systems*, 32(13): e3997, 2019.

[9] Zuin Silvia, Calzavara Martina, Sgarbossa Fabio, and Persona Alessandro. Ultra wide band indoor positioning system: analysis and testing of an ips technology. *IFAC-PapersOnLine*, 51(11):1488–1492, 2018.

[10] Sangmo Sung, Hokeun Kim, and Jae-Il Jung. Accurate indoor positioning for uwb-based personal devices using deep learning. *IEEE Access*, 11:20095–20113, 2023.

[11] Andrea Volpi, Roberto Montanari, Letizia Tebaldi, and Marco Mambrioni. Low-cost real-time locating system solution development and implementation in manufacturing industry. *Journal of Sensor and Actuator Networks*, 12(4), 2023. ISSN: 2224-2708. doi:10.3390/jsan12040054.

[12] Shaojie Zhuang, Jarissa Maselyne, Annelies Van Nuffel, Jürgen Vangeyte, and Bart Sonck. Tracking group housed sows with an ultra-wideband indoor positioning system: A feasibility study. *Biosystems Engineering*, 200:176–187, 2020.