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Asset location using BLE technology for Industrial floor

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July 28, 2023

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Resumo

Bluetooth Low Energy é uma tecnologia que tem vindo a evoluir nos últimos anos, principalmente na área da Internet of Things. O uso desta tecnologia para o rastreamento de bens é um campo ainda pouco explorado.
Saber a localização exata de bens e valores, dentro de uma fábrica, por empresas industriais é atualmente um problema vital. Este conhecimento é fundamental para a organização das empresas e a otimização dos seus processos internos.

As soluções existentes geralmente são baseadas em RFID ou outras tecnologias NFC. Estes dependem do uso de muitas antenas (portas de acoplamento indutivo) dentro da instalação ou de um sistema que se move pela fábrica para localizar os bens. Estas soluções são dispendiosas em termos de custo de infraestrutura e energia consumida para alimentar o sistema e carecem da flexibilidade que o BLE pode fornecer ao localizar ativos em movimento contínuo.

Entre as várias tecnologias analisadas, o AoA usando BLE foi aquela que mostrou o melhor potencial.

O trabalho realizado focou-se na implementação e otimização de um sistema de Proof-Of-Concept baseado numa antenas com doze sensores. O sistema utiliza a diferença de fase entre as antenas receptoras para calcular o ângulo de incidência e estimar o ângulo de chegada do asset. A solução final permite a localização de ativos em um ambiente tridimensional (3D), incorporando ângulos de azimute e altitude juntamente com medições de distância.

Ao longo do processo de implementação e teste, o desempenho do sistema foi afetado por valores discrepantes e ruído nas estimativas. Para mitigar esses desafios, diversas técnicas foram exploradas, com ênfase especial na detecção de valores discrepantes usando algoritmos de clustering. Os resultados demonstram o potencial do sistema para localizar com precisão ativos e superar as limitações impostas por valores discrepantes e ruído.

Keywords: Asset Location, Bluetooth-Low-Energy, Angle-of-Arrival, Angle-of-Departure, RSSI, Indoor Positioning

Abstract

Bluetooth Low Energy is a technology that has been evolving in the last years, mainly in the Internet of Things area. The use of this technology for asset tracking is a field yet ill-explored. Knowing the exact location of assets and valuables, inside a shop floor, by industrial enterprises is currently a vital problem. This knowledge is critical to companies' organization and the optimization of their internal processes.

The existing solutions are often based on RFID or other NFC static technologies. These depend on using many antennas (inductive coupling gates) inside the facility or a system that has to move along the floor to keep track of the assets. These are expensive either in infrastructure cost and energy consumed to power the system and lack the potential flexibility BLE can provide when locating continuously moving assets.

Among the multiple technologies analysed, the AoA using BLE was the one that showed the best potential.

The work done focused on the implementation and optimization of a Proof-of-Concept system based on an antenna array with twelve sensors. The system utilizes the phase difference between receiver antennas to calculate the angle of incidence and estimate the asset's angle of arrival. The final solution enables the localization of assets in a three-dimensional (3D) environment by incorporating azimuth and altitude angles along with distance measurements.

Throughout the implementation and testing process, the system's performance was affected by outliers and noise in the estimations. To mitigate these challenges, various techniques were explored, with a particular emphasis on outlier detection using clustering algorithms. The results demonstrate the system's potential for accurately localizing assets and overcoming the limitations imposed by outliers and noise.

Keywords: Asset Location, Bluetooth-Low-Energy, Angle-of-Arrival, Angle-of-Departure, RSSI, Indoor Positioning

Agradecimentos

Antes de mais, gostaria de agradecer a todos os professores e funcionários da FEUP pelo excelente trabalho que fazem todos os dias e que permite manter o excelente nível de ensino. Um agradecimento especial ao Departamento de Engenharia Informática DEI. Um agradecimento também à Fraunhofer Portugal AICOS pela oportunidade de desenvolver a disertação num ambiente empresarial.

Estou profundamento grato à minha família, em especial à minha Mãe, à minha Avó, à minha Kita e ao meu Pai pelo apoio e o eventuais raspanetes que me deram ao longo dos últimos 23 anos. Estou também muito agradecido aos amigos que fui conhecendo ao longo da vida que sempre me ajudaram nos momentos menos bons, e com os quais partilhei muitos bons momentos e que sempre souberam escolher o OS certo.

Agradeço ao Professor Antonio Monteiro pela disponibilidade e orientação e ao Miguel Roque da Fraunhofer pelo apoio ao longo da dissertação.

Todos e todas desempenharam um papel significativo na minha formação profissional e proporcionaram-me uma valiosa experiência de aprendizagem. Estou genuinamente grato pelo apoio ao longo desta jornada de 5 anos.

Miguel Pinto

"Computer Science is no more about computers than astronomy is about telescopes"

E.W. Dijkstra

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Abbreviations

AoA	Angle of Arrival
AoD	Angle of Departure
BLE	Bluetooth Low Energy
DK	Development Kit
EM	Electromagnetic
EMF	Electromotive Force
FFC	Far-Field Coupling
GPS	Global Positioning System
GNSS	Global Navigation Satellite System
IF	Industrial Floor
IPS	Indoor Positioning System
LoS	Line of Sight
MAE	Mean Absolute Error
NFC	Near-Field Coupling
POW	Proof of Work
RFID	Radio-Frequency Identification
RPI	Raspberry PI
RSME	Root Squared Mean Error
RSSI	Received Signal Strength Indication
RTOS	Real-time operating system
SF	Shop Floor
UWB	Ultra-wideband
VLP	Visual Light Positioning
WLAN	Wireless local area networks

Chapter 1

Introduction

This chapter will comprise the initial description of the problem at hand, contextualization of the issue and the motifs that lead to this dissertation theme, and the main goals of the work developed. It will also describe in more detail the structure of the document and its parts.

1.1 Context

The present dissertation was proposed by Fraunhofer Portugal AICOS, in the context of the group Indoor Location. The group had been working on solutions for this problem. It came up with the idea of exploring the use of BLE in the context of asset location, which could overcome the main problems found when exploring the application of asset location to an environment with as complex requirements as an industrial floor has. Furthermore, there was a specific interest in exploring the innovations introduced by the BLE 5.1 standard, particularly the potential to determine the angle of arrival of a signal. This feature opens up new possibilities for location-based applications and enhances the capabilities of Bluetooth technology in terms of spatial awareness.

1.2 Motivation

Industrial enterprises today acknowledge that knowing the exact position of assets, resources, and other items on a shop floor is an issue [6]. Additionally, accurate and up-to-date tracking of those values inside a warehouse is crucial for process optimization by reducing searching times and providing data that can be used for further analysis of the processes. Some commercially available methods leverage approximation sensors or static RFID gates to return the asset location when paired with building schematic knowledge (close to the sampling infrastructure).
These solutions do not address such needs as a specific asset's continuous location, status, and condition. Furthermore, these solutions are not fit for dynamic environments where the change in the layout of the building may render the system inaccurate. The material itself of the walls and ceiling may pose problems to the systems or even make some solutions fail completely. Following those problems, the idea of using technologies that enable more active tracking led to exploring

BLE as an alternative to RFID-based solutions. BLE has the potential to allow for real-time solutions with higher precision while keeping costs down.

1.3 Goals

The primary purpose of this document is to analyze and synthesize the work developed in the area of this dissertation and guide further development upon the conclusions drawn while searching, leading to an informed decision on the course of the methodology that will be used when developing a working solution. In order to guide the development of the work, four questions were made:

- Which BLE-based approach shows more potential to be used to do asset tracking?
- What are the main constraints and drawbacks of this solution when compared to the existing ones?
- Can a BLE-based approach be used successfully in the context of asset tracking inside an industrial floor?
- What can be done to overcome possible scalability issues regarding the technologies used?

Finally, the main goal will be to develop a Proof-Of-Concept (POW) based on the conclusions drawn from the State of the Art analysis and test its effectiveness in a dynamic environment such as a shop floor.

The work done should contribute to a solution that can deal with the problems and restrictions often found on an Industrial Floor.

1.4 Document Structure

- **Introduction:** This chapter sets the context and motivation for the document. It also outlines the goals of the document and provides an overview of the document's structure.
- **State Of The Art:** This chapter provides an overview of the current state of indoor positioning systems, including measuring techniques and algorithms, and a comparison of different technologies. It also includes a section on Bluetooth Low Energy (BLE) and an evaluation of BLE techniques.
- **Project Requirements and Desired Functionalities:** This chapter presents the objectives of the project, its requirements and functionalities, and real-world applications. It covers topics such as asset localization, cost-effectiveness, energy efficiency, and compatibility with low-budget computers.
- **Solution Architecture and Implementation's High-Level View:** This chapter provides a high-level view of the solution architecture and its implementation. It includes sections on logical and hardware architecture.

- **Implementation and Experimentation Sprints:** This chapter provides an in-depth exploration of the development process employed for the asset localization system. The development approach embraced a sprint-based methodology, with each sprint typically lasting two weeks. This iterative approach allowed for incremental progress, building upon previous work and leveraging experimentations and results to drive design decisions. The chapter elucidates the implementation process and highlights the critical aspects of each sprint. It also discusses the experiments, challenges encountered, and insights gained from analyzing the results.

- **Discussion** This chapter will analyse the work done and compare it with the solutions found on the State of the Art.

- **Conclusion** This chapter will conclude on the goals of the dissertation and the overall usability of the system in the context of this dissertation.

Chapter 2

State Of The Art

This chapter englobes the revision of the state-of-the-art important to better understand the problem in hands. It is structured as follows: an overview of Indoor Positioning Systems (IPSs), followed by a discussion on existing solutions for the problem, and conclusions on why BLE was the chosen technology. After that, a further debate on BLE and, more specifically, the techniques that can be used to solve the problem using BLE.

2.1 Indoor Positioning Systems

An accurate way to find the position of assets inside buildings has been a concern of the scientific community over the years. In fact, high-precision systems with low latency and relatively low costs have been used for outdoor scenarios, such as Global Navigation Satellite System (GNSS) systems, more prominently GPS.
However, such a dominant system with good overall accuracy and high scalability is not a reality for indoor scenarios. Such environments pose difficulties as they vary in requirements and conditions. More specifically, industrial floors are often characterised as big buildings both in area and height. Also, warehouses and shop floors are highly dynamic with moving assets, people, and machinery where line of sight cannot always be assured, and other kinds of interference lead solutions to either high cost of setup and maintenance, or poor accuracy. Also, systems are often sensitive to the lousy positioning of sensors. Existing obstacles, either temporary or structural, pose a physical barrier to the system's operation by reflecting or absorbing signals. The materials of the building can also interfere with signal propagation.

In order to establish a common ground about terms often used, there is the need to establish and define such terms, mainly Anchor and Tag. *Anchors* are the piece of infrastructure on IPS (Indoor Positioning Systems) that are usually fixed; these serve the purpose of identifying the position of multiple assets. On the other hand, the assets that need to be located, generally need to be coupled with specific hardware that allows to keep track of movable objects. These pieces of hardware are called *Tags*. IPS can be evaluated by considering a multitude of criteria, such as:

- *Accuracy* - Accuracy commonly is the mean distance error using Euclidean distance between the estimated and the actual location.
- *Cost* - The cost of the initial setup plus the cost of maintaining the infrastructure.
- *Power Consumption* - The power consumption of the *Tags* and how long can they last without being charged.
- *Scalability* - How well the system handles the increase of *Tags*.
- *Density* - The number of *Anchors* that are needed per unit of space.
- *Update Rate* - The frequency of successive updates on the location of *Tags*.

These criteria are greatly co-dependant. When increasing performance in one metric other metrics may be hindered. Higher density results in higher costs. An increase in accuracy may lead to an increase in power consumption.

Considering the context of the dissertation, mainly industrial floors, one can make preassumptions about the needs of Industrial Floors (IFs) and the importance of the specified criteria when evaluating solutions. The critical factors, considering the context, are Accuracy, Power Consumption, Scalability, and Update Rate.

- The accuracy level does not need to be on the centimetre values. That said, the level of accuracy should allow pointing to a specific region depending on the size of the IF. Accuracies over 5m cannot be considered as they defeat the purpose of IPS for IF.
- When analysing power consumption, solutions should allow for a battery autonomy of *Tags* of over one year. It also has to be considered that some systems do not need *Tags* to operate; thus, energy consumption on *Tags* is not a concern.
- A IPS, when considering an IF, should allow for a fair amount of Tags. Depending on the use case, the needs may be in the thousands. A system capable of handling that amount of *Tags* is needed.
- The system also has to be capable of handling real-time tracking while being able to handle updating a considerable number of *Tags*

Given the requirements for indoor location, more specifically, Industrial Floor Location, an overview of existing solutions is in need as well as the exploration of common techniques used in said solutions and their usability in the context of this dissertation.

2.1.1 Measuring Techniques

When analysing work done in the area, most papers have common measuring techniques and algorithms that are either briefly explained or referenced and are needed to understand the concepts being discussed. Even though different technologies differ in how they can be used to identify the position of assets, most have similar measuring techniques that can be described at a higher level among technologies.

Most measuring techniques described here are based on the physical attributes of RF waves. These, however, often suffer performance degradation due to the environment, mainly caused by temperature and humidity changes and multipath measurements. Multipath can be described as a signal sent by a tag received multiple times due to reflections on the surrounding environment.

2.1.1.1 ToA - Time of Arrival

Time of arrival measurements is based on the time a specific signal takes to travel the distance between the two points being measured, e.g., a Tag and an Anchor. Knowing the transmission time and propagation speed, one can calculate the distance the signal traveled in that period, which is the distance between the two points [41].
In order to be able to use ToA, specific criteria must be met. As it depends on calculating the distance using the time of travel, the clocks of both devices must be in sync, so the entire network of devices must have their clocks synchronized. The devices must also be able to exchange information. In the case of ToA, the initial time must be transmitted along with the signal. Once the signal is received, the initial time is compared with the device's current time, calculating the time difference [25].
In situations where RF is used, the devices' internal clocks must have high precision to deal with the short times of travel due to the high speed of light. These restrictions make ToA limited in use.

2.1.1.2 TDoA - Time Difference of Arrival

The time difference of arrival is based on the difference between the ToA values measured by different Anchors [25]. This allows for removing the restriction of synchronization of the entire system. With TDoA, only the receivers need to synchronize their clocks, as only the difference between the received times is used. This technique is, for example, applied by the GPS [12].
While other techniques do not require more than one Anchor to get measurement, TDoA requires two Anchors in 2D scenarios and three Anchors in 3D scenarios to be usable, as they rely on relative values between anchors.

2.1.1.3 RSSi - Received signal strength indication

RSSI and RSSI-based solutions for distance estimation are used in technologies such as BLE, WIFI, traditional Bluetooth, and Ultra Wideband (UWB). RSSI is a popular solution, mainly due to its easiness of use and the fact that no special hardware is needed. However, this solution often produces results that are not precise enough for real applications.

A significant feature of radio transmission is that the signal intensity drops as the distance rises. Several studies [34] on signals in various transmission environments concluded that there is no reliable model for indoor radio propagation. Everything from the position to the environment's materials can significantly impact the indoor propagation of the signal.

Equations exist, derived from empirical tests, that allow estimating the distance to the reader, such as the *Log-Distance Path Loss*:

$$d = 10^{\frac{RSSI(d_0)-RSSI(d)}{10\times n}} \text{ [34]}$$

Symbol	Description
d	point which distance is being measured
d_0	point 1m away from the receiver
$RSSI(f)$	value of RSSI to the point f
n	path loss index

RSSI has an advantage over other methods, no synchronization of clocks is needed. On the other hand, RSSI-based estimations are highly dependent on environmental variables such as humidity, temperature, and the layout of the environment.

2.1.1.4 AoA - Angle of Arrival

Another approach that can be used when identifying the position of assets is using Direction instead of Distance. Considering the imaginary straight line connecting two devices, the Direction is the angle the line makes with the plane of the device. AoA offers multiple advantages, such as the reduced number of measurements when using triangulation. Another advantage of AoA is the ability to calculate the values without the need for clock synchronization [25].
On the other hand, AoA suffers from the multipath problem as signals from different directions highly impact the measurements. Another drawback of such a method is the required hardware, as, unlike the other methods described, AoA often needs specialized hardware to be able to calculate the angles.

2.1.1.5 RToF - Round trip time of flight

RToF operates in a similar way to ToA based on the principles of common radar. A device transmits a signal to another device that acts as a "reflective surface", retransmitting the signal. Once the original device receives the signal retransmitted by the Anchor, it knows the amount of time the signal was on the flight between the two devices without the need for clock synchronization. Then it can divide that time by two, retrieve the time spent between both devices, and calculate the distance.
This, however, poses some problems. Unlike common radar, the reflection period is not zero. The delay introduced by the Anchor needs to be taken into consideration.
RToF uses the simplicity of ToA and removes the requirement for clock synchronization while keeping the same drawbacks of ToA, such as multipath reading.

2.1.2 Measuring Algorithms

High-level algorithms that use values calculated by the techniques described in 2.1.1 are shared among the technologies used in IPS. In order to better understand the technologies described in 2.1.3, an overview of those algorithms must be done.

After obtaining values using the aforementioned methods (e.g., ToA, AoA, RSSI), there is a need to combine them in order to calculate the position of the desired device. For that, the existing algorithms can be divided into two categories:

- Triangulation 2.1.2.1
- Scene Analysis 2.1.2.2

Such algorithms are also often used to consider the errors introduced by such methods and minimise their influence on the final solution.

2.1.2.1 Triangulation

Triangulation methods rely on the mathematical properties of triangles to calculate the desired position. Two different methods can be used Lateration and Angulation [25].

The Lateration method uses the side of the triangles to calculate the final position. The sides of the triangle are measured by the distance estimation methods described before [25]. In a 2D scenario, if the position of two anchors is known, and the distance between those anchors to the device being tracked, we can generate two triangles that include both Anchors and the tag. The device's position can be estimated if a third anchor is added. Due to distance estimation errors, this method often does not allow calculating a single point but a region where the point must be.

Angulation works by calculating the angle between the anchors and the wanted device [25]. An important feature of triangles is that they can be uniquely described by three edges, in this case, three distances. Also, by two angles, as the third can be derived since the sum of the internal angle of a triangle always adds up to 180º. This allows us to use the angulation method, relying on fewer anchors than in alteration. It can be done by calculating the angle between each anchor and the device, which is sufficient to calculate a single point. Due to estimation errors, angulation in 3D scenarios often needs to consider a region rather than a single point, as the lines of the angle may not intersect.

Another approach is the use of angulation and distance. One can calculate the angle a device makes with an anchor, giving the direction, and calculate the estimated distance. Intersecting the direction with the circle created by the distance, one can estimate the device's position, solely relying on one anchor.

2.1.2.2 Scene Analysis - Fingerprinting

Another approach to estimate the Tags' positions is using scene analysis methods such as fingerprinting. Such a method is based on pre-calculating measuring values (RSSI, for instance) along the desired floor. The pre-calculated values are then compared to the values read at the tracking time. These systems often depend on a high density of Anchors to improve their performance. When using values from RSSI, they do not map to distance values but are used to position the Tags on the space, often using values read from multiple Anchors.

Fingerprinting methods often produce systems with high accuracy, even when using techniques such as RSSI. However, they usually come with the drawbacks of complex setups timewise, as they need to pre-calculate values from multiple points on the floor. This leads to systems with weak immunity to environmental changes, such as layout changes.

2.1.3 Indoor Positioning Technologies

2.1.3.1 VLP - Visible Light Positioning

The interest in using visible light in applications such as positioning has been increasing. The low cost of transmitters, based on LED technology, associated with the flexibility of the technology, makes this approach an interesting one when considering IPS. In this context, anchors are usually called receivers, and tags are called transmitters. This technology also allows exchanging of information between a tag and the anchor, often used for timestamp exchanges that are then used by positioning algorithms.

These systems generally work by having a receiver, camera and/or light sensors, multiple transmitters, and LEDs. The LEDs encode a message containing the tag ID and other helpful information. Then, the receiver reads and decodes the message and proceeds with the localization [7]. The technology allows for distance calculation, RSS and TOA, and direction calculation using AoA methods, exploring the ability of cameras to perceive the angle of the incoming signal. The use of TOA has been limited in practical uses due to the high speed of light, which requires the use of very precise clocks for indoor applications [7]. Other approaches include identifying the presence of a tag and Fingerprinting using previously collected RSS values.

However, the uses of such technology suffer from some drawbacks when considering its application in IF. Both natural and artificial lighting, always present in IF, can interfere with VLP [7]. To solve this problem, approaches exist where the frequency of the light being emitted differs from that of common light sources. This way, the interference is reduced [24]. Another constraint in such systems is managing communication interferences caused by signal collision. To solve this, time division techniques such as TDM [29] are applied. Another often explored solution (FDM) is the division of the light spectrum, giving each LED a different frequency [29].

Nevertheless, the main problem with VLP is the absolute need for LoS[7] since visual light techniques are highly impacted by signal reflections. In the context of this dissertation, where IF is the target environment, the need to ensure LoS is not achievable while keeping transmitters density and costs low due to the highly dynamic environment and building with high dimensions.

Using the comparison of articles aggregated by [7], the following comparison table was created:

Table 2.1: Comparison between Different Methods applied with VLC

# Anchors	# Tags	Test Dimensions	Accuracy	Method	Ref
1	4	6m x 6m x 4.2m	RMS error of 6.1cm	Trilateration RSS	[18]
1	4	10m x 9m x 3.1m	Highest variance error is 0.3m2	Fingerprinting	[39]
1	5	0.71m x 0.43m x 2.36m	90 th percentile of 10cm	AoA	[22]

The three methods compared use RSS, Fingerprinting, and AoA. The accuracies obtained are excellent when considering the desired application. However, the size of the environments where they were tested raises some concerns about the ability of VLC to be applied in big-scale environments such as IF. Particularly the AoA method has significant errors even when considering such a small test bed.

2.1.3.2 RFID - Radio-Frequency Identification

Radio Frequency Identification (RFID) systems usually consist of two parts: the *tags* and the *readers*. Even though different systems may exist, a typical one usually consists of a stationary or mobile *reader* and several *tags* usually affixed to the object of interest. Each *reader* is responsible for interacting with the *tags* that can be found within the range of the wireless signal [11][33] [40]. The use of RFID is often related to the idea of anchor points, and its accuracy depends highly on the density of such points. Two techniques can be used when talking about the coupling between the reader and the tags: NFC and FFC.

NFC requires a close distance between the *reader* and the *tag* and is based on the Inductive Coupling principle. This principle requires the reader to create an EM field; that field will generate an EMF on the tag coil. The EMF on the receiver will then generate an electric current which will, in turn, generate an EM field that the reader antenna can pick up [11].

Three different types of RFID *tags* exist; passive *tags* that rely upon the *reader*'s wave and reflect it back to the *reader* antenna, a phenomenon known as backscattering; a semi-passive *tag* that also uses backscattering and has no transmitter, however, it has a power source usually used to power an Integrated circuit (IC) which enables the storage and communication of dynamic information (e.g., ambient temperature); and active *tags* that have a transmitter and are powered not relying on backscattering [11][5].

Typical implementations of RFID depend on installing readers of passing points, such as doors, those do not apply to the context of this dissertation as IFs may differ in layout, and ample spaces without doors are common in such contexts [16]. Other approaches exist where active tags are used, instead of passive tags, that allow a higher range for each tag [36]:

Table 2.2: Comparison between Different Methods applied with RFID

# Anchors	Accuracy	Method	Ref
16	50th at 0.5m	Fingerprinting RSSI	[19]
-	0.47m	Fingerprinting RSSI	[30]

Available work about RFID is noticeably old when considering state-of-the-art. Available surveys, such as [36] and [13] refer solutions that date back to 2003 [30] and 2000 [19].

2.1.3.3 UWB - Ultra-wide-band

ITU-R defines UWB as a transmission whose bandwidth is larger than 500MHz. It works by transmitting ultra-short pulses over the desired spectrum. UWB system generally uses TOA to calculate distances between Tags and Anchors. Unlike other technologies, TOA is possible in UWB with great results due to high temporal precision, a result of the wide bandwidth and short pulses [17]. UWB can also remain immune to interference caused by electromagnetic waves due to the multitude of frequencies used [25]. The short pulses of UWB enable this technology to filter the influence of multipath reading easier [25]. Also, considering scenarios where Tags and Anchors have their clock synchronized, the technology allows for good accuracies under 15cm in indoor scenarios [41].

Analyzing the pros and cons of UWB in the context of an indoor location in IF, one can conclude this is a promising solution. The accuracy obtained is the biggest advantage of this technology, allied with the excellent adaptability to indoor environments and the ability to filter multipath readings. Also, the ability of UWB to remain immune to interferences caused by other RF systems on the premises makes it a suitable technology for such environments. This, however, comes with its drawback, mainly the price. Deak, Gabriel, et al. (2012) point out costs of $16.875[13], which do not scale to be used on IFs.

2.1.3.4 WLAN - Wireless local area networks

Wifi is the IEEE standard 802.1 for WLAN [26]. Wifi-based solutions are common on IPS systems [25]. It operates on the 2.4GHz and 5.0 GHz bands. Both bands have their drawbacks and advantages. While 2.4GHz allows for more extensive ranges, 5.0GHz has more resistance to fast-fading of the signal [15]. The technology allows for common techniques, such as AoA, TOA and TDOA; however, RSSI is the most commonly used technique when considering Wifi due to the easiness of calculation while keeping good results [28].

One of the most significant advantages of Wifi is the ability to reuse existing infrastructure. Wifi networks are commonly available for other uses than positioning. By reusing existing infrastructure, wifi solutions can achieve a lower budget than solutions where there is the need to introduce readers with the sole purpose of being used in IPS.
Another advantage of using wifi-based solutions is the ability to include smartphones, a common item people carry with them. However, smartphone manufacturers have been throttling wifi scanning due to privacy issues and concerns about these systems being used for actively tracking people without their consent [31]. These policies threaten the ability to use such systems for asset location.

Most work done in the area of Wifi is based on Fingerprinting using RSSI values [20]. Most papers use the same technology and approach; however, they try to improve how the position is found among the Fingerprint information. KNN [8], and Weighted Probabilistic [43] are common techniques used to estimate a tag's position when considering the RSSI values read from the anchors [20].

When analysing the ability to use a Wifi-based technique in an IF environment, one of the most significant challenges in this technology is the problem of multipath, which can lead to a decrease in the system's accuracy.

Analysing the work done with Wifi, based on the information gathered in [20],[25], the following results were taken:

Table 2.3: Comparison between Different Methods applied with Wifi

# Anchors	# Tags	Test Dimensions	Accuracy	Method	Ref	Notes
3	-	43.5m x 22.5m	2.94m at 50%	Fingerprinting RSS	[8]	Used 70 Reference Points
21	-	68.2m x 25.9m	0.6m at 50%	Fingerprinting RSS	[43]	Used 110 + 62 Reference Points

As the solutions described use the Fingerprint approach, the dynamics of the environment can pose a problem to solutions that depend on pre-calculated values of RSSI. However, the result shows good accuracy for both papers, but mainly for [43]. This comes with a problem, the high density of anchors needed to achieve the accuracy showed. Also, both solutions depend on a high value of reference points (70 and 172 reference points). This makes the solution hardly adjustable to environmental changes and complicates the setup process. The first solution([8]) is promising and keeps the needed anchors at a reasonable amount, considering the area of tests. The accuracy is not as good as the other solution but is yet practical considering the size of IFs and the desired accuracy of the final system.

2.1.3.5 BLE - Bluetooth-Low-Energy

Bluetooth Low Energy was introduced to solve problems often found in standard Bluetooth, mainly the high energy consumption. It operates on the 2.4GHz band (similar to wifi) and has most advantages and drawbacks of Wifi-based solutions. It allows the use of RSSI, TDoA, ToA and, more recently, the calculation of AoA. The introduction of the ability to calculate AoA in the BLE standard turn BLE into a powerful alternative to Wifi solutions, allowing for more flexible solutions.

BLE also allows for the use of technology to transmit information between Tags and Anchors, making those systems useful for more than asset location.

Table 2.4: Comparison between Different Methods applied with BLE

# Anchors	# Tags	Test Dimensions	Accuracy	Method	Ref
6	-	6.1m x 12.2m	1.7m	Fingerprinting RSSI	[32]
3	-	-	1.5m	Trilateration RSSI	[27]

The use of BLE results in values that allow for accurate localization of assets while keeping the consumption of energy and setup costs low, allowing real-time tracking.

2.1.4 Technologies Comparison

When comparing the results obtained from the multiple technologies described in this chapter and putting them under a critical view, some technologies are discarded when considering them for the context of this dissertation. VLC requires the ability to maintain LoS, which is often impossible while keeping a viable number of Anchors.
Considering RFID, the two possibilities explored are both inadequate for IFs. The use of readers on passing points, e.g., doors, cannot be achieved since IFs are often ample buildings without clear divisions. The fingerprinting approach is also not viable since it would lead to expensive

setup costs due to the high density of readers.

After the first filtering step, the technologies left are the ones that allow using techniques other than fingerprinting and do not have the requirement of LoS. Only UWB, BLE, and Wifi meet those requirements. UWB presented excellent results and high immunity to the multipath problem. However, the use of such technology is yet too expensive for ample buildings such as IFs.

Considering the cost criteria, only Wifi and BLE are left in this context. When comparing both technologies, one has to consider that they both use similar approaches and are RF based, using the same 2.4GHz band. Between these solutions, BLE stands out for the ability to calculate AoA, an interesting approach to be considered, and the low energy consumption compared with Wifi.

After considering the available information, always keeping the context of IFs, and the ability to use the solution to exchange information rather than only use it for location purposes, BLE stands out. Even though it is not the technology with higher resolutions, it is the one that allows for more flexible approaches and low costs, which is essential for IFs.

2.2 BLE - Bluetooth Low Energy

After the considerations made in the previous section, the focus of the investigation must change to understand BLE and the techniques that this technology allows to use.

The BLE technology was introduced in 2006 by Nokia under Wibree and later into the Bluetooth standard as Bluetooth Low Energy[4]. The main focus of the technology is in scenarios where low energy consumption is needed. BLE allows for more than the common uses of Bluetooth (audio streaming and data transfer). The standard also allows for Location Services and Device networks. Device networks are enabled by the multiple device communication layouts, not limited to the Point-To-Point. It includes Point-To-Point, Mesh, and Broadcast [1]. As for the Location Services, they can be divided into three different approaches:

- Presence (Section 2.2.1)
- Distance (Section 2.2.2)
- Direction (Section 2.2.3)

A network can be composed of many roles. The two mainly used are **Central** and **Peripheral**. A **Peripheral**s is usually an embedded device with low energy consumption requirements. A **Central** is usually the other end of the system, devices where energy consumption is not as restricted as in **Peripheral**. This is due to the differences between both roles, as the **Central** role has higher consumption levels.

The process of communication begins with the **Advertising**. The **Peripheral** sends a transmission known as **advertisement**. This transmission contains an identifier of the **Peripheral** and Manufacturer Information and PDU; PDU (Protocol Data Unit) includes the type of packet transmitted and custom data. In addition, an extra part known as CTE can be added to the end of the packet, being used in applications such as direction finding. This packet, even though limited in size, can be used in multiple scenarios other than information sharing and connection establishment. These include Direction Finding, RSSI measurements, and simple presence detection. When a **Peripheral** is only responsible for sending **advertisement** packets without the need for a connection, it becomes a **Broadcaster**. Following the same principle, a **Central** that is only interested in **advertisement** packets is called an **Observer**.

A **Central** is responsible for the **Scanning** process. The **Central** periodically scans the previously established Advertisement channels looking for an advertisement sent by the **Peripheral**. BLE operates on the 2.4GHz spectrum (2.402 - 2.480 GHz) and divides the spectrum into 40 channels each with a 2MHz width. Three channels are the Primary advertising channels, whilst the remaining 37 are Data/Secondary advertising channels. Figure 2.1.

Regarding Advertisement, two types of advertising PDUs exist, the Legacy and the Extended, introduced in the 5.0 standard. The Extended mode also includes PDUs described in the pre-5.0 version. The PDU can often be described as a composition of the following terms:

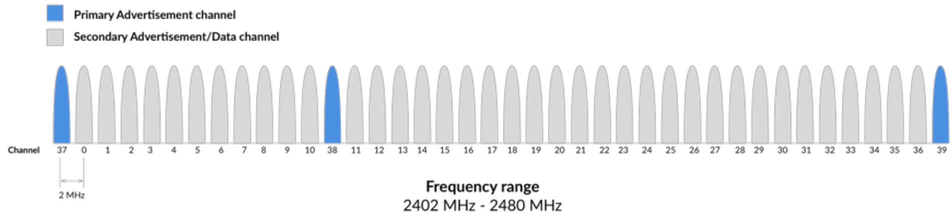

Figure 2.1: BLE Channels

- **Connectable** vs. **Non-Connectable**. it describes whether the advertising device accepts or not a connection request.
- **Directed** vs. **Undirected**. It describes whether the advertising device accepts (**Undirected**) or not (**Directed**) connection requests from unknown peer devices.
- **Scannable** vs. **Non-Scannable**. Scannable devices allow a request to be made by the **Central/Observer** to the advertiser, followed by a response back to the **Central/Observer**. This is useful when there is a need to exchange more information than the amount allowed in the advertising packet.

A significant change in the PDUs included in the 5.0 standard is the introduction of special PDUs with an increased payload of 252 bytes per packet compared to the 31 bytes allowed in the Legacy type.

Table 2.5: PDU table

Name	Channel	Connectable	Undirected	Scannable
ADV_IND	Primary	X	X	
ADV_DIRECT_IND	Primary	X		
ADV_NONCONN_IND	Primary			
ADV_SCAN_IND	Primary	X	X	X

The Extended mode uses the ADV_EXT_IND and AUX_ADV_IND. The ADV_EXT_IND is used for advertising on the primary channel and cannot hold any data; this is used to specify the secondary channel the central should scan. After this, the **Peripheral** device sends AUX_ADV_IND to the specified secondary channel, which can hold up to 252 custom bytes of data. The type of connection (as in the legacy mode) should be specified in both ADV_EXT_IND and AUX_ADV_IND packets.

The use of the extended mode, in association with a scan request, can allow a connectionless communication of up to 504 (252 + 252) bytes instead of the 62 (31 + 31) bytes of legacy mode with a scan request.

The location services (Presence, Distance, and Direction) need nothing more than the Advertisement process, as they only rely on the Transmission itself rather than the transmitted data.

Direction also needs the CTE extension; This, however, can be included in the advertisement transmission. The Connected mode is only needed for a system that requires more information than allowed in the advertisement process.

Following the advertising step, a Central may connect to a **Peripheral** which PDU indicates the device allows for connections.
The **Central** sends a request to connect. Once the advertiser receives the request, the connection is established. From now on, both the **Central** and the **Peripheral** can initiate data exchange.

The connected mode allows for more data exchange than the connectionless mode. However, most devices (Centrals) limit the number of connected nodes simultaneously. This limitation poses a problem to the system's scalability. The connectionless-mode is also limited, by the number of advertisement packets that can be sent which in turn is limited by signal interference from multiple **Peripherals**. This interference is hard to quantify has it is caused by RF interference.

2.2.1 Presence

One of the applications of BLE concerning location is the identification of devices in close range. This can be done in one of two ways:

- By calculating the distance between the **Central** and the **Peripheral** more in subsection 2.2.2.
- By relying on received packets.

The presence of a device may be identified by the use of Advertisement packets sent by the device. The device sends Advertisement packets, either upon a trigger or periodically; once the **Central** receives the packet, it can proceed with further information exchange. Since the **Central** has been able to communicate with said device, it can conclude on its presence. This system, however, is hardly reliable as the device range is often hard to control and measure, rendering this approach only practical to systems where coarse presence information is needed.

2.2.2 Distance

BLE is often used to calculate the distance between two devices. Distance estimation allows calculating a spherical surface when considering a 3D environment or a circle for 2D scenarios.

These represent every point that distances the same to the reference point. When associated with other methods, such as trilateration, one can intersect three circles or four spherical surfaces from different reference points and find the position of the wanted device. In reality, intersecting with known obstacles often reduces the number of anchors needed. For instance, if a device is known to be on the floor, the floor provides a surface of reference, reducing the needed 3D anchors from four to three. Also, when a room schematic is known previously, one can assume a device position to be on a shelf, possibly reducing the number of needed anchors.

Other approaches combine distance estimations with other types of methods. Also, approaches exist where a ring is used instead of a circle, taking measurement errors into consideration [38].

Regarding distance calculation itself, some new methods are appearing based on the Constant Tone Extension (CTE), refer to [44]. However, the most used method is based on RSSI of the BLE signal.

2.2.2.1 RSSI - Received signal strength indication

Work developed, such as [38], take different approaches when calculating the distance value, and achieve errors below the 1m value. These methods, however, depend highly on environmental variables and are prone to errors introduced by reflections. And its accuracy is highly dependent on the values read on the initial setup.

RSSI on BLE can be measured at every received transmission. Both Advertisement-related packets and communications in connected mode provide the ability to read the signal strength. This fact allows combining the read of the RSSI value with the transmission of important information as well as the use of the direction-finding capabilities of BLE.

As mentioned in Section 2.2.1, RSSI-based distance measurements allow the identification of a device's presence at a much higher precision than the solution presented by the sole use of Advertisement transmissions.

2.2.3 Direction

Another approach that can be used when identifying the position of assets is using Direction instead of Distance. Considering the imaginary straight line connecting two devices, the Direction is the angle the line makes with the plane of the device. When considering two devices, an anchor and the device being located, two techniques can be derived:

- Angle-Of-Arrival in Section 2.2.3.1
- Angle-Of-Departure.

The Direction calculation alone does not solve the location problem, as it only provides a vector where the device is located with an unknown length. In order to find the proper location, there is a need to find the vector length. This can be achieved by combining it with another anchoring device, given that the two anchors and the device are not colinear. The intersection of two vectors from two anchors allows one to locate the device. Another way is to combine it with distance estimation, where the distance to the device is the length of the vector.

As in distance estimation, real-life situations can provide opportunities to improve the system and reduce the need for anchors. Considering the devices are on the floor, and the plane of the anchor device is parallel to the floor, being the distance between the said plane and the floor known, one can calculate the intersection between the floor and the Direction, finding the device location.

2.2.3.1 AoA - Angle of Arrival

The ability to calculate Angle-Of-Arrival using BLE was introduced in Bluetooth standard 5.1. The standard itself provides the necessary features to calculate the angle. It introduced the CTE

(Constant Tone Extension) that enables the extraction of the I and Q component of the sent CTE upon receiving the signal. Fig 2.2.

I and Q can then be used to calculate the phase of the received signal at the antenna by using the following function $cos(Q/I)$.

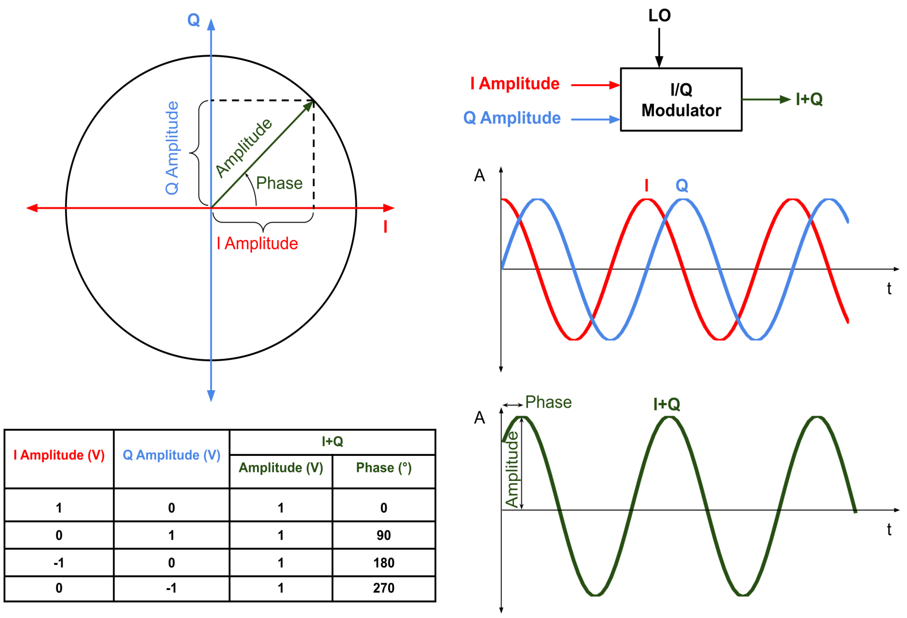

Figure 2.2: I and Q

The receiving device samples the CTE in a way that, if the same antenna reads the signal, the phase is always the same. The number of samples depends on the device manufacturer. However, it is related to the number of cycles of the CTE as well as the frequency of the signal.

The receiving device needs to be able to switch the antennas that are reading the signal. Different antennas have different propagation times, so the phase reading will differ between antennas. Knowing the phase difference and the distance between the antennas, a simple trigonometric equation can be used to calculate the angle to the device:

$$\theta = arccos(\frac{\psi\lambda}{2\pi d})$$

.

Symbol	**Description**
ψ	The phase difference between the antennas
λ	The wavelength of the CTE signal
d	The distance between the antennas

When calculating the AOA, a special receiver is needed. The receiver needs to be able to switch between antennas in order to receive the signal and calculate the Phase difference between readings of the antennas.

Such a receiver, an array of antennas, may have antennas both in horizontal and vertical alignments. This allows for the calculation of the angle in a 3D scenario. Further, even though the simplest method relies on using the phase shift between two antennas, other methods such as MUSIC[23] and PDDA[42] use more than two, improving results.

2.3 BLE Techniques Evaluation

Based on the conclusions drawn from this chapter, when considering the context of the dissertation and its requirements, the final solution will be based on BLE. Analyzing the available techniques, the usability of Fingerprinting would be a possible solution; however, this has the drawback of a complex setup step, and the result is heavily hindered by the presence of objects and people that were only introduced after the setup stage. When considering the triangulation approach, mainly the use of trilateration or angulation, both solutions require a high level of Anchors to work, even though angulation, as specified before, can achieve positioning with only two anchors within the tag range.

Hybrid approaches often combine unique features of multiple techniques to achieve better results. With that in mind, the proposed approach is a hybrid approach between angulation and trilateration. This is mainly due to the ability to, with this approach, reduce the required number of anchors to one, given it is in range of the tags. This allows for a reduced density of Anchors to achieve a solution that can scale to an ample building, where the main constraint is the range of the devices.

The approach is based on AoA plus a distance measurement. The AoA gives the ability to estimate the direction, and the distance estimation will give the distance along that direction. This allows to use a single anchor to estimate the position of each tag.

Chapter 3

Project Requirements and Desired Functionalities

3.1 Formal presentation of objectives

This chapter provides a clear and structured overview of the project's goals, highlighting the key areas that will be addressed throughout the project's lifecycle. By formalizing the objectives, the chapter establishes a solid foundation for the subsequent research, development, and evaluation stages.

Each objective is presented concisely and logically, emphasizing the importance of various aspects such as cost-effectiveness, signal processing algorithms, energy optimization, low-budget computing, system efficiency, accuracy, and reliability. The chapter serves as a roadmap for the project, guiding the reader through the specific targets that will be pursued to accomplish the ultimate goal of achieving affordable and accurate asset localization using BLE technology.

1. Implement signal processing algorithms:
    - Study the Bluetooth direction finding specifications and understand the signal parameters available for analysis (e.g., AoA, AoD, received signal strength).
    - Develop software algorithms to extract and process the relevant signal measurements from each antenna in the array.
    - Explore techniques for signal filtering, noise reduction, and calibration to enhance the accuracy of the measurements.
2. Achieve 3D asset localization using the array of antennas as the sole reference:
    - Investigate location estimation methods suitable for Bluetooth direction finding, such as triangulation, trilateration, or multilateration.
    - Develop algorithms that leverage the antenna array measurements to estimate the asset's location in three-dimensional space.

- Consider factors like antenna geometry, signal propagation characteristics, and potential signal reflections for accurate positioning.

3. Enable the use of low-budget computers for processing the antenna array data:

   - Develop software compatible with low-budget computers, utilizing lightweight programming languages and frameworks.
   - Optimize the software implementation to run efficiently on the limited resources of the chosen low-budget computers.
   - Ensure seamless communication between the antenna array and the low-budget computers, allowing data retrieval and processing.

4. Ensure the system can operate efficiently with limited power sources:

   - Consider the power requirements of the chosen low-budget computers and design the system to operate within their power capabilities.
   - Optimize the software algorithms to minimize computational load and maximize power efficiency.
   - Explore energy harvesting techniques, such as solar or kinetic energy, to supplement or extend the power source for the asset tracking system.

5. Design the system to provide accurate and reliable asset localization in various environments:

   - Conduct extensive testing in different environments, including indoor and outdoor scenarios, to evaluate the system's performance and identify potential challenges.
   - Fine-tune the signal processing algorithms to account for environmental factors like signal interference, multipath propagation, and varying signal strengths.
   - Incorporate error correction mechanisms and validation techniques to improve the accuracy and reliability of asset localization.

6. Explore location estimation techniques:

   - Investigate the suitability of location estimation techniques such as triangulation, trilateration, or multilateration considering the antenna array configuration and signal measurements available.
   - Develop algorithms specific to the chosen technique, accounting for the geometric layout of the antenna array.
   - Optimize the algorithms for accuracy and efficiency, considering factors like noise mitigation, estimation errors, and computational complexity.

7. Validate the performance of the system through rigorous testing and evaluation in different scenarios:

- Create test scenarios representing various asset positions and orientations within the system's coverage area.
- Collect data from the antenna array and compare the calculated asset positions with ground truth measurements to assess accuracy.
- Perform statistical analysis to evaluate the system's performance metrics, such as localization error, precision, and robustness against environmental factors.

3.2 Requirements and functionalities

3.2.1 Asset Localization

The system should provide highly accurate localization of the asset in three-dimensional space using the array of antennas as the sole reference. The localization precision should meet the specified project requirements.

The asset localization requirement is essential for the project's success. The system needs to accurately determine the asset's position and orientation in 3D space based on the received signal measurements. The localization precision should be carefully defined and determined based on the specific use case and application requirements. Factors such as the desired accuracy, distance range, and environmental conditions should be considered during the analysis.

3.2.2 Cost-Effectiveness

The project should be designed with a focus on affordability, utilizing cost-effective Bluetooth antennas and low-budget computing resources. The overall cost of the system should be within a predetermined budget limit.

Cost-effectiveness is a critical factor for the successful implementation of the project. The choice of Bluetooth antennas should be based on their cost, performance, and compatibility with the direction-finding feature introduced in the Bluetooth Low Energy 5.1 specification. Additionally, low-budget computing resources, such as Raspberry Pi Zero W, should be utilized to keep the overall system cost within the specified budget limit. A thorough analysis of available options and cost-performance trade-offs should be conducted during the selection of components and resources.

3.2.3 Energy Efficiency

The asset end of the system should exhibit optimized energy consumption to prolong battery life and minimize power requirements. Power management techniques, such as duty cycling, sleep modes, and energy-efficient algorithms, should be employed to achieve energy efficiency.

Energy efficiency is crucial to ensure long battery life and reduce the need for frequent recharging or replacement. The power consumption of the asset end should be carefully analyzed to identify energy-intensive components or operations. Power management techniques, such as duty cycling and sleep modes, can be implemented to reduce energy consumption during idle periods. Additionally, energy-efficient algorithms should be employed to minimize computational load and optimize the use of available resources.

3.2.4 Compatibility with Low-Budget Computers

The system should be designed to work seamlessly with low-budget computers, such as Raspberry Pi Zero W, enabling the processing of antenna array data without substantial power consumption. The software should be tailored to the limited resources of these computers and ensure efficient data exchange with the array.

Compatibility with low-budget computers is essential for extending the system's usability and affordability. The software should be optimized to run efficiently on the limited resources (processing power, memory) of low-budget computers. Data exchange protocols and interfaces should be designed to minimize power consumption during communication with the antenna array. The compatibility analysis should consider the capabilities and limitations of the chosen low-budget computers to ensure seamless integration and optimal performance.

3.3 Project Use Cases and real-world applications

To better understand the project and its implications, it is crucial to specify the use cases where the system can be deployed. Use cases define the specific scenarios, environments, and challenges that the project aims to address. By clearly defining use cases, we can delve into the technical and functional requirements unique to each application domain. This allows for a more comprehensive analysis of the system's capabilities, constraints, and potential benefits in real-world settings. Additionally, use cases provide a practical framework for evaluating the project's performance, ensuring that the developed solution meets the specific needs and expectations of the targeted industries or applications. By specifying use cases, we can gain deeper insights into the project's relevance, feasibility, and potential impact, enabling more effective development, implementation, and validation of the asset localization system.

3.3.1 Industrial Asset Tracking

The project can be applied in industrial environments to track and locate valuable assets, such as machinery, tools, or equipment. By attaching Bluetooth-enabled tags to the assets, their precise location can be determined using the array of antennas. This allows for efficient asset management, inventory control, and optimization of asset utilization within the industrial setting.

Technical Aspects:

- Bluetooth-Enabled Tags: Attach Bluetooth tags to each asset of interest, programmed to transmit their unique identifiers periodically.

- Antenna Array Configuration: Deploy a carefully designed array of antennas, strategically placed within the industrial environment to ensure optimal coverage and signal reception.
- Signal Processing: Develop sophisticated algorithms to process the received signal measurements from the antenna array, including signal filtering, noise reduction, and calibration.
- Localization Estimation: Utilize advanced localization techniques, such as trilateration or multilateration, to estimate the precise position of each asset based on the received signal measurements from multiple antennas.
- Data Visualization and Asset Management: Provide a user-friendly interface or dashboard to visualize the real-time location of assets, track their movements, and manage inventory efficiently.

Benefits:

- Enhanced Asset Utilization: Accurate asset tracking enables efficient allocation of resources, reduces asset search time, and optimizes asset utilization within the industrial environment.
- Improved Inventory Control: Real-time visibility of asset location allows for better inventory management, preventing loss or misplacement and facilitating inventory audits.
- Streamlined Maintenance Operations: Knowing the precise location of assets simplifies maintenance operations, enabling faster response times, proactive servicing, and improved maintenance scheduling.
- Cost Savings: Avoiding the need for manual asset searches and reducing asset loss or misplacement leads to cost savings in terms of time, labor, and asset replacement.

3.3.2 Warehouse Inventory Management

The project can be applied in warehouse operations to track and manage inventory. Bluetooth-enabled tags attached to items can be accurately located using the antenna array. The system can provide real-time information on the location and availability of inventory, enabling streamlined order fulfillment, improved inventory accuracy, and efficient warehouse operations.

Technical Aspects:

- Bluetooth-Enabled Tags: Attach Bluetooth tags to each inventory item, programmed to transmit their unique identifiers periodically.
- Antenna Array Configuration: Deploy a strategically designed array of antennas throughout the warehouse to ensure comprehensive coverage and reliable signal reception.
- Signal Processing: Develop algorithms to process the received signal measurements from the antenna array, extracting relevant information and filtering out noise or interference.

- Localization Estimation: Utilize precise localization techniques, such as trilateration or multilateration, to estimate the position of each tagged item based on the received signal measurements from multiple antennas.
- Warehouse Management System Integration: Integrate the asset tracking system with a warehouse management system or inventory management software to provide real-time updates on inventory location, stock levels, and movement history.

Benefits:

- Accurate Inventory Tracking: Real-time information on the location and availability of inventory items enables efficient order fulfillment, reduces stockouts, and improves inventory accuracy.
- Improved Warehouse Efficiency: Asset localization streamlines warehouse operations by reducing the time spent searching for items, optimizing picking routes, and facilitating inventory audits.
- Increased Customer Satisfaction: Prompt order fulfillment, accurate inventory availability, and reduced delivery lead times contribute to enhanced customer satisfaction and loyalty.
- Error Reduction: By automating inventory tracking and reducing manual data entry, the system minimizes human errors, ensuring accurate inventory records and reducing the likelihood of shipping incorrect items.

3.3.3 Healthcare Asset Management

The project can be applied in healthcare facilities for asset tracking and management. Bluetooth tags attached to medical equipment or mobile assets, such as infusion pumps or wheelchairs, can be located using the antenna array. This allows for efficient asset utilization, reduction of equipment loss, and improved patient care by ensuring the availability of critical assets when needed.

Technical Aspects:

- Bluetooth-Enabled Tags: Attach Bluetooth tags to medical equipment or assets, programmed to transmit their unique identifiers periodically.
- Signal Processing: Develop algorithms to process the received signal measurements from the antenna array, applying noise reduction, calibration, and filtering techniques to enhance accuracy.
- Localization Estimation: Utilize advanced localization techniques, such as trilateration or multilateration, to estimate the position of each tagged asset based on the received signal measurements from multiple antennas.

- Asset Tracking Integration: Integrate the asset tracking system with the hospital's asset management software or medical equipment inventory system to provide real-time asset location information and enable efficient asset allocation and utilization.

Benefits:

- Enhanced Asset Visibility: Real-time asset tracking and location information ensure the availability and timely access to critical medical equipment, improving patient care and reducing equipment search time.
- Efficient Asset Utilization: Accurate asset tracking enables better resource allocation, reduces equipment hoarding, and improves overall equipment utilization in healthcare facilities.
- Cost Savings: Minimizing equipment loss or misplacement and optimizing equipment utilization leads to cost savings by reducing replacement costs and improving operational efficiency.

These use cases demonstrate the versatility and potential of the project in addressing asset tracking and management challenges in various domains, including industrial settings, warehouses, and healthcare facilities. By leveraging accurate asset localization, the project provides tangible benefits such as optimized asset utilization, improved inventory control, and enhanced operational efficiency in real-world applications.

The results obtained from the project and its application to specific use cases provide valuable insights and answers to critical questions, further enhancing our understanding of the solution and identifying potential drawbacks. These results enable us to gain deeper knowledge about the performance and limitations of the asset localization system in real-world scenarios. By analyzing the results, we can address the following key questions:

1. **Accuracy and Precision:** How accurate and precise is the asset localization system in different environments and conditions? What is the extent of error or deviation in determining the asset's position in three-dimensional space?
2. **Reliability and Robustness:** How reliable is the system's performance over extended periods? Does it exhibit consistent accuracy and maintain reliability even in the presence of signal interference, obstructions, or challenging environmental factors?
3. **Real-world Performance:** How does the system perform in real-world applications and use cases? Does it meet the specific requirements and objectives of the targeted industries or applications, and what are the key performance indicators for success?
4. **Scalability and Expansion:** Can the system be easily scaled up to accommodate a larger number of assets or an expanded coverage area? What are the considerations and limitations when expanding the system's capabilities?

5. **Future Enhancements and Development Opportunities:** Based on the project's results, what are the potential areas for further improvements or future development? What additional features, functionalities, or enhancements could be incorporated to optimize the system's performance and address evolving industry needs?

Chapter 4

Solution Architecture and Implementation's High-Level View

The architecture of a system plays a vital role in defining its structure, components, and interactions. In the context of the project, the architecture chapter provides a comprehensive overview of the system's design, components, and their interconnections. This chapter delves into the technical aspects of the project, presenting a detailed analysis of the solution's architecture and the underlying principles guiding its implementation.

The primary objective of this chapter is to provide a clear understanding of how the various components of the asset localization system are organized and function together to achieve accurate asset tracking. By presenting the architecture, we aim to elucidate the logical and physical arrangement of the system, including the roles and relationships of the key elements involved. This allows for a holistic view of the project's structure, enabling stakeholders to grasp the system's intricacies and the flow of information within it.

Throughout this chapter, we will explore the core components of the architecture, including the Bluetooth-enabled tags, antenna array, signal processing module, localization algorithm, and data visualization and management component. Each component's purpose, functionalities, and integration within the overall system will be elucidated, providing a comprehensive understanding of their roles in enabling accurate asset localization.

4.1 Logical High-Level Architecture

The high-level diagram presented in this sub-section specifically focuses on the software approach of the project architecture. It provides an overview of the key software components and their interactions within the asset localization system. While the diagram emphasizes the software aspect, it is important to note that hardware components, such as Bluetooth-enabled tags and the antenna array, are essential elements of the complete system. However, the high-level diagram primarily aims to illustrate the logical flow and dependencies of the software components involved in achieving accurate asset localization. Further sub-section 4.2 will delve into the hardware components and their organization, including the configuration and deployment of the antenna array and the integration of Bluetooth-enabled tags.

The system can be specified, on a high level by the following diagram:

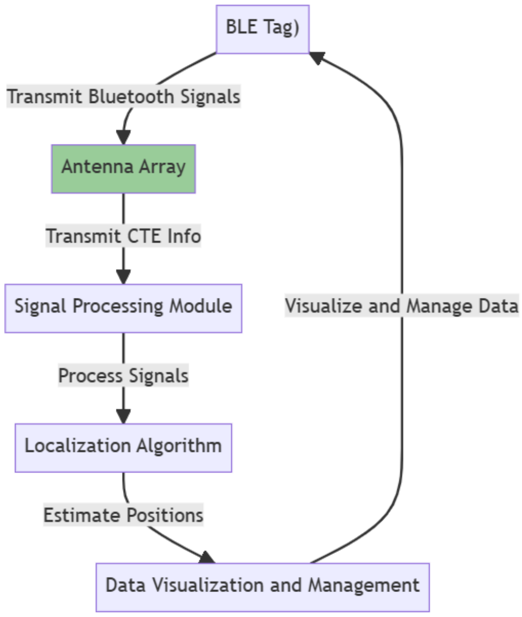

Figure 4.1: High-level Diagram of the Execution Pipeline

1. **Bluetooth-Enabled Tags:** The Bluetooth-enabled tags are attached to the assets that need to be tracked and localized. These tags periodically transmit their unique identifiers using BLE technology. The transmitted signals serve as the basis for asset localization.

2. **Antenna Array:** The antenna array consists of multiple antennas strategically positioned within the deployment area. The array is designed to receive the signals transmitted by the Bluetooth tags. The antennas are arranged to ensure comprehensive coverage of the area of interest and optimize signal reception.

3. **Signal Processing Module:** The signal processing module receives the signals captured by the antenna array. It performs various processing tasks, noise filtering, and interference mitigation. The module applies advanced signal processing algorithms to enhance the received signal quality and extract relevant information for accurate localization.

4. **Localization Algorithm:** The localization algorithm utilizes the processed signal measurements from the signal processing module to estimate the position of the assets in three-dimensional space. The algorithm employs techniques based on the angle of arrival.

5. **Data Visualization and Management:** The localization results are visualized and presented through a user interface or dashboard. This component allows users to monitor the real-time locations of assets, track their movements, and manage inventory efficiently. It provides a user-friendly interface that displays asset positions on a map or floor plan.

The project architecture revolves around the interaction between the Bluetooth-enabled tags, antenna array, signal processing module, localization algorithm, and data visualization and management component. The tags transmit signals that are captured by the antenna array, and the signal processing module enhances and analyzes these signals. The localization algorithm then processes the signal measurements to determine the precise positions of the assets. Finally, the data visualization and management component presents the localization results in a user-friendly manner, allowing users to efficiently track and manage assets.

By incorporating these components into the project architecture, the asset localization system enables accurate tracking and management of assets in real-world applications. The detailed architecture ensures a systematic and efficient flow of data, signal processing, and visualization, leading to reliable and actionable asset localization information.

4.2 Hardware High-Level Architecture

The hardware architecture of the system consists of two main components: the asset with a BLE tag and the station with an antenna array and a computer. The BLE tag transmits signals that serve as the source for localization, while the antenna array together with a DK captures these signals and provides input to the localization system. The computer hosts the signal processing module and localization algorithm, responsible for processing the signals and estimating the asset's position.

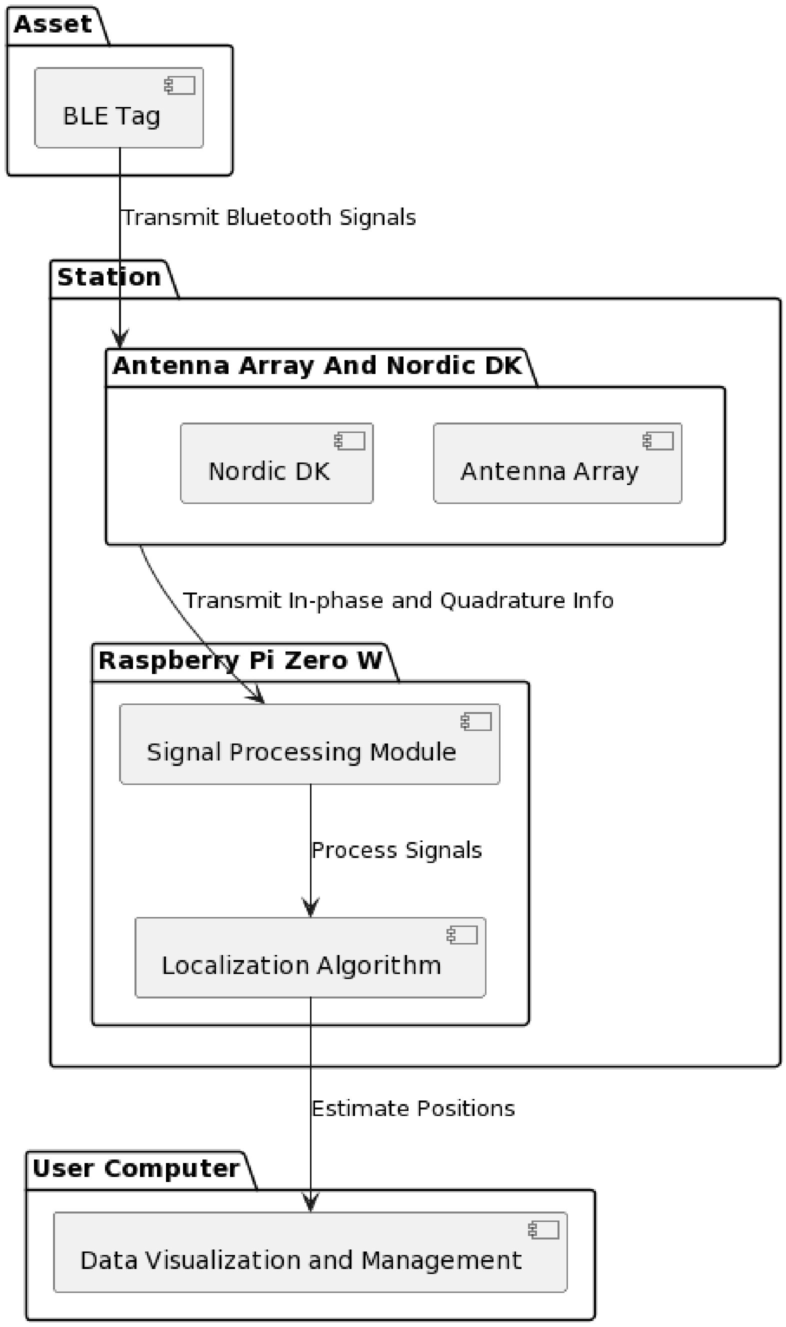

Figure 4.2: High-level Diagram of the Execution Pipeline Focusing on the Hardware organization

4.3 System in-depth description

There is the need to explain in detail the way the system works.

The system is comprised by:

- Two Nordic DK, more specifically two Nordic nrf 52833 that are responsible for the AoA low level part
- One RPI Zero W which is responsible for the computational part of the system
- An Array of antennas, that is essential to allow AoA calculations

The two Nordic DKs start by synchronizing before they can start the communication with the CTE info that allows for the AoA. The BLE 5.1 standard allowed for the introduction of the CTE part on the end of the BLE packets, see 4.3.

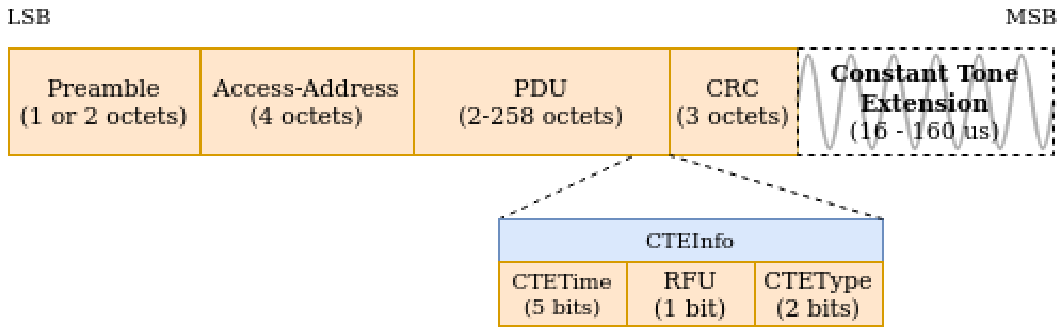

Figure 4.3: Packet with CTE

The asset then sends an advertisement packet with the CTE. This is read by the receiving DK with the help of the array of antennas (Fig. 4.4).

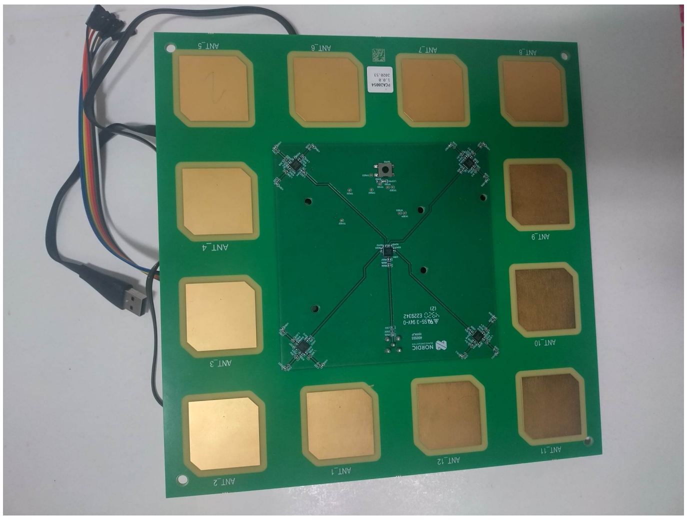

Figure 4.4: Photo of the array of antennas

The receiving DK is coupled to the array of antennas and uses it to receive the signals sent to it. When it reaches the time to read the CTE, it starts the sample process. It however does not sample the CTE always with the same antenna, in fact it switches periodically between antennas to retrieve I and Q information of the CTE from different antennas of the array. This switch is fundamental to the work of the AoA. Looking at figure 4.5, we can understand the way the angle is calculated.

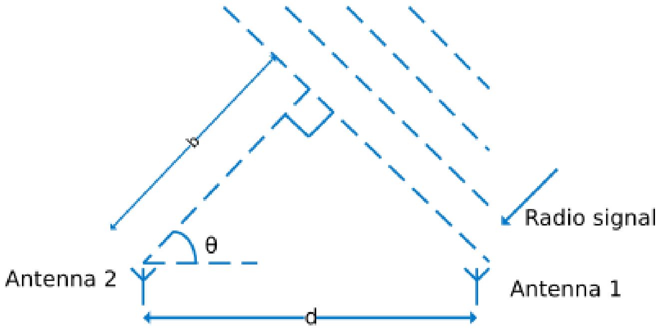

Figure 4.5: AoA Basis

In this case we want to calculate the angle θ. An important requirement for the system to work is that the wave that reaches the antenna is already planar, otherwise equations do not work as the wave would reach different antennas in unpredictable ways.

`b` is the distance the signal has to travel from when it reaches the antenna 1 until it reaches antenna 2. This distance `b` depends on θ.In the context of the equation $\theta = \arccos\left(\frac{b}{d}\right)$, where θ represents the angle of interest, d represents the distance between the antennas, and b represents the unknown value that needs further calculation, it is essential to determine the value of b in order to accurately estimate the angle.

The whole point of the CTE is to allow to identify, on the receiving end the phase the signal reaches each reading antenna. If two samples are made form the same antenna, the phase of the signal should be of 0 rad. In cases where the phase drifts from the 0 rad value it means that the two readings were not made from the same antenna and the phase difference actually represents the delay of the signal to reach one of the antennas after it reached the other.

Since we know the wavelength of the signal, which represents a full cycle, one can leverage that in order to find the distance `b`. Since samples allows us to identify the phase of the signal when it reaches each antenna, we can calculate the phase difference between two antennas. We can then relate it with the distance travelled by the signal on a full cycle and we reach

$$b = \frac{\psi\lambda}{2\pi},$$

where ψ is the phase difference and λ is the wavelength both in meters.

Then, in order to find θ we only need to use the $arccos()$ trigonometrical function and end up with:

$$\theta = \frac{\psi\lambda}{2\pi d}.$$

An important design feature of the array of antennas is the existence of antennas in two different directions, this allows to calculate both azimuth and altitude, which in turn allows to find a vector direction.

This calculations however do not occur on the DK. The station's DK is only responsible to extract the I and Q values of the CTE using the array. Those values are then transmitted to the RPI using a USB cable.

The RPI then calculates the angles and applies all the filtering and clustering in order to improve the results. The results are then transmitted to an external computer using HTTPS which shows the estimated location on real-time in a visual way.

Chapter 5

Implementation and Experimentation Sprints

This chapter provides an in-depth exploration of the development process employed for the asset localization system. Throughout the project, the development approach embraced a sprint-based methodology, with each sprint typically lasting two weeks. This iterative approach allowed for incremental progress, building upon previous work and leveraging experimentations and results to drive design decisions.

This chapter aims to elucidate the implementation process and highlight the critical aspects of each sprint. The iterative nature of the sprints enabled us to tackle challenges, refine algorithms, and make informed design choices based on the insights gained from experimentation and analysis of the system's performance.

We focused on specific objectives during each sprint, such as improving signal processing techniques, enhancing localization algorithms, or refining data visualization and management. The results from each sprint served as valuable feedback, informing subsequent iterations and shaping the system's evolution.

By following a sprint-based approach, the development process fostered adaptability, responsiveness, and continuous improvement. Experimentations within each sprint allowed us to validate hypotheses, assess the feasibility of design choices, and identify areas for optimization and refinement. The outcomes of these experiments played a pivotal role in driving the project forward, ensuring that decisions were grounded in practical evidence and aligned with the project's objectives.

Throughout this chapter, we will delve into the details of each sprint, outlining the objectives, methodologies, and outcomes. We will discuss the experiments, challenges encountered, and insights gained from analyzing the results. Additionally, we will explore how the findings from previous sprints influenced subsequent design decisions, leading to an iterative and progressive development process.

5.1 Hardware sanity check and First Setup

In the initial stage of the implementation phase, the focus was on conducting a hardware sanity check and establishing the fundamental setup for the asset localization system. This stage aimed to validate the functionality and compatibility of the hardware components, ensuring a solid foundation for subsequent development iterations.

The primary objective of this thesis stage was to assess the hardware components' performance and their ability to capture and process signals accurately. Were conducted rigorous tests to verify the functionality and reliability of the Bluetooth-enabled tags and antenna array. This included verifying signal reception, transmission reliability, and compatibility between the components.

The results and insights gained from this stage laid the groundwork for subsequent stages, shaping the development roadmap and influencing design decisions. The hardware sanity check and the initial software setup provided a solid starting point for further refinement and enhancement of the asset localization system.

In the following sections, we will delve into the details of the experiments conducted, the challenges encountered, and the outcomes of this stage. This will provide a comprehensive understanding of the initial steps taken to ensure the proper functioning of the hardware components and the establishment of a robust software foundation for the project.

5.1.1 Check Antenna Sanity using RSSI Values

In the process of developing the asset localization system, it is crucial to ensure the proper functioning and reliability of the antenna array. One of the key aspects to validate is the signal strength received by each of the 12 antennas in the array. To assess the performance and sanity of the antennas, this section was dedicated to evaluating the RSSI values obtained from empirical tests.

The RSSI values serve as quantitative measurements that indicate the signal strength of the received Bluetooth signals from the assets. By conducting empirical tests, it was gathered a set of RSSI values corresponding to the same asset position and distance from the antenna array. These values provide insights into the performance characteristics of each antenna and serve as a basis for analyzing the signal reception quality and potential variations among the antennas.

Ensuring that the signal readings across the antennas remain stable and consistent is of utmost importance. Any significant deviation in the readings of a particular antenna from the others may indicate a hardware malfunction, rendering the use of such antennas undesirable. To evaluate the stability of the antennas, a test was conducted involving twenty measurements of the RSSI received by each antenna. These measurements were then averaged to obtain a representative value for each antenna. This process was repeated ten times, with a time gap of ten minutes between each round of measurements.

By averaging the RSSI values over multiple measurements and repeating the process with time intervals, the test aimed to minimize the impact of temporary fluctuations and capture the general behaviour of each antenna's signal reception capabilities. This approach provides a more accurate assessment of the antennas' performance and stability, enabling the identification of any outliers or inconsistencies.

The results obtained from this test were instrumental in determining the suitability of each antenna for the asset localization system. Antennas exhibiting stable and consistent signal readings will be deemed reliable for subsequent localization calculations. At the same time, those demonstrating significant deviations could necessitate further investigation or replacement to ensure accurate and reliable asset tracking.

The tests were performed using the default transmission power of 0dBm on the DK device. The distance between the asset and the array was set to 5 meters, and there were no vertical or horizontal angles between them. Additionally, care was taken to ensure that there were no obstacles obstructing the line of sight between the asset and the array.

Table 5.1: Signal strength reading of each antenna given the same distance

Ant. 1	Ant. 2	Ant. 3	Ant. 4	Ant. 5	Ant. 6	Ant. 7	Ant. 8	Ant. 9	Ant. 10	Ant. 11	Ant. 12
-62	-62	-62	-60	-63	-60	-62	-62	-62	-56	-61	-68
-62	-64	-63	-62	-63	-60	-62	-59	-67	-63	-60	-66
-63	-64	-64	-63	-64	-61	-64	-63	-57	-64	-59	-57
-62	-62	-67	-61	-64	-61	-64	-63	-70	-60	-61	-73
-62	-60	-63	-62	-62	-59	-58	-60	-70	-60	-64	-57
-63	-66	-58	-63	-62	-59	-57	-60	-61	-62	-60	-61
-61	-65	-60	-62	-61	-61	-61	-64	-61	-64	-57	-61
-62	-65	-58	-62	-66	-61	-61	-60	-62	-58	-59	-64
-59	-61	-62	-60	-63	-60	-60	-60	-62	-63	-73	-60
-64	-63	-62	-60	-62	-59	-60	-63	-65	-65	-56	-57

Table 5.2: Summary of Analysis for RSSI Values

Antenna	**Average RSSI (dBm)**	**Standard Deviation (dBm)**	**Coefficient of Variation (CV)**
1	-62.0	1.333	2.15%
2	-63.2	1.932	3.06%
3	-61.9	2.726	4.40%
4	-61.5	1.179	1.92%
5	-63.0	1.414	2.24%
6	-60.1	0.876	1.46%
7	-60.9	2.283	3.75%
8	-61.4	1.776	2.89%
9	-63.7	4.218	6.62%
10	-61.5	2.915	4.74%
11	-61.0	4.761	7.80%
12	-62.4	5.337	8.55%

Based on the analysis of the RSSI values, it can be observed that the antennas' results fall within an expected range. The average RSSI averages for all antennas range from -63.7 dBm to -60.1 dBm, indicating a reasonably consistent signal reception across the array. The standard deviations, ranging from 0.876 dBm to 5.337 dBm, reflect the variations in the received signal strengths, but they are within acceptable limits for the context of the asset localization system.

The analysis of the standard deviations for the RSSI values across multiple measurements provides evidence that the variations between different temporal instances are not significant. The relatively low standard deviation values indicate that the RSSI values for each antenna remain consistent over time.

The standard deviation measures the spread or dispersion of the RSSI values around the average. A lower standard deviation suggests that the data points are closer to the mean, indicating a higher level of consistency. In this case, the standard deviation values, ranging from 0.876 dBm to 5.337 dBm, provide assurance that the RSSI values for the antennas do not exhibit substantial fluctuations or significant variations between different temporal instances.

This consistency in the RSSI values over time is a favorable characteristic for the asset localization system. It ensures that the antennas provide reliable and stable signal reception, facilitating accurate asset tracking and localization calculations. The consistent performance of the antennas over time also enhances the system's overall reliability and robustness. It also validates the connections between the DK and each antenna, that are configured by the multiplexers as well as the consistency between the ICs.

Therefore, based on the analysis of the standard deviations, it can be concluded that the RSSI values remain consistent and reliable across different temporal instances. This finding reinforces the suitability of the antennas for the asset localization system, as they demonstrate consistent performance and maintain a stable signal reception characteristic over time.

5.1.2 Check Antenna switching Sanity and Empirical time check

Given that the fundamental principle of the antenna array is the ability to switch between antennas at a consistent time, it was crucial to analyze whether the antennas were following the desired behaviour and if the switch values were within the expected range, as defined by the BLE standard 5.1 [10].

To ensure the proper functioning of the antenna array, it was necessary to verify that the switching between antennas occurred at the specified time intervals. Any deviation from the expected switching behaviour could affect the accuracy and reliability of the asset localization system.

Furthermore, the analysis aimed to validate whether the switch values complied with the standards set by the BLE 5.1 specification [10]. This involved examining if the timing between antenna switches adhered to the defined parameters, such as the time duration for each antenna activation and the synchronization of the switch signals.

By assessing the antenna behaviour and comparing it against the expected standards, it was possible to ascertain the effectiveness and adherence of the antenna array to the BLE 5.1 specification [10]. This analysis was vital in ensuring that the antenna array functioned as intended, enabling accurate asset localization based on the defined switching principles and standards.

Based on the explanation in 2.2.3.1, the array was set with a Constant Tone Extension (CTE) duration of 160 μs, divided into three distinct periods: the Guard-Period of 4 μs, the Reference-Period of 8 μs, and the remaining 148 μs allocated to each individual antenna. The sampling timing was set to 1 μs per sample, with 1 μs dedicated to sampling and 1 μs for antenna switching. The array followed a cyclic pattern of antenna selection: antennas 1 to 12.

With these settings, the digital logic analyzer should display a 160 μs period, starting with 12 μs without any changes. This initial duration consists of the 4 μs Guard-Period and the subsequent 8 μs Reference-Period. Following this, there should be 74 samples, which corresponds to half of the remaining 148 μs (148/2), considering that each antenna takes 2 μs (1 μs for sampling and 1 μs for switching).

The behavior of the multiplexers within the array should be cyclic, switching antennas every 2 μs (1 + 1 μs). Therefore, the digital logic analyzer should display a total of 82 samples: 8 samples from the Reference-Period (corresponding to the 8 μs duration) and 74 samples from the subsequent period.

By observing the captured signals on the digital logic analyzer, one should expect to see a 160 μs time interval, with an initial section of 12 μs without changes, followed by 82 samples reflecting the cyclic behavior of the antenna switching pattern. This pattern includes 8 samples from the Reference-Period and 74 samples from the subsequent period.

In order to analyse the correctness of the multiplexers' operation, a Digital Logic Analyser was used.

A digital logic analyser is an electronic test instrument that captures and analyses digital signals in a circuit. It provides a visual representation of the signals, allowing engineers to observe timing relationships and detect anomalies. With multiple input channels and advanced triggering capabilities, it aids in debugging, verifying system functionality, and optimising designs [9].

Together with the software PulseView, the digital logic analyser provided a simple and convenient means to view the output of the multiplexers. The multiplexers are responsible for the change of state of the Antenna Array. Integrating the digital logic analyser with PulseView facilitated efficient signal visualisation and analysis, aiding in debugging and optimising the Antenna Array's functionality.

The analysis of the data received, extracted using the logical analyzer, confirmed that the switching times between antennas followed the specified timings outlined in the BLE 5.1 specifications. By examining the captured signals, it was observed that the antenna switching occurred at the expected intervals within the Constant Tone Extension (CTE) duration.

5.2 First I and Q values

During the second stage of the project, the focus shifted towards obtaining the first In-phase (I) and Quadrature (Q) values from the received signal.

Obtaining the first In-phase (I) and Quadrature (Q) values from the received signal was a crucial step that enabled the visualization of initial, albeit crude, estimations of angles. This step played a significant role in driving the subsequent steps of the project by providing valuable insights and discoveries.

The visualizations of the crude angle estimations served as a reference point for evaluating the effectiveness of different algorithms and techniques. By comparing the observed angles with the expected angles based on known positions or reference measurements, the system's performance could be assessed and refined.

5.2.1 First Implementation Details

The implementation of the project utilized the Nordic SDK, which relies on the Zephyr real-time operating system (RTOS) for the development boards. This provided a range of features that facilitated the communication of the data obtained during the project.

To extract the In-phase (I) and Quadrature (Q) values from the Constant Tone Extension (CTE) in the received signal, the initial implementation leveraged sample code specifically designed for Angle of Arrival (AOA) estimations. This code enabled the extraction of the I and Q values, which were crucial for further analysis and processing.

In order to process and analyze the extracted I and Q values, it was necessary to transfer this information to an external computing device capable of running more complex code. Initially, a regular laptop was utilized for this purpose.

The following code snippet was employed to handle the I and Q values and transmit them to the external computer:

```c
for (int i = 0; i < report->sample_count; i++) {
        int vq = report->sample[i].q;
        int vi = report->sample[i].i;
        printk("%d %d\n", vq, vi);
}
printk("END\n");
```

Listing 5.1: C code for Extracting I and Q

The code iterated through the pointer report->sample, which represented the I and Q values obtained from the CTE. The values were then printed, with each iteration representing a single sample of the I and Q values. The "END" string served as a delimiter, allowing the identification of the beginning and end of each transmission.

After transmitting the I and Q values using `printk`, the values were received by the connected computer through a serial communication interface, typically using a USB connection.

Upon receiving the transmitted data, it was necessary to process and extract the relevant information. The received data was split into individual samples and transmissions, enabling the extraction of specific values for angle calculation.

The processing of the received data involved parsing the transmitted values and organizing them into the appropriate data structures or variables. This included separating the I and Q values for each sample, as well as identifying the boundaries between individual transmissions.

In the first implementation of the project, the focus was on obtaining the angle on the horizontal plane (azimuth) using antennas 11 and 12. The initial tests were conducted without a defined testbed or specific positioning setup. The primary objective at this stage was to gather values of the In-phase (I) and Quadrature (Q) components.

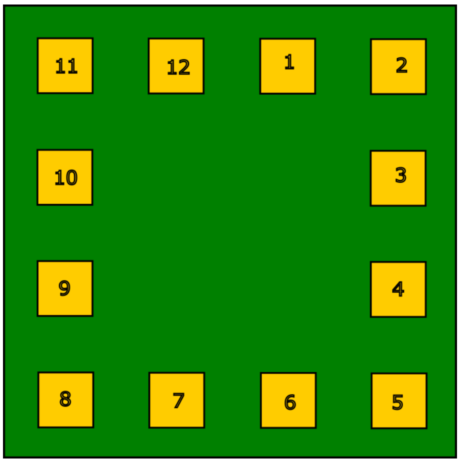

Figure 5.1: Visual representation of the antenna array

To achieve this, a switch pattern of antennas 11 to 12 was used, which was repeated for the remaining samples. This switch pattern ensured that the captured data included the necessary I and Q values for subsequent analysis and angle estimation.

Based on the equations presented in Section 2.2.3.1, the phase of each antenna was first calculated using the cosine function. The phase calculation involved dividing the Quadrature (Q) component by the In-phase (I) component for each antenna. After obtaining the phases for both antennas, the AOA was calculated using the following equation:

Table 5.3: Constants used for the Angle Calculation

Symbol	Description	Value
ψ	The phase difference between the antennas	—
λ	The wavelength of the CTE signal	12.5 cm
d	The distance between the antennas	5 cm

$$\theta = arccos(\frac{\psi\lambda}{2\pi d}) \text{ [2]}$$

It is important to acknowledge that while mathematical equations provide a framework for angle estimation, there are various factors to consider in real-world scenarios. Environmental conditions, such as signal reflections and multipath effects, can introduce uncertainties and affect the accuracy of angle estimation.

By considering these factors and taking appropriate measures to mitigate noise and outliers, it is possible to improve the accuracy and reliability of angle estimation in real-world scenarios.

5.2.2 First Measurements

The first working version of the system encountered stability issues in terms of the obtained values. The approach used in this version involved averaging the results obtained for each transmission. However, this method resulted in inconsistent values between transmissions due to the introduction of environmental noise during the readings.

The presence of environmental noise can significantly impact the stability and consistency of the obtained values. Factors such as electromagnetic interference, multipath reflections, and other environmental variables can introduce variations and distortions in the received signal.

This approach lead to the image 5.2

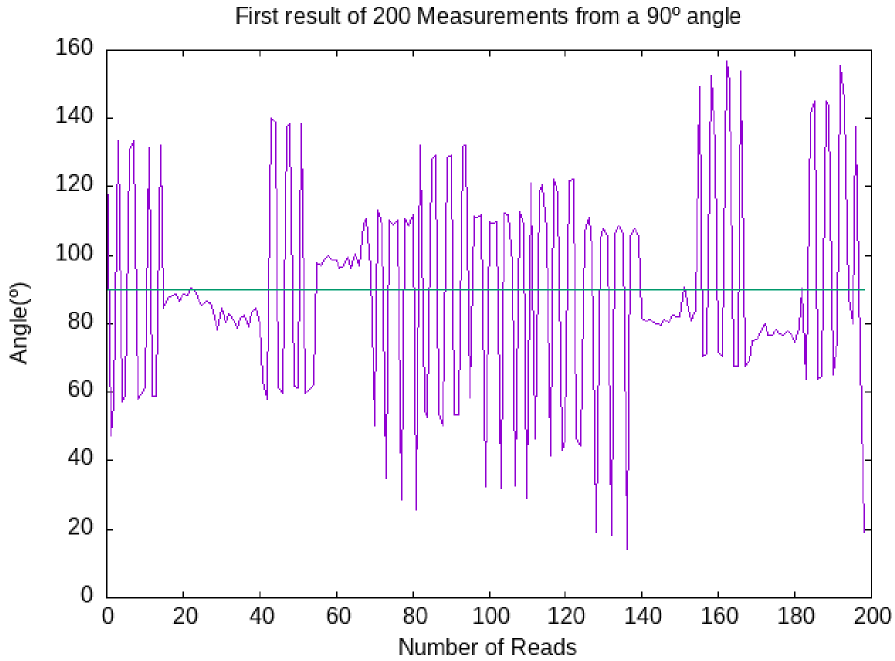

Figure 5.2: First result of 200 Measurements from a 90º angle

The approach was made by isolating each round for the estimations, as the values were simply averaged in each round instead of taking into consideration multiple rounds. This led to unstable reading between successive rounds.

The tests conducted involved extracting 200 measurements from a fixed position, where an asset was positioned 2 meters from the Antenna Array. Both the asset and the Array were positioned 1 meter above the ground. The measurements were taken with a clear line of sight between the asset and the antennas, see Figure 5.3

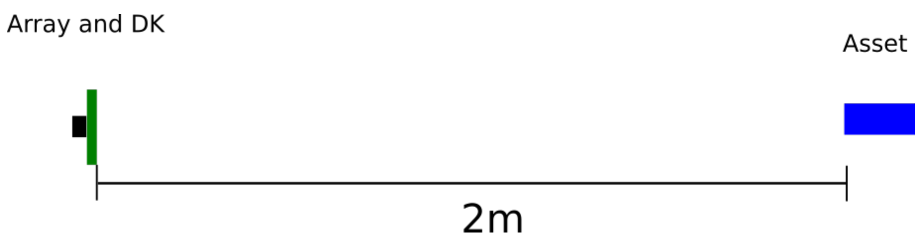

Figure 5.3: Test for the first results

It is important to note that during these tests, existing interference could not be directly measured due to the high number of devices in the environment transmitting at the same frequency (2.4 GHz). The interference caused by these devices was considered a part of the environmental noise and was not explicitly quantified in the measurements. This highlights the importance of further refining the system's algorithms, signal processing techniques, and hardware components to mitigate the impact of such interference and enhance the system's performance in real-world environments.

By extracting multiple measurements from the same fixed position, the objective was to evaluate the system's performance and stability under controlled conditions. This approach allowed for the analysis of the consistency and accuracy of the obtained values and the assessment of any potential variations or limitations in the system.

The choice of a clear line of sight between the asset and the Antenna Array aimed to minimize signal obstructions and interference caused by physical obstacles. This enabled a more direct and reliable signal transmission between the asset and the antennas, facilitating the evaluation of the system's performance in an ideal scenario.

The positioning of the asset at a known distance of 2 meters from the Antenna Array provided a basis for assessing the accuracy of the direction finding and localization capabilities. By comparing the obtained measurements with the known position, the system's precision and reliability could be evaluated.

The results of the test can be consulted in Appendix C.

A quick observation of figure 5.2, shows that the values are quite unstable, however, there is a noticeable tendency for the readings to revolve around the desired value of 90 degrees.

It is worth noting that consecutive readings often exhibit abrupt changes, where the angle jumps from a value over 90 degrees to slightly under 90 degrees. This jump is approximately around 80 degrees.

Table 5.4: Evaluation Metrics for the First Measurements

Evaluation Metric	Value
Median	85.51 º
Average	89.51 º
Standard Deviation	31.25 º
Coefficient of Variation	0.35
Mean Absolute Error	25.32 º
Root Squared Mean Error	31.17 º

Based on the provided table, let's evaluate the results considering the real value is 90 degrees:

- Median: The median value of 85.51º suggests that, on average, the obtained values tend to be slightly lower than the expected value of 90 degrees. This indicates a slight negative bias in the measurements.

- Average: The average value of 89.51º also indicates that the obtained values are slightly lower than the expected value. It confirms the presence of a negative bias in the measurements. However, this is not significant for the application as half a degree is an error with a low impact on the location results.

- Standard Deviation: The standard deviation of 31.25 represents the spread or variability of the obtained values around the mean. A higher standard deviation indicates a larger dispersion in the measurements. In this case, the relatively high standard deviation suggests a considerable variability in the angle estimations.

- Coefficient of Variation: The coefficient of variation (CV) of 0.35, calculated as the ratio of the standard deviation to the mean, provides a measure of relative variability. A higher CV indicates a relatively higher dispersion relative to the mean. In this case, the CV value suggests a moderate relative variability in the angle estimations.

- Mean Absolute Error: The mean absolute error (MAE) of 25.32 represents the average absolute difference between the obtained values and the expected value of 90 degrees. The MAE indicates that, on average, the angle estimations deviate by approximately 25.32 degrees from the expected value.

- Root Squared Mean Error: The root squared mean error (RMSE) of 31.17 provides a measure of the overall deviation between the obtained values and the expected value. The RMSE penalizes larger errors more heavily. In this case, the RMSE indicates an average deviation of approximately 31.17 degrees.

Overall, the results indicate a systematic deviation of the obtained angle estimations from the expected value of 90 degrees. The measurements are slightly lower on average, and there is considerable variability in the estimations. The mean absolute error and root squared mean error further confirm the presence of deviation and provide quantitative measures of the average and overall deviation, respectively. This means there is the need to remove outliers to reduce the variation, as this can lead to instability of the estimations for the actual position.

Considering these findings when interpreting the accuracy and reliability of the angle estimations is essential. Further analysis and refinement of the system or measurement process may be necessary to reduce the bias and improve the consistency and precision of the angle estimations toward the expected value.

The obtained results demonstrate an interesting tendency for the angle estimations to cluster around the 90 degrees mark. This suggests that the measurements may have some degree of stability or consistency. However, it is important to note that the results may not be fully accurate due to the presence of noise and outliers.

To obtain more accurate and reliable results, further steps can be taken to mitigate the impact of noise and outliers. Some possible approaches include:

- **Outlier detection and removal:** Identify and remove any extreme or erroneous data points that significantly deviate from the expected pattern. This can help eliminate outliers that may introduce inaccuracies in the analysis.

- **Data averaging:** Calculate the average or median value of multiple measurements taken at each angle to minimize the impact of individual measurement variations. Averaging can help reduce the influence of random errors and provide a more reliable estimate of the true angle.

By implementing these steps, it is possible to enhance the accuracy and reliability of the angle estimations, allowing for more precise localization or positioning of assets. It is important to carefully analyze the noise and outliers present in the data and apply suitable techniques to obtain accurate and meaningful results.

5.2.3 Averaging the Instant Values Obtained

By analyzing the data presented in Table 5.4, it is evident that the obtained values are not consistently stable. However, upon closer inspection, it can be observed that the average of the measurements tends to hover around the desired value of 90 degrees. This indicates a potential trend or tendency towards the intended angle.

Considering this observation, an investigation was conducted to determine whether averaging the results over time would lead to a stabilization of the estimations around the desired values. The idea behind this approach was to mitigate the impact of random variations and outliers present in the individual measurements.

By analyzing the results of the averaged estimations, it was possible to assess the stability and consistency of the angle estimations over time. If the averaging process successfully reduced the impact of noise and outliers, the stabilized estimations would exhibit reduced variability and a closer alignment with the desired values.

In order to test this hypothesis, the values used as estimations were now the result of averaging every angle calculation obtained over time. For obvious reasons, this would not be able to respond to changes in the actual angle, but since the test angle was always the same at this point, this provided a simple way to test whether averaging would improve the results. To test the results with accuracy, the method was applied over the results of the previous method; being the source values the same, we exclude other possible interferences when comparing the results of the average method.

The resulting values can be seen in figure 5.4:

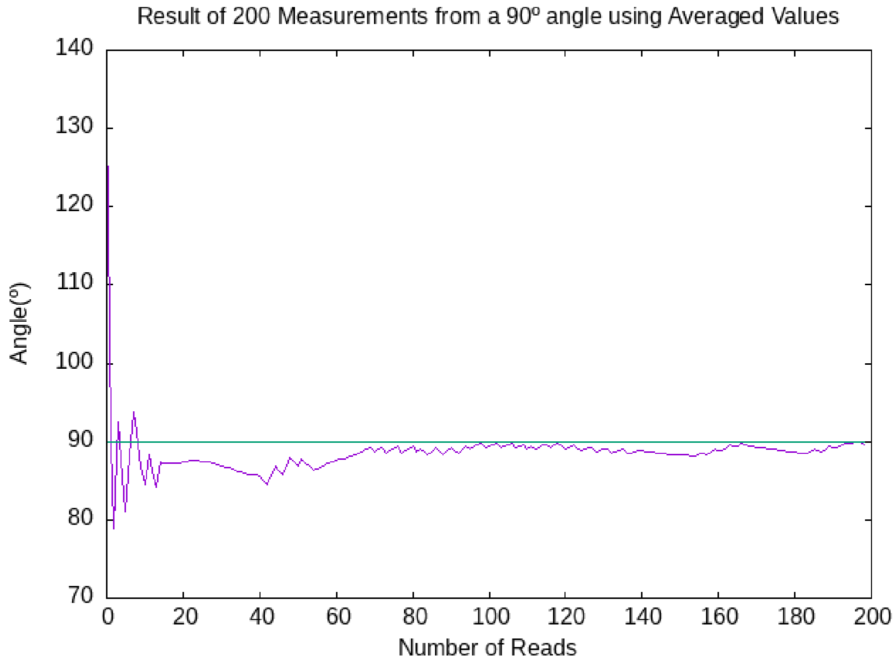

Figure 5.4: Result of 200 Measurements from a 90º angle using Averaged Values

A first look allows for the immediate observation that the obtained estimations are quick to stabilize after only 14 measurements, unlike what can be observed in 5.2, which is unstable even after multiple readings. This stabilization is due to the use of the averaging method.

Table 5.5: Evaluation Metrics for the Averaged First Measurements

Evaluation Metric	Value (º)
Median	88.75
Average	88.55
Standard Deviation	3.48
Coefficient of Variation	0.04
Mean Absolute Error	1.94
Root Squared Mean Error	3.76

By comparing the results with the ones obtained in 5.2.2, we can observe the following:

- **Median:** The median value has increased from 85.51 to 88.75 degrees, indicating a shift towards the desired value of 90 degrees. This suggests that averaging the estimations over time has helped improve the stability and alignment with the desired angle.
- **Average:** The average value has slightly decreased from 89.51 to 88.55 degrees. Although it deviates slightly from the desired value, the actual final value of the estimation is much closer to the real value than the estimations from the original approach.

- **Standard Deviation:** The standard deviation has significantly reduced from 31.25 to 3.48 degrees. This substantial decrease indicates a significant improvement in the consistency and reduction in variability of the angle estimations. The smaller standard deviation reflects a higher level of stability and precision in the averaged results.
- **Coefficient of Variation:** The coefficient of variation has also significantly reduced from 0.35 to 0.04. This decrease further reinforces the improved consistency and reduced variability in the estimations. The lower coefficient of variation indicates a higher level of relative stability and precision in the averaged results.
- **Mean Absolute Error:** The mean absolute error has reduced from 25.32 to 1.94 degrees. This reduction signifies a significant improvement in the average deviation between the estimations and the desired angle. The smaller mean absolute error indicates a higher level of accuracy and closer alignment with the intended angle.
- **Root Squared Mean Error:** The root squared mean error has decreased from 31.17 to 3.76 degrees. This decrease represents an improvement in the overall deviation between the estimations and the desired value. The smaller root squared mean error indicates a higher level of accuracy and reduced overall error in the averaged results. The analysis of the results also reveals a reduction in the presence of outliers, which are values significantly distant from the actual angle. This is particularly evident when considering the Root Squared Mean Error (RSME) metric. The smaller RSME indicates that the averaged estimations are now more closely clustered around the desired angle, with fewer extreme values. This reduction in outliers demonstrates the effectiveness of the averaging technique in mitigating the impact of noise and improving the overall reliability of the angle estimations.

Overall, the comparison highlights the positive impact of averaging the estimations over time. The averaged results show improved stability, reduced variability, higher precision, and better alignment with the desired angle compared to the previous results. This suggests that the averaging technique has effectively mitigated the influence of noise and outliers, resulting in more reliable and accurate angle estimations.

A notable observation is that the RMSE is significantly larger than the MAE in both cases. In a hypothetical scenario where every absolute error equals the MAE value, the RMSE would be lower than the MAE. However, the fact that the RMSE is greater suggests the presence of extreme error values that deviate from the MAE. This indicates that there are estimations that are both significantly lower and higher than the MAE.

Such diverse error values suggest the possibility of utilizing clustering algorithms to detect outliers, as the estimations do not cluster closely around the MAE value but around the real value. By identifying and handling these outliers, further improvements can be made in refining the accuracy and reliability of the angle estimations.

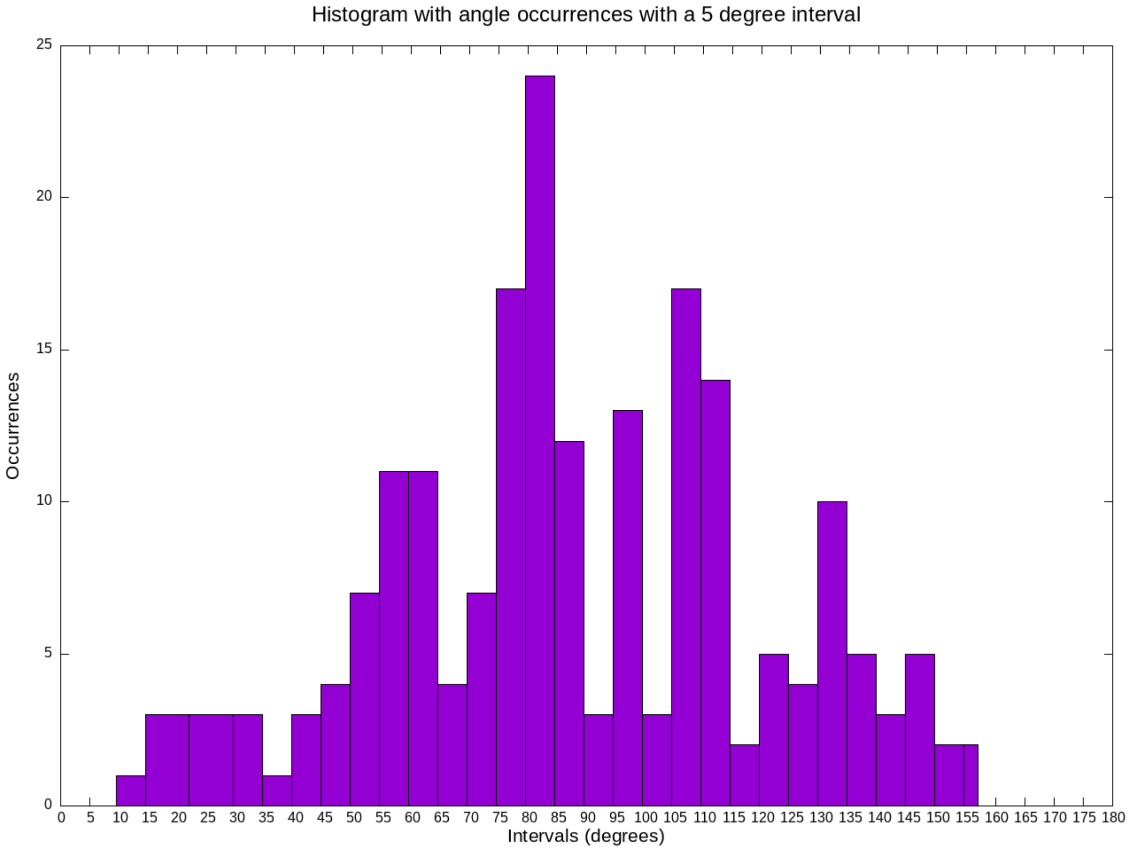

Figure 5.5: Histogram with angle occurrences with a 5º interval

The analysis of the histogram presented in Figure 5.5 reveals the presence of three noticeable spike clusters within the data. These clusters are observed in the ranges of 50 to 65, 75 to 90, and 105 to 115. Among these clusters, the most prominent one aligns closely with the expected value of 90 degrees, which was the intended angle in the tests. This observation reinforces the potential usefulness of employing a clustering algorithm to filter and identify estimations that fall within the desired range. By leveraging such an algorithm, it may be possible to differentiate between accurate estimations and outliers, thereby improving the overall reliability and precision of the angle estimation process.

5.3 Responsive measurement, Sliding Window and Simple Outlier Detection

This section is dedicated to a crucial aspect of data analysis and anomaly detection. As highlighted in the previous stage of our analysis (see Section 5.2.2), the obtained results frequently exhibit irregularities or outliers that have the potential to greatly influence the accuracy and reliability of our analysis. Thus, it becomes imperative to detect and handle these outliers effectively in order to preserve the integrity and quality of our data analysis outcomes.

In this section, the analysis was extended to consider the case of changing angles, as opposed to the previous scenario where the angle was stationary at 90 degrees. While the previous analysis provided valuable insights into the performance of our angle estimation system under static conditions, it is equally essential to evaluate its performance in scenarios where the angle of interest is not fixed. Real-world situations often involve dynamic movement, where the angle of an object or signal continuously changes over time.

5.3.1 Sliding Window

In Section 5.2.3, it was discussed the introduction of average calculation among multiple rounds, which provides stability that cannot be achieved by simply averaging each round. However, this approach introduces a trade-off in responsiveness, especially when dealing with changing angles.

To illustrate this trade-off, let's consider a scenario where 1000 rounds of measurements are obtained at a fixed angle of 90 degrees, followed by 20 rounds at 120 degrees. If we were to calculate the average of all the rounds, the final result would be approximately 90.59 degrees. This outcome is influenced by the large number of rounds at 90 degrees, which outweighs the smaller number of rounds at 120 degrees. Consequently, the resulting estimation is biased towards the more frequent angle, leading to a decreased responsiveness to changes.

To address this problem, it was introduced the concept of a sliding window. The sliding window operates similarly to a First-In-First-Out (FIFO) queue. As new values are obtained, they are added to the window, and if the size of the window exceeds a predefined threshold, the oldest values are automatically discarded (Fig. 5.6). This approach allows for a balance between stability and responsiveness in angle estimation.

By using a sliding window, stability is achieved by considering values from multiple rounds rather than relying solely on a single round. This reduces the impact of outliers or erratic measurements in individual rounds and provides more robust estimations. At the same time, the sliding window ensures responsiveness by considering each round's measurements within a specific time frame, allowing the estimation to adapt to changing angles more effectively.

While stability is challenging to quantify precisely, responsiveness can be controlled by defining a hard limit using the sliding window threshold. In practical terms, considering that each round takes one second to complete, the threshold size in rounds can be viewed as a limiter on the system's responsiveness in seconds.

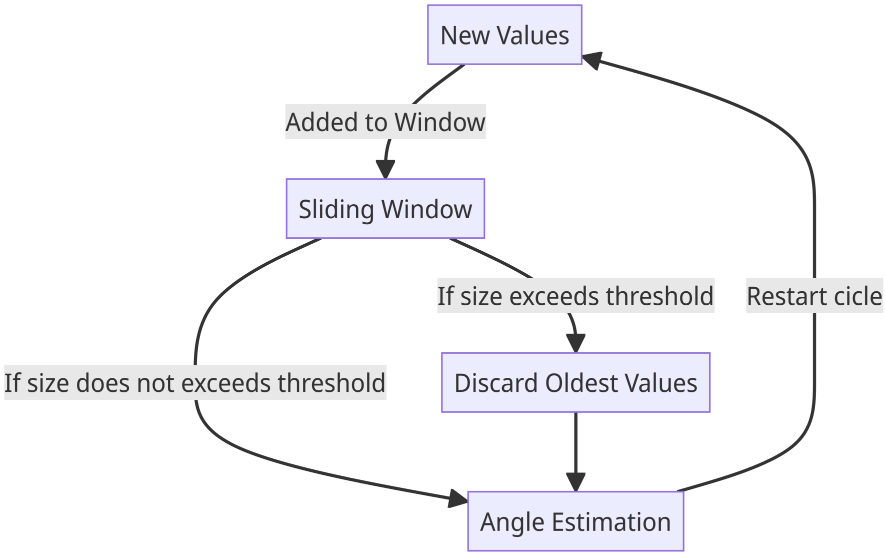

Figure 5.6: Visual description of the sliding window flow

For instance, a threshold of 20 rounds implies that the system can fully eliminate past position rounds within 20 seconds. This means that new measurements will have a significant impact on the estimated angle within this time frame. On the other hand, if the threshold is set to a higher value, such as 50 rounds, it would take 50 seconds for the system to fully integrate new measurements and adapt to changes in the angle.

By adjusting the threshold size, we can strike a balance between responsiveness and stability according to the specific requirements of the application. A smaller threshold allows for more rapid adaptation to changes but may introduce more variability due to the limited number of measurements considered. Conversely, a larger threshold provides smoother estimations and greater stability but at the expense of responsiveness to immediate changes.

After considering the trade-off between stability and responsiveness, a suitable sliding window threshold value needed to be chosen. It was determined that extremely long thresholds, such as those exceeding 5 minutes or 300 rounds, would not meet the desired responsiveness criteria. These prolonged thresholds would limit the system's ability to adapt to changes in the angle within an acceptable timeframe while maintaining stability.

Referring to the obtained values shown in Figure 5.4, it was observed that stabilization occurred within the range of 14 to 20 rounds. Within this range, the angle estimations converged to a relatively consistent value. Taking this into account, a sliding window threshold value of 20 rounds was selected.

By choosing this threshold value, the system balances stability and responsiveness. The window of 20 rounds ensures that recent measurements have a significant impact on the estimated angle while still maintaining stability and filtering out noise and outliers from past measurements.

5.3.2 Simple Outlier Detection

Outliers, or anomalous data points, can have a significant impact on the accuracy and reliability of data analysis. They are data points that deviate significantly from the typical patterns or distribution of the dataset. Outliers can arise due to various factors, such as measurement errors, data corruption, or rare events, and they can distort statistical analysis, affect model performance, and lead to inaccurate conclusions.

Detecting and handling outliers is a crucial step in data analysis, as it allows for the identification and removal of these anomalous points or the implementation of appropriate measures to account for their presence. Simple outlier detection methods provide a quick and straightforward way to identify outliers and address their impact on the data analysis process.

Simple outlier detection techniques often involve the use of statistical measures, such as mean, median or standard deviation to define a threshold for identifying data points that deviate significantly from the expected range. These methods do not require complex algorithms or extensive computational resources, making them accessible and applicable in various domains and scenarios.

The following algorithm (7) was used to remove outliers, on a first stage:

```
def reject_outliers(data, m=5.0):
    l_data = np.array(data)
    d = np.abs(l_data - np.median(l_data))
    mdev = np.median(d)
    s = d / (mdev if mdev else 1.)
    return list(l_data[s < m])
```

Listing 5.2: Python code for Outlier Detection

The main motivation behind using this algorithm is to identify and eliminate outliers that deviate significantly from the central tendency of the data. Outliers can arise due to various reasons, such as measurement errors, data corruption, or rare events, and they can distort statistical analysis, affect model performance, and lead to inaccurate conclusions.

In the algorithm, the median is employed as a measure of central tendency instead of the average. The median is less sensitive to extreme values and provides a more robust estimate of the typical value in the presence of outliers. By using the median, the algorithm aims to identify values that deviate significantly from the central position of the data.

The algorithm calculates the absolute deviation of each data point from the median and compares it to the median absolute deviation (MAD), which is a robust measure of dispersion. A threshold parameter (m) is used to determine the acceptable level of deviation from the median. Data points with deviations exceeding the threshold are considered outliers and are removed from the values to be used for the estimation.

The simple outlier detection algorithm using the median as a central tendency measure helps mitigate the influence of outliers in the dataset. However, it is important to consider two potential problems that may arise:

- **Values from different directions:** If the window includes measurements from different directions, it is possible that the temporary inclusion of outliers or noise can temporarily shift the median away from the real values. This situation can lead to the exclusion of the actual values during that specific window. However, as the window moves and includes measurements primarily from a single direction, the median will gradually align with the real values.
- **Outliers larger or smaller than real values:** The algorithm's effectiveness relies on the assumption that outliers are typically spread uniformly. In cases where this is not true, the central tendency value can be distant from the real value. In such cases, using the median instead of the average as the central tendency measure helps reduce the impact of outliers. The median is less affected by extreme values, making it a robust measure in the presence of outliers.

5.3.3 Changing Angle Tests

The sliding window algorithm and the performance of the system were tested using three different positions. Each position had an altitude of 90 degrees and azimuth angles of 75, 90, and 105 degrees. The testing was conducted from a fixed distance of 3 meters away from the antenna array.

By varying the azimuth angle while keeping the altitude constant, the test aimed to evaluate the system's ability to accurately estimate the changing angles over time. The sliding window algorithm was employed to improve stability and responsiveness, ensuring that the estimations would align with the actual angles.

Throughout the test, the system collected multiple rounds of angle estimations using the antenna array. The sliding window, with its defined threshold, allowed for the inclusion of recent rounds while discarding older rounds to maintain responsiveness within an acceptable timeframe. This approach provided a balance between stability and responsiveness, enabling accurate angle estimations.

The collected data from the test was analyzed to assess the system's performance in estimating the changing azimuth angles. The evaluation included metrics such as average error, standard deviation, and response time. These metrics provided insights into the accuracy, consistency, and timeliness of the estimations.

To evaluate the effectiveness of the approach, the obtained values were subjected to testing through three different pipelines. These pipelines incorporated variations in filtering techniques and data processing methods while maintaining the same original values. The purpose of this testing was to assess the impact of different approaches on the final results.

The three pipelines used in the testing process were as follows:

Table 5.6: Approaches for the angle estimation

Section
The values were averaged without applying the filtering (See section 5.3.2)
The estimations used the median and filtering was applied (See section 5.3.2)
The values were averaged applying the filtering (See section 5.3.2)

5.3.3.1 Filtering and Window Results

The first method applied in the testing process was similar to the approach described in subsection 5.2.3. In this method, the obtained values were averaged without applying any filtering techniques. However, a key difference was the incorporation of the sliding window concept to limit the time duration of the values used for averaging.

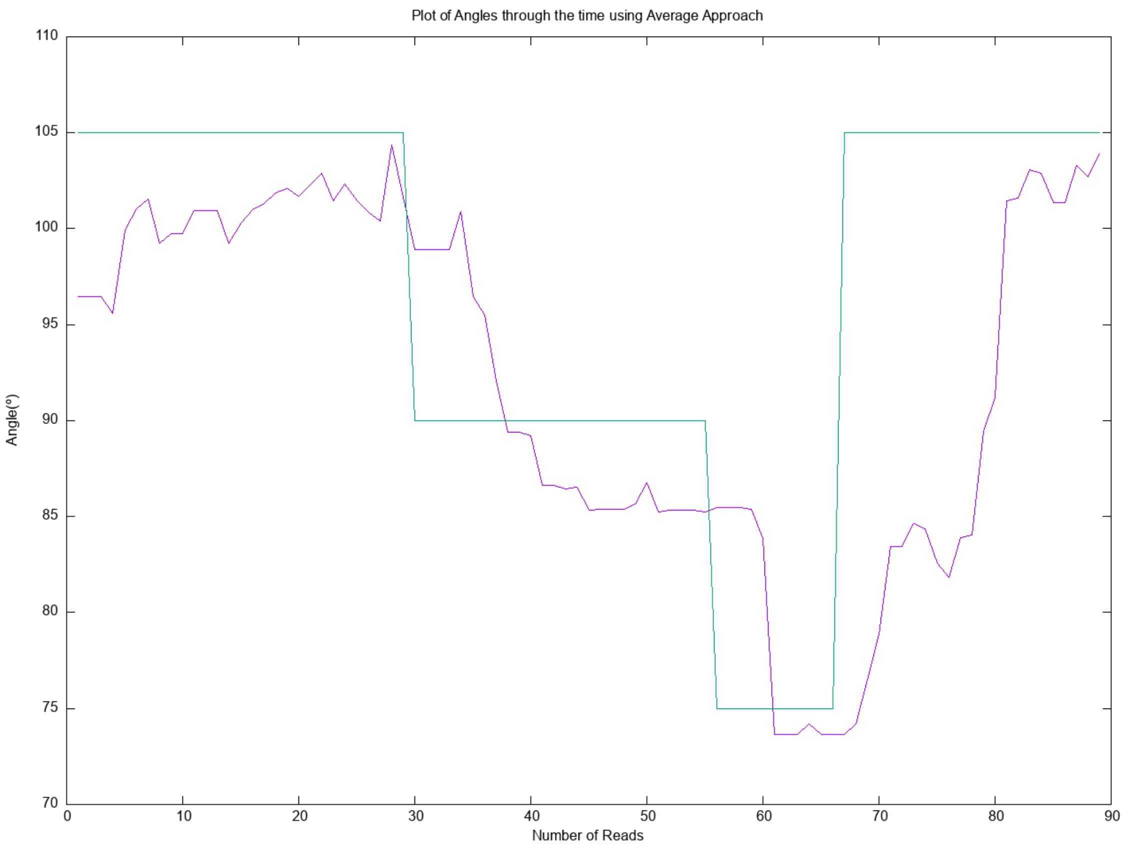

Figure 5.7: Angle estimations with varying real value using average without filtering

The analysis of figures 5.7, 5.8 and 5.9 reveal several important observations. The green line represents the ground truth and the purple line represents the estimations. Firstly, there is a clear

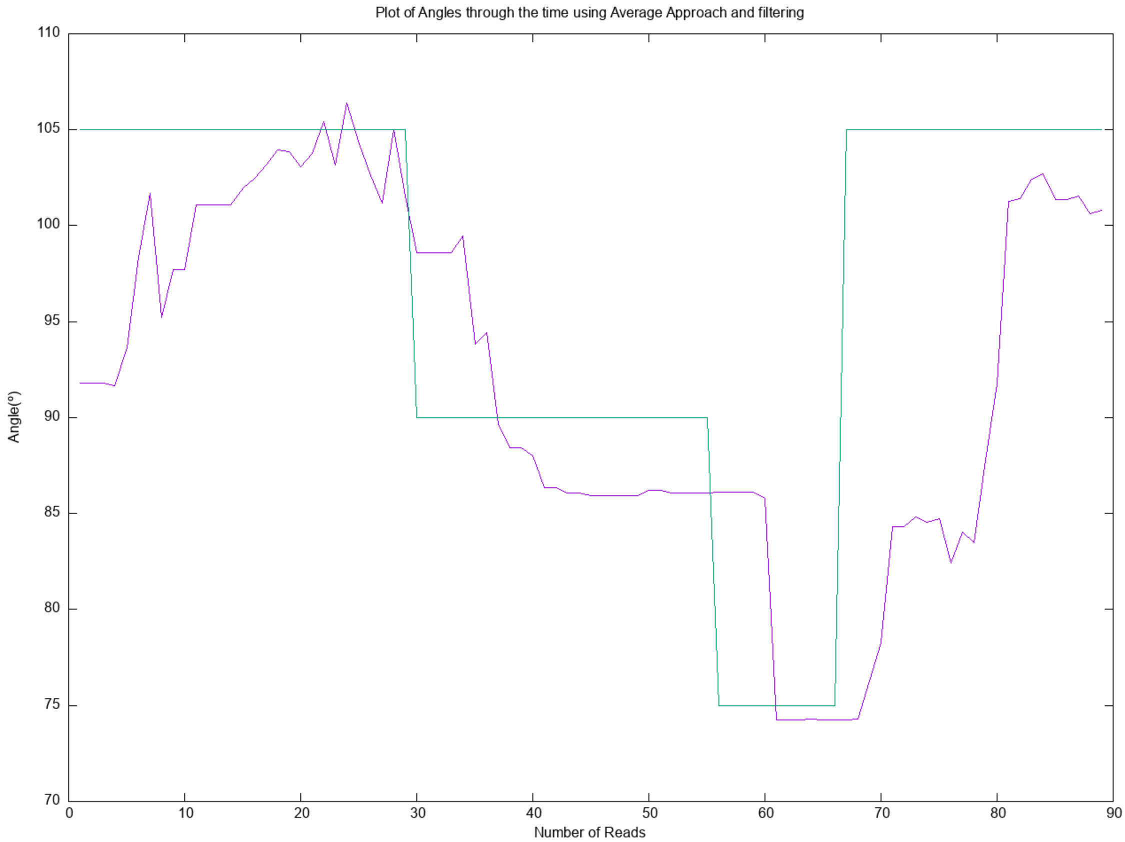

Figure 5.8: Angle estimations with varying real value using average and filtering

tendency in the estimations, as they align closely with the real values. This indicates that the system is capable of capturing the changes in angles and adjusting the estimations accordingly.

However, it is worth noting that there is a noticeable delay (5 to 10 measurements) between the change in angle and the corresponding change in the estimations. This delay can be attributed to the sliding window mechanism, which introduces a certain time lag due to the inclusion of previous rounds in the calculation. While this delay is expected and acceptable for the purposes of stability and responsiveness, it should be taken into consideration in real-time applications.

Additionally, it is evident that there is a significant error between the estimations and the real values. This discrepancy highlights the inherent limitations and challenges in accurately estimating angles based on signal measurements. Further improvements in the algorithm and signal processing techniques could help reduce this error and enhance the accuracy of the system.

The comparison between the three methods can be challenging to assess solely by visually inspecting the plots. However, upon closer examination, certain patterns and similarities emerge, particularly among the filtered estimations.

The filtered methods, which incorporate a filtering step in their pipeline, exhibit a higher level of stability compared to the method without filtering. This stability is evident in the consistency of the estimations over time, showing less fluctuation and smoother transitions between angles. This

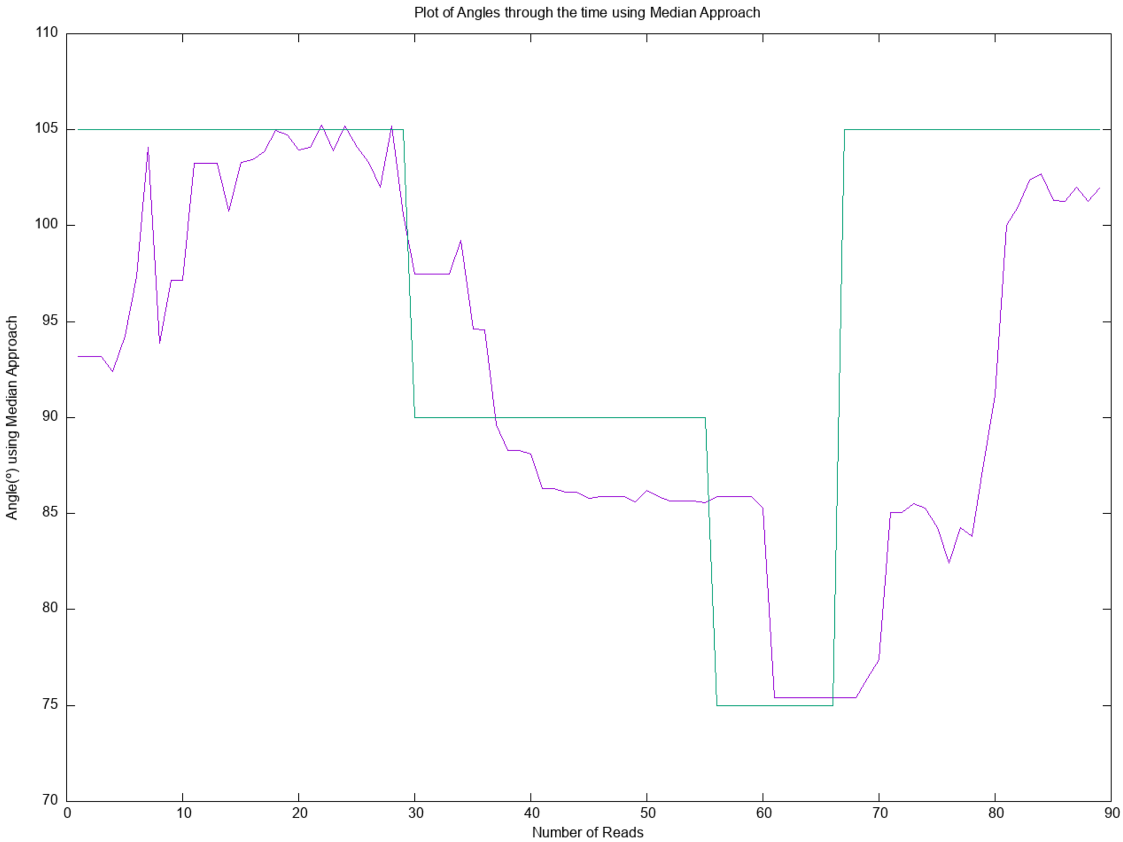

Figure 5.9: Angle estimations with varying real value using median and filtering

suggests that the filtering process helps to mitigate the effects of noise and outliers, resulting in more reliable and stable estimations.

On the other hand, the method without filtering demonstrates more variability and fluctuations in the estimations. This indicates that without the filtering step, the estimations are more susceptible to the influence of noise and outliers in the data, leading to less stable results.

A more comprehensive statistical analysis was conducted, and the findings were compiled in Table 5.7:

Table 5.7: Comparison of Different Approaches

Approach	**Mean Absolute Error (º)**	**Root Squared Mean Error (º)**
Averaging no Filter	7.38	10.41
Averaging	7.45	10.60
Median	7.14	10.37

Upon analyzing the values of MAE and RMSE in Table 5.7, it can be inferred that the Median approach with filtering yields better results compared to the other two methods. However, it is important to note that these error metrics take into account the influence of past angles, which may introduce a delay in the estimations rather than representing a true error.

Furthermore, the introduction of outlier filtering in the data processing stage can lead to the elimination of actual values during the transition between angles. This phenomenon occurs when the new angle is outnumbered by the old angle values in the sliding window. An example of this can be observed around sample 60 (see figure 5.9), where there is a sudden change in the estimated angle. This abrupt change is a result of the outliers filtering out the previous angle values that were dominant before the transition. Once the estimations around the new angle become predominant, the previous values are removed by the outlier filtering, resulting in a sudden shift in the estimation.

The results obtained in this stage demonstrate the responsiveness of the system and its ability to stabilize over time. The system showed prompt adjustments to changes in the angle of arrival, providing estimations that closely followed the actual values. Additionally, the introduction of the sliding window technique allowed for improved stability by considering multiple rounds of data.

5.4 Testbed creation and further tests

The current section will delve into the description of the testbed and the tests that were performed, as well as the results and the discussions of said results. It will also be discussed the introduction of a clustering algorithm in order to identify outliers.

In order to ensure a controlled and replicable test environment, a dedicated testbed was set up for the experiments. The testbed configuration was designed to eliminate potential interference from environmental factors and focus solely on evaluating the system's performance. Section 5.4.2

The antenna array was positioned at a height of 1 meter above the ground, and placed in close proximity to the back wall. The specific arrangement of the antennas was chosen to capture the desired angle between the asset and the array, particularly the angle formed with the wall. For this purpose, antennas 11 and 12 were selected as they provided the relevant angle information for the experiments.

The positioning of antennas 11, 12, 1, and 2 formed a line parallel to the floor plane, while antennas 2, 3, 4, and 5 formed a line perpendicular to the floor plane (see figure 5.10). By carefully configuring the antenna array in this manner, the focus was directed toward capturing the angle of interest and minimizing any potential interference from other angles or environmental factors.

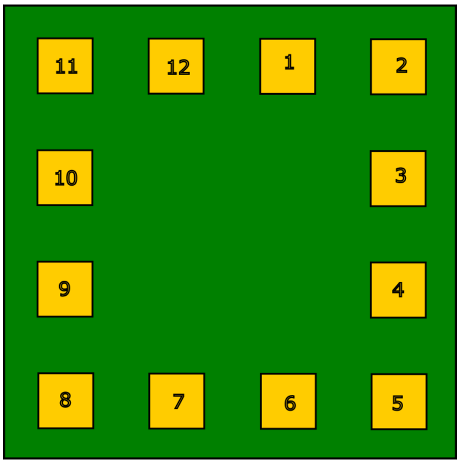

Figure 5.10: Visual representation of the antenna array

This dedicated test-bed setup allowed for precise control over the test conditions and minimized the influence of external factors on the system's performance evaluation. By isolating the relevant angles and ensuring consistency in the test environment, the results obtained could be confidently attributed to the system's performance rather than external variables.

5.4.1 Clustering for Outlier Detection

The presence of distinct peaks in the histogram 5.5 suggests the presence of multiple clusters or groups within the data as explained in section 5.2.3. This observation opens up the possibility of utilizing clustering algorithms to identify and exclude outliers from the dataset. By identifying the major cluster and considering points outside of this cluster as outliers, we can potentially improve the accuracy and reliability of the estimations.

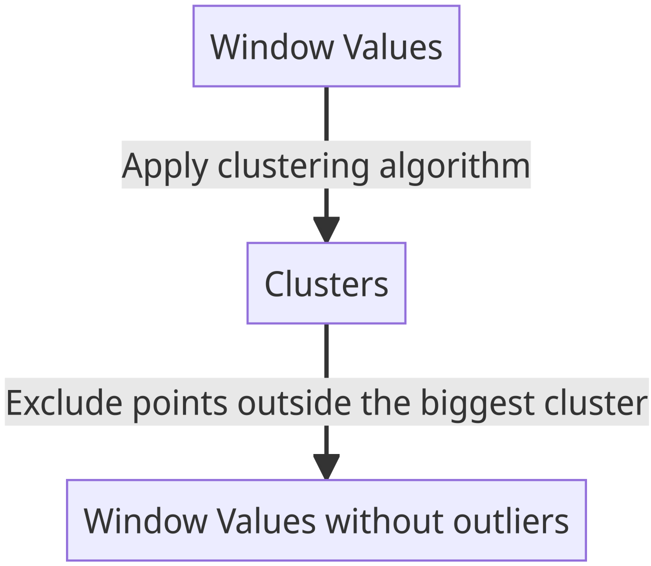

Figure 5.11: Representation of the Clustering pipeline

The choice of the clustering algorithm was of utter importance, and so the characteristics of the problem in hands were taken into consideration to choose the appropriate algorithm. The most important characteristic was the ability to find clusterings without the need to specify the number of clusters. Popular algorithms such as K-means have this problem. The algorithm also had to be able to handle outliers and noise outside the clusters. For these reasons, the DBSCAN algorithm was chosen over others:

- Ability to handle irregularly shaped clusters: DBSCAN does not assume that the clusters are spherical or have a particular shape. It can detect clusters of arbitrary shape, making it suitable for scenarios where the clusters may have complex geometries [14].
- Robustness to noise and outliers: DBSCAN is designed to handle noisy data and can effectively distinguish outliers from the main clusters. It defines clusters as dense regions of points separated by sparser regions, allowing it to identify and ignore outliers that do not meet the density criteria [35].
- No requirement for specifying the number of clusters: DBSCAN does not require prior knowledge of the number of clusters in the data. It automatically determines the number of clusters based on the density of the data points, making it flexible and adaptive to different datasets [37].

- Parameter tuning: DBSCAN has two important parameters, namely epsilon (ε) and the minimum number of points (MinPts). These parameters can be tuned based on the characteristics of the data and the desired clustering behavior. By adjusting these parameters, one can control the sensitivity of the algorithm to density and noise, allowing for fine-tuning to the specific dataset [21].

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based clustering algorithm that partitions data points into clusters based on their density. It works by defining a neighborhood around each data point and identifying dense regions separated by sparser regions.

The algorithm operates as follows [14]:

1. For each data point, DBSCAN calculates its neighborhood by finding all the data points within a specified distance epsilon (ε) from it. This distance defines the radius of the neighborhood.

2. If the number of data points within the neighborhood exceeds a specified threshold called the minimum number of points (MinPts), the data point is considered a core point. Core points are the foundation of clusters and represent dense regions.

3. DBSCAN then expands the clusters by iteratively finding and adding neighboring data points to the cluster. A data point is considered part of a cluster if it is a core point or within the neighborhood of a core point.

4. Data points that are not core points and do not have enough neighboring points within their epsilon neighborhood are classified as noise or outliers. These data points do not belong to any cluster.

5.4.2 Test-bed description

Figure 5.12 provides a visual representation of the test-bed setup, illustrating the positions of the assets and the antenna array. The assets were positioned at a distance of 3 meters from the antenna array, forming a range of angles between 15º and 165º with a 15º interval between consecutive positions.

The incremental intervals of 15º between consecutive positions enabled the assessment of the system's performance at regular intervals across the entire range of angles. This step-wise approach provided valuable insights into how the system responded to changes in the angle of the assets, highlighting any trends, patterns, or potential limitations in the estimation accuracy.

The choice of a 3-meter distance for the testbed was influenced by several factors, including the limitations of the available space and the requirements of the technology used. Due to the constraints of the testing area, it was not feasible to use distances larger than 3 meters.

Additionally, the technology being utilized in the system had certain specifications that needed to be met. One such requirement was that the distance between the antennas and the assets should be at least 10 times the wavelength of the signal. In this particular case, with a desired wavelength of 0.125 meters, the minimum distance needed to satisfy this criterion was approximately 1.25 meters (0.125 * 10). The reason for this is that in order to achieve the proper functioning of the system, the waves need to be planar once they reach the antennas.

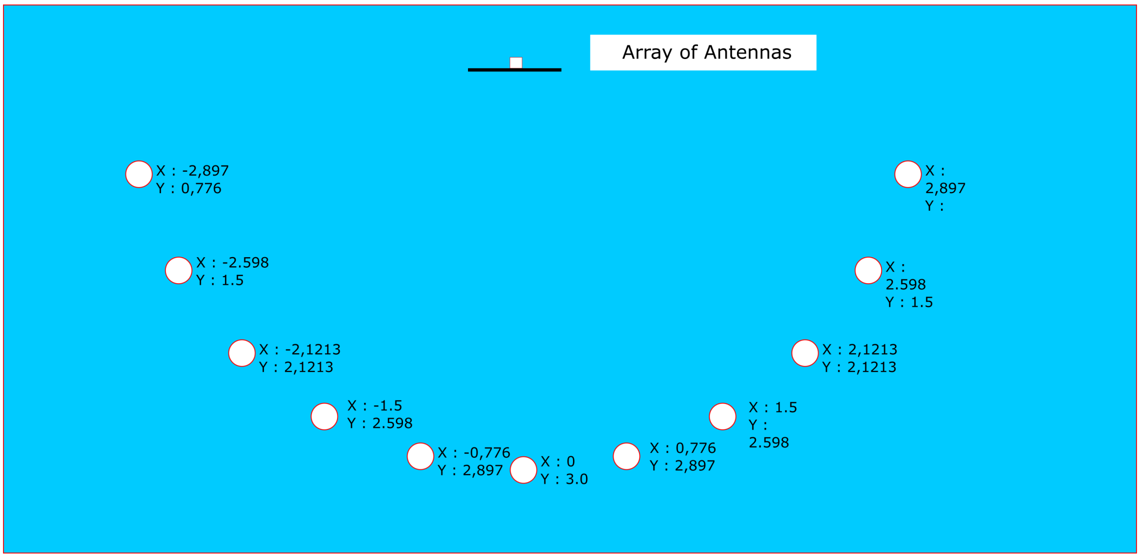

Figure 5.12: 2D testbed visual representation

The space chosen for conducting the tests was characterized by its spaciousness and height of 3 meters. The vast area allowed for ample room for the antenna array and the assets, ensuring that the signals could propagate without significant obstructions or interference. The height of 3 meters provided sufficient vertical clearance, enabling the signals to propagate relatively unobstructedly.

It is important to note that the reported results do not encompass transition times between different test positions. This is because the tests were intentionally paused and resumed at each new position, ensuring that a clean window was used for estimation. By omitting the transition periods, the analysis focused solely on the stabilized performance of the system at each specific position, providing a clear understanding of the estimation accuracy. As previously mentioned, worst-case scenario, there can be a delay of up to 20 seconds before the system stabilizes. However, once the system stabilizes, the results analyzed in this section apply.

In order to streamline the analysis and facilitate the interpretation of the results, the focus will primarily be on the outcomes obtained with the median approach using filtering as the default method. Other approaches will be specified when considered. This arrangement ensures that all the necessary information is available for a comprehensive evaluation and comparison of the different approaches employed in the study.

The tests were made following the times defined in Table 5.8:

Table 5.8: Times spent on the test for each angle

Angle (º)	15	30	45	60	75	90	105	120	135	150
Time (s)	47	41	81	76	53	56	54	49	46	45

Upon analyzing Figure 5.13, it is evident that the system's performance is generally favorable, particularly in the range 90 ± 45 degrees. In this range, the estimated values closely align with the desired values, indicating a high level of responsiveness and accuracy. Outside that range, there is a clear deviation. This deviation from the desired values suggests a limitation or potential challenge in accurately estimating the angle of arrival in this particular range.

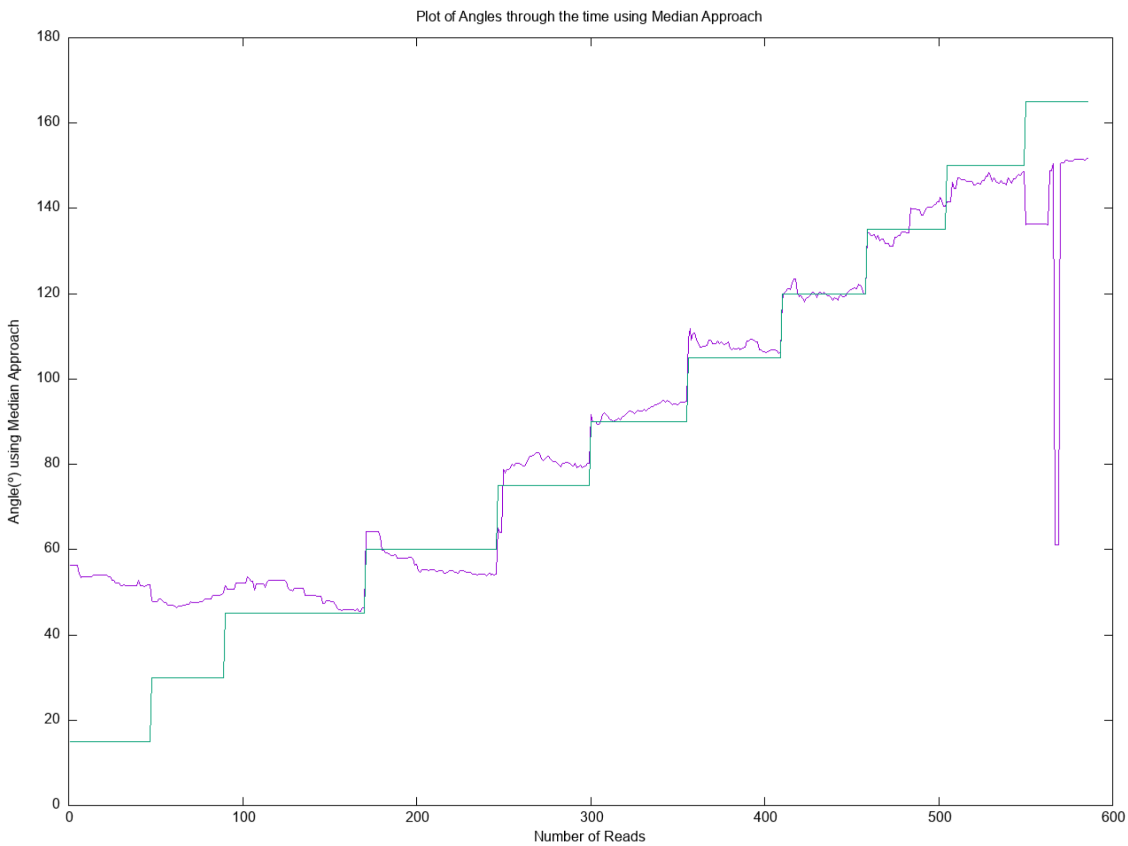

Figure 5.13: Result of the tests on the test-bed when compared with the real angles

An analysis of the Mean Absolute Error (MAE) values for each test position, as shown in Table 5.9, provides valuable insights into the performance of the system. The results indicate that the estimations for angles between 45º and 135º exhibit relatively low error, suggesting accurate position estimations within this range. Furthermore, the MAE values for the 150º position also fall within an acceptable range.

However, an interesting observation arises when comparing the MAE values of the symmetric angle (30º) with its corresponding position (150º). In an ideal condition without any external

Table 5.9: Performance Analysis at Different Angles

Angle (º)	**Count**	**Mean Absolute Error (º)**	**Root Squared Mean Error (º)**
15	47	38.11	38.14
30	42	17.87	17.89
45	81	4.86	5.48
60	76	4.16	4.49
75	53	5.67	5.89
90	56	2.56	3.02
105	54	2.96	3.21
120	49	0.94	1.23
135	46	3.42	3.97
150	45	3.71	4.02
165	37	26.85	35.95

influences, we would expect the MAE values for symmetric angles to be similar. However, the presence of a nearby wall introduced additional complexities and reflections into the system, visible on 30º. As a result, the MAE values for angles lower than 90º are noticeably higher compared to their symmetric counterparts.

Table 5.10: Comparison of Different Approaches among every position

Approach	**Mean Absolute Error (º)**	**Root Squared Mean Error (º)**
Averaging no Filter	9.03	15.49
Averaging	8.93	15.35
Median	8.91	15.35

An analysis of the results for each test position (table 5.10) reveals a lower performance compared to the previous analysis discussed in section 5.3.3.1. The results show that the system has difficulty accurately estimating the angles of 15º and 165º, as indicated by the figure 5.13 and table 5.9. These angles exhibit instability and higher errors, making them unreliable for accurate estimations. Additionally, the results obtained for the 30º angle are heavily influenced by environmental factors, further affecting their accuracy.

Considering the limitations discussed, we can exclude these problematic angles (15º, 165º, and 30º) from further analysis. By doing so, we obtain a refined set of results shown in table 5.11. These results indicate that the system may not be suitable for accurately estimating angles in these excluded ranges. However, for the remaining angles, the system demonstrates improved performance and stability.

Table 5.11: Comparison of Different Approaches excluding angles out of the acceptable range

Approach	Mean Absolute Error (º)	Root Squared Mean Error (º)
Averaging no Filter	3.80	4.47
Averaging	3.66	4.31
Median	3.66	4.30

Comparing the results obtained by excluding the angles outside the acceptable range (table 5.11) with the results obtained for every angle (table 5.10), we can observe a significant improvement in the performance of all approaches.

Specifically, for the excluded angles, the MAE values decrease from around 8.91 to approximately 3.66, and the RSME values decrease from around 15.35 to approximately 4.30. This demonstrates a substantial improvement in the estimation accuracy by excluding the problematic angles highlighting the importance of considering the specific range of angles for which the system performs well.

5.5 Enabling support for more than two antennas simultaneously

Until this point, the system was only using two antennas in order to detect the angle of arrival. Expanding the antenna array to include four consecutive antennas in each direction had several advantages. Firstly, it increased the range of antennas involved in the measurements, which allowed for a broader coverage of the signal and a more comprehensive understanding of the environment. Secondly, by including multiple antennas, the system could mitigate the effects of noise and multipath interference, as the measurements from different antennas could be combined and analyzed to obtain more accurate results.

5.5.1 Code Refactor

To accommodate the use of more than two antennas, a code refactor was necessary. However, it's important to note that increasing the number of antennas did not directly result in an increase in the number of phase readings. The number of phase readings was still determined by the length of the CTE and the duration of sampling. As a result, with more antennas in the array, each antenna's contribution to the phase readings was reduced in each sampling round.

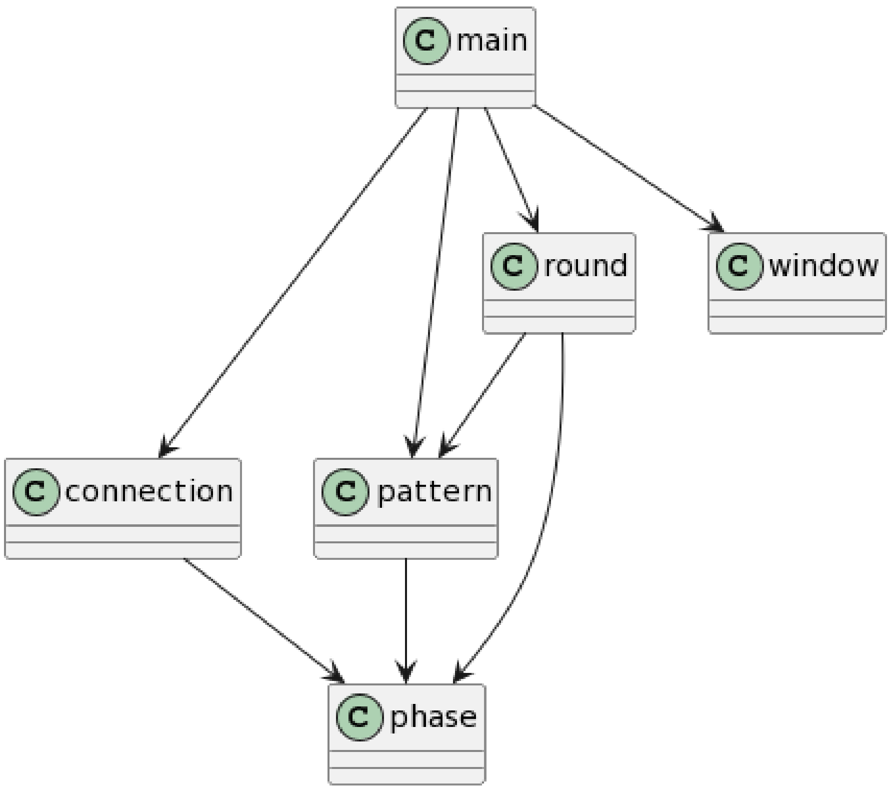

Figure 5.14: Class Diagram

To improve code organization and maintainability, the code was refactored into classes, with each class serving a specific purpose. This modular approach allowed for better separation of concerns and easier codebase management. Each class was responsible for a specific task, such as data acquisition, signal processing, angle estimation, or result analysis. This division of code into classes promoted code reusability, readability, and easier maintenance in the long run.

One of the key aspects of the code is the `get_angle` function in the `Round` class, which facilitates easy configuration. This function takes a list of parameters that define the structure of the input values, specifically the sequence and direction.

For instance, when considering the transmitted values of I and Q with the antenna order of 11, 12, 1, and 2, the code refactor enables the selection of antennas to be used and their sequence based on the received values. This allows for identifying the two phase values required for calculating the phase difference.

```
current_round.get_angles([
    pattern.Pattern(0, 1, False),
    pattern.Pattern(1, 2, False),
    pattern.Pattern(2, 3, False)
])
```

Listing 5.3: Python code to Configure the phase reading sequence

The `Pattern` class has three parameters. The first parameter is the index of the first phase value to be used, and the second parameter is the index of the second phase value. These two indices are used to calculate the phase difference between the corresponding antennas. The third parameter specifies the direction of the reading.

In the example code provided, the `Pattern` class is used to represent three phase differences: 11 <-> 12, 12 <-> 1, and 1 <-> 2. The direction of reading is determined based on the third parameter. For example, a phase difference read from antenna 12 to antenna 1 is different from a phase difference read from antenna 1 to antenna 12. To account for this, the third parameter is set to `False` for reading from left to right in the antenna array, and `True` for reading from right to left.

Once all the patterns are consumed, it indicates that the antenna array has completed a full cycle and returned to the first antenna of the sequence. At this point, the `get_angles` function will start again from the first pattern and cycle through the patterns until all the phase values (I and Q) for the round have been transmitted and processed. This allows for continuous operation of the system, ensuring that all the necessary phase values are captured and utilized for angle estimation.

5.5.2 Tests using 4 antennas

In order to evaluate the system's performance with more than two antennas, a set of tests was conducted using a test bed setup similar to the one described in Section 5.4.2.

For this particular test, a total of four antennas were chosen to be part of the array. The selected antennas were numbered 11, 12, 1, and 2, in sequential order. The sequence of antennas followed a specific pattern: 11 -> 12 -> 1 -> 2.

Figure 5.15 provides a visual representation of the antenna array setup, showing the sequential order of the antennas.

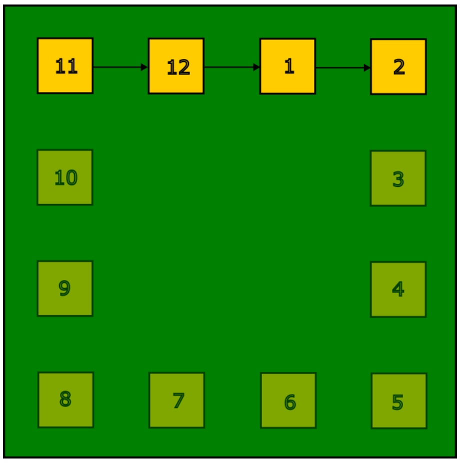

Figure 5.15: Visual representation of the array focused on the sequence between antenna 11 and antenna 2

The results of the tests can be analysed in table 5.12. Upon examining the results, it is evident that there is a modest improvement in the accuracy of angle estimation for angles ranging between 45 and 135 degrees. These findings suggest that the system's performance has shown some progress in accurately estimating angles within this particular range.

Table 5.12: Comparison of Different Angles (Excluding Outliers)

Angle (º)	**Count**	**Mean Absolute Error (º)**	**Root Squared Mean Error (º)**
15	231	20.96	24.91
30	236	8.40	14.35
45	234	2.79	3.54
60	235	3.65	4.31
75	236	1.46	2.15
90	432	4.01	4.40
105	279	4.35	4.63
120	220	3.03	3.32
135	208	2.68	3.59
150	168	31.26	42.15

A similar line of thought applied before to reject the measurements higher than 135º and lower than 45º can be applied in this situation as they do not provide results good enough to be considered. With that in mind, we can have the following metrics (tables 5.13 and):

Table 5.13: Comparison of Different Approaches with four antennas

Approach	Mean Absolute Error (º)	Root Squared Mean Error (º)
Averaging no Filter	3.26	3.88
Averaging	3.2	3.84
Median	3.27	3.89

Looking at the results, it can be observed that Table 5.13, shows slightly lower mean absolute error and root squared mean error values compared to the values presented in Table 5.11, present in the previous section. Although the differences are minimal, they suggest that considering all angles provides slightly more accurate angle estimation results.

The low values of the RSME considering the MAE indicate that the angle estimation results are generally stable and do not exhibit significant outliers or extreme variations. The RSME provides a measure of the overall dispersion or spread of the error values, and its low values suggest that the errors are consistently close to the mean value.

5.6 3D angle - Calculate azimuth and altitude

In the pursuit of developing a comprehensive localization system, the determination of a suitable antenna array position in the 3D space became essential. After careful consideration, it was decided to mount the antenna array on the ceiling of the room. This positioning choice offers several advantages, including improved clearance and enhanced range for the antenna system.

Furthermore, mounting the antenna array on the ceiling helped to optimize the coverage area. As signals transmit from an elevated position, they can effectively reach a larger portion of the room, reducing the likelihood of signal loss or attenuation. This expanded coverage area enhances the system's ability to accurately detect and estimate the angles of arrival.

It is worth noting that these tests were conducted in the same room as the previous experiments, maintaining consistency in the testing environment. This approach allows for reliable comparison and evaluation of the system's performance under different antenna positions.

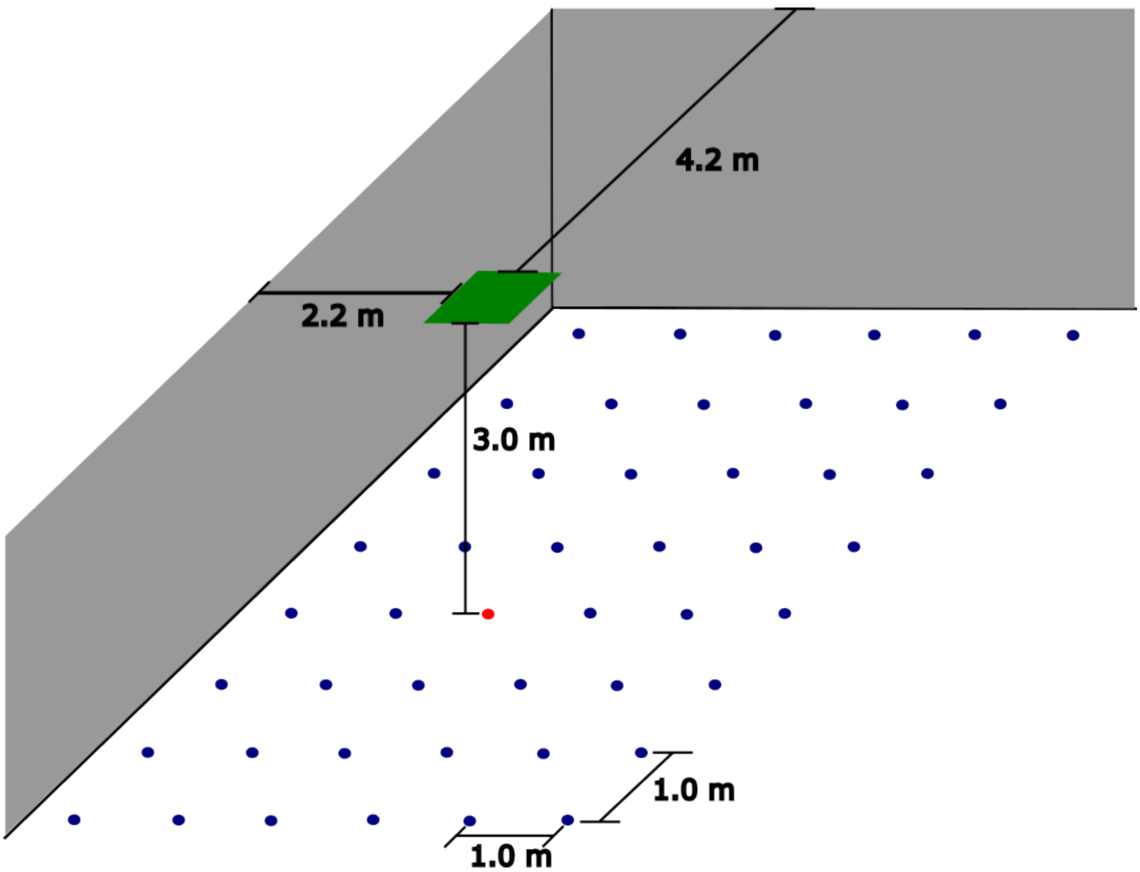

Figure 5.16: Visual representation of the 3d test-bed

Figure 5.16 provides a visual representation of the environment and the test-bed setup:

- **Green square:** represents the antenna array, positioned on the ceiling.

- **Dots** indicate the positions where the tests were conducted. Each dot represents a specific test position, and they are uniformly spaced at a distance of 1 meter from each other along the axis parallel to the walls.
- **Red Dot:** The red dot represents the dot directly below the array of antennas on ground level. It represents the origin of the coordinates, being the array of antennas at position (0,0,3)m.

The code had to be again refactored, this time, the configuration function received also a char that specified the direction of the angles. The values specified with "H" were separated from the ones with "V", and the normal pipeline was applied independently for both values.

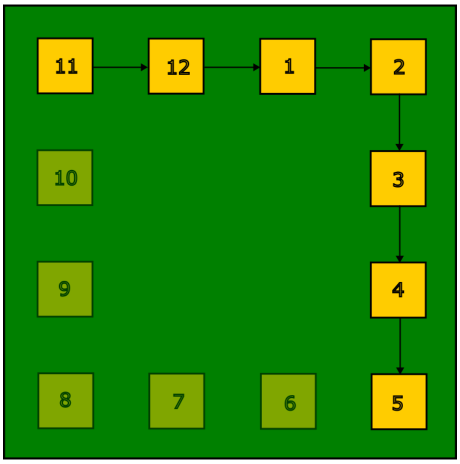

Figure 5.17: Visual representation the array focused on the sequence between antenna 11 and antenna 5

The antenna array was configured with a specific sequence of antennas: 11, 12, 1, 2, 3, 4, and 5 (see 5.17). This sequence was chosen to encompass antennas from both directions of the array, providing comprehensive coverage of the surrounding space. As a result, a single CTE transmission is utilized to retrieve angle information from both the azimuth and altitude directions, see figure 5.18.

The figure provides a visual representation of the two angles obtained by the system: azimuth and altitude. The azimuth angle represents the horizontal rotation or bearing of the vector, while the altitude angle represents the vertical inclination or elevation of the vector.

To facilitate understanding, the example in the figure is depicted in an upside-down orientation, where the ground is at the top and the ceiling is at the bottom. However, in the actual scenario, the antenna array is positioned on the ceiling.

It is important to note that both the azimuth and altitude angles are constrained within the range of 0 to 180 degrees. This means that instead of the traditional range of 0 to 360 degrees for azimuth and 0 to 90 degrees for altitude, the system operates within a half-sphere, where both angles are limited to 0 to 180 degrees. This configuration allows the system to define any vector with a positive altitude, capturing the full range of possible positions within the given space.

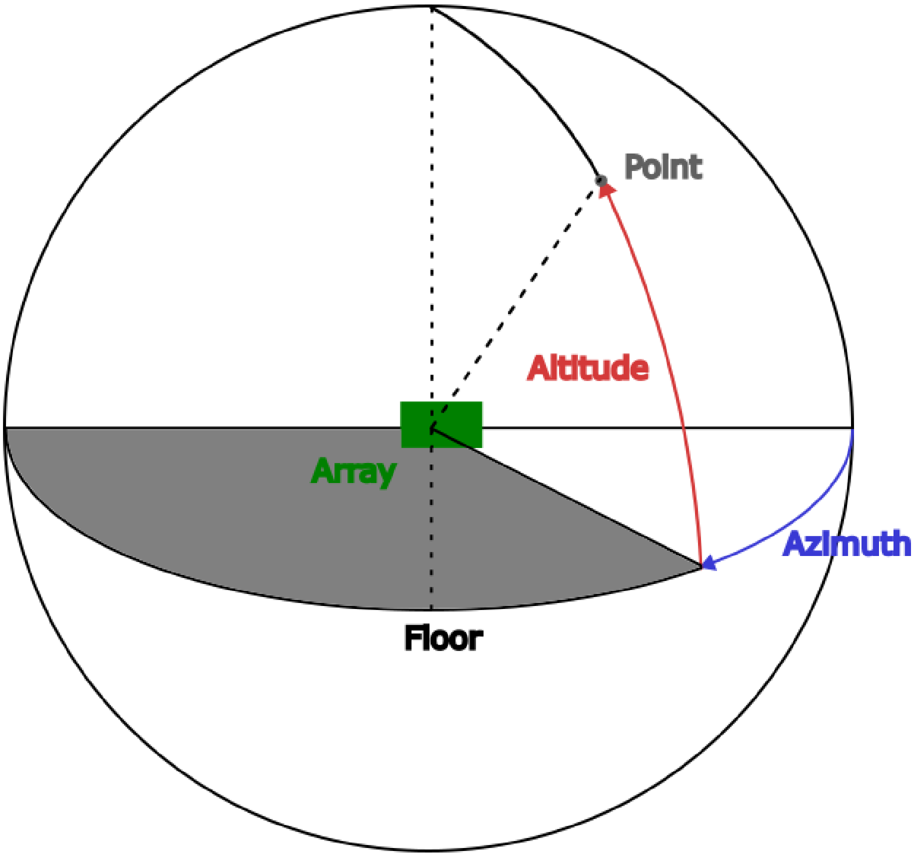

Figure 5.18: Visual representation of the Azimuth and Altitude Rotated

5.6.1 Positioning using Set height

In the initial phase of the experimentation, a simplified approach was employed that assumed all assets to be located on the ground floor. This approach allowed for rapid testing of the 3D localization model. As a result, the distance along the Z-axis (vertical axis) was fixed at 3 meters (see figure 5.16), representing the distance between the antenna array and the floor.

The simplified approach served as an initial proof-of-concept and provided valuable insights into the system's ability to estimate angles in a 3d scenario. Nevertheless, it should be noted that this approach has limitations when applied to real-world scenarios where assets can be located at various heights.

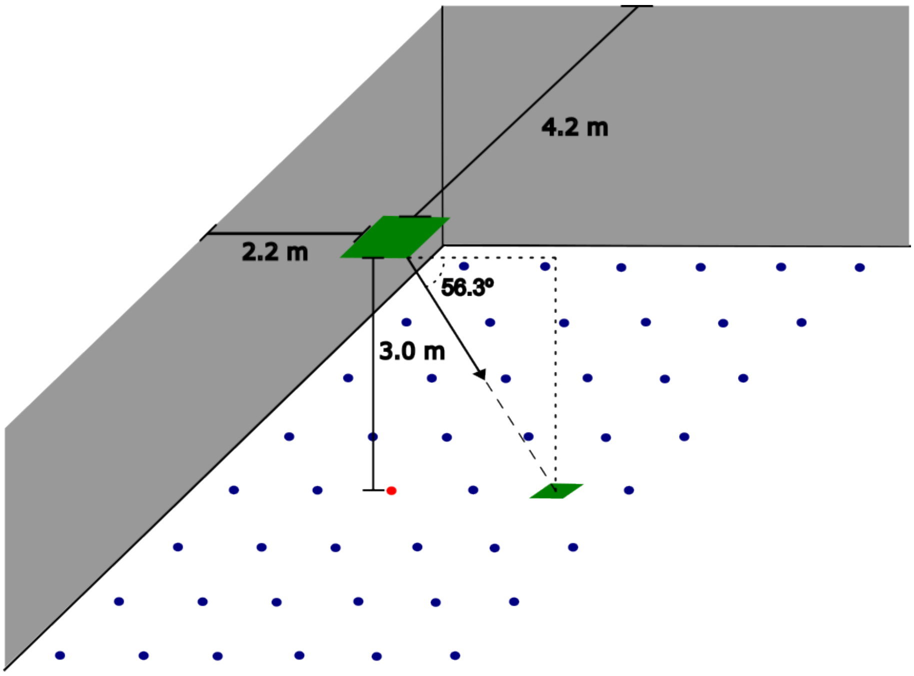

Figure 5.19: Visual representation of the Test-bed with an asset using the height approach

Take for example the scenario depicted in figure 5.19, Where the azimuth is 90º and the altitude 56.3º. There is first the need to convert this into Cartesian coordinates. To do so, the following equations were utilized:

```
x = math.sin(altitude_rad) * math.cos(azimuth_rad)
y = math.cos(altitude_rad)
z = 3 - math.sin(altitude_rad) * math.sin(azimuth_rad)
```

Listing 5.4: Polar to Cartesian Code

The equation for x represents the projection of the vector onto the x-axis, the equation for y represents the projection of the vector onto the y-axis, and the equation for z represents the projection of the vector onto the z-axis.

It is important to note that the value of z was subtracted from 3 because the coordinate system's origin is located at the point on the ground, while the measurements were made with the center of the antenna array as the reference point (0, 0, 3) m.

As depicted in the figure, the angles (azimuth and altitude) allow us to determine the direction of the vector. However, to find the actual position of the asset, the distance from the antenna array needs to be determined. Since only the altitude (height) information is available, the radius or distance from the array is unknown. To resolve this, the vector is extended while maintaining its direction until it intersects the ground plane.

This intersection problem can be formulated as finding the intersection point between an infinite line defined by the vector direction and the floor plane defined by the equation $Z = 0$. By expressing the vector as $\vec{v} = a\hat{\imath} + b\hat{\jmath} + c\hat{k}$, the line can be represented parametrically as $(x,y,z) = (at, bt, 3 - ct)$.

$$
\begin{gathered}
3 - c.t = 0 \Leftrightarrow \\
\Leftrightarrow c.t = 3 \Leftrightarrow \\
t = 3/c \Rightarrow \\
\Rightarrow (x,y,z) = (\tfrac{a.3}{c}, \tfrac{b.3}{c}, 3 - \tfrac{c.3}{c}) \Leftrightarrow \\
\Leftrightarrow (x,y,z) = (\tfrac{a.3}{c}, \tfrac{b.3}{c}, 0)
\end{gathered}
$$

This yields a point that lies on the line defined by the vector direction and intersects the floor plane, providing the coordinates of the asset.

Tests were conducted for each point on the test bed to evaluate the accuracy of the system in estimating the asset's position. From the testbed described before, 12 points were chosen in order to maximize the cover of the space. The tests were done by placing the asset at the desired positions and at the ground level. For each position, 20 estimations were gathered. Here is a brief overview of an example result:

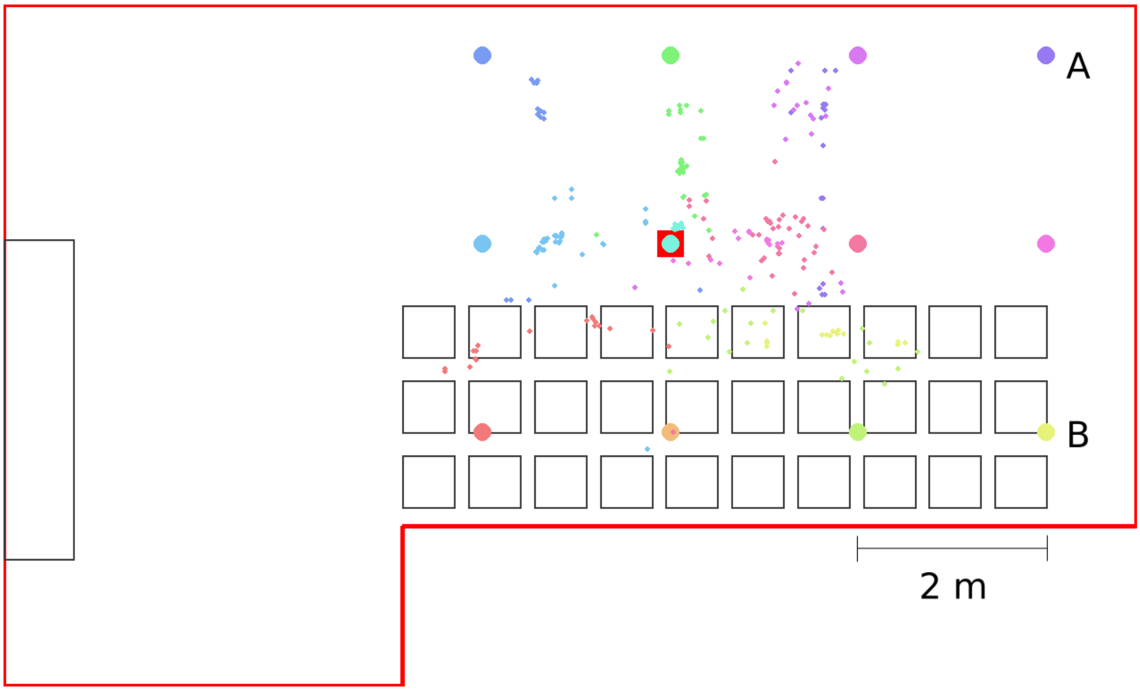

Figure 5.20: Visual representation of the results for Set height with 20 points

In Figure 5.20, the large points represent the real locations of the assets, while the small points represent the estimations for the position of the asset based on the angle of arrival calculations. The red square represents the position of the antenna array. The points have as the center, the array of antennas (0,0)m. The coordinates go from (2,2)m for the upper left point, to (-4,-2)m on the lower right point. Being point A (-4,2)m and point B (-4,-2)m.

By comparing the large points (real locations) with the small points (estimations), we can visually assess the accuracy of the system in determining the asset positions. Ideally, the small points should closely align with the large points, indicating accurate estimations.

Looking at Figure 5.20, we can observe that the estimations for the asset positions, represented by the small points, tend to cluster around the location of the antenna array, represented by the red square.

Even for points that are relatively far away from the array, such as the point marked as A (-4,2)m, the estimations still fall close to the array. This indicates that the system has a tendency to bias the estimations toward the array location.

As mentioned previously, angles outside the range of 45º to 135º can pose challenges in terms of accuracy. In the case of point A with ideal measurements, the azimuth angle of 56.3º falls within the acceptable range, but the altitude angle of 29.1º is outside the range. Consequently, this can lead to poorer results for such points.

Although the points outside the acceptable range may have lower accuracy, it is interesting to note that there is a tendency for the estimated points to align relatively close to a line connecting the array and the estimation point. This can be observed in Figure 5.21, where the estimated point B is shown.

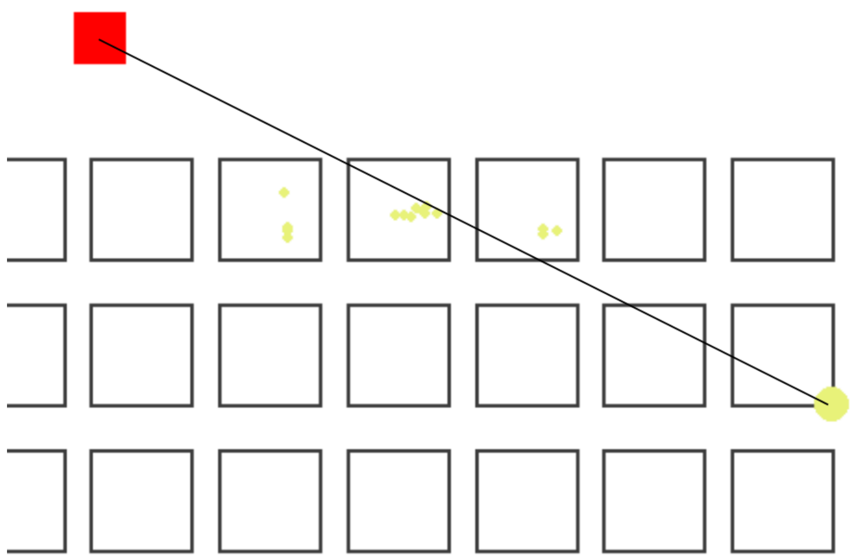

Figure 5.21: Imaginary line between real point and the array of antennas

This alignment suggests that, despite the limitations and errors in estimating the exact angles, the system is able to capture the general direction of the signal and provide estimations that are relatively close to the expected line of sight.

The results of the experiment yielded the following metrics:

Table 5.14: Error Metrics for Set Height Approach

Coordinates	**MAE (m)**	**RMSE (m)**
(2.0,-2.0,0)	1.36	1.45
(2.0,2.0,0)	1.29	1.58
(2.0,-2.0,0)	1.4	1.5
(-4.0,0.0,0)	3.22	3.24
(0.0,0.0,0)	0.18	0.19
(-4.0,2.0,0)	2.74	2.77
(0.0,2.0,0)	1.15	1.2
(-2.0,0.0,0)	1.02	1.13
(2.0,0.0,0)	0.96	1.07
(-4.0,-2.0,0)	2.72	2.84
(-2.0,2.0,0)	1.36	1.62

It is interesting to note that, as expected, the points that are further away from the array, such as points A and B, exhibit substantially higher errors compared to the points closer to the array. This observation aligns with our expectations, as the accuracy of the angle estimation tends to decrease with increasing distance between the antenna and the asset since the angles fall outside the 45º to 135 º range as seen in figure 5.22

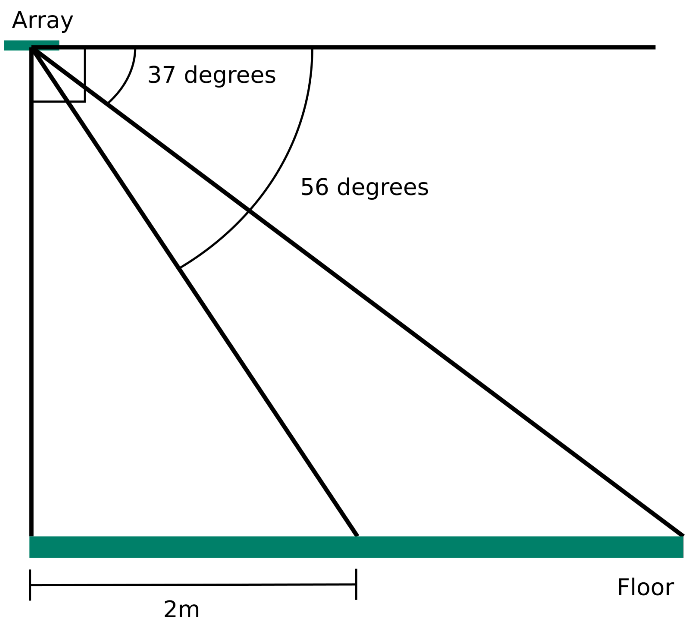

Figure 5.22: Visualization of the increase of the angle as the distance from the array increases

5.6.1.1 Observation of the algorithm stabilization

Taking into consideration the algorithm and the implementation of the sliding window, one can expect that the values will stabilize after a short period of time, leading to better estimations as time passes. This observation is consistent with the findings presented in the previous section (5.3.3.1), where it was demonstrated that the system becomes more responsive and accurate over time.

If we consider only the last 10 measurements of the system for each point, we observe a notable improvement in both visual representation and error metrics when compared to figure 5.20 and table 5.14:

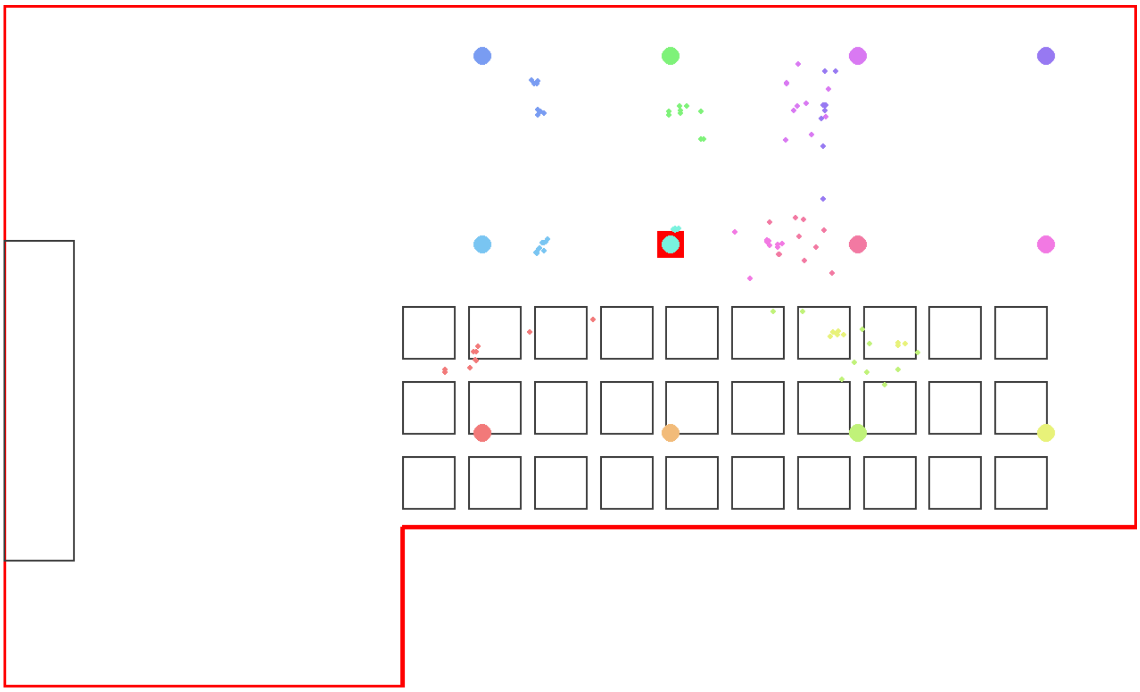

Figure 5.23: Visual representation of the results for Set height with 10 points

Table 5.15: Error Metrics for Last 10 Measurements

Point	MAE (m)	RMSE(m)
(2.0,-2.0,0)	0.93	0.97
(2.0,2.0,0)	0.71	0.72
(-2.0,-2.0,0)	0.97	1.02
(-4.0,0.0,0)	2.97	2.97
(0.0,0.0,0)	0.15	0.16
(-4.0,2.0,0)	2.45	2.46
(0.0,2.0,0)	0.66	0.68
(-2.0,0.0,0)	0.67	0.7
(2.0,0.0,0)	0.63	0.63
(-4.0,-2.0,0)	2.27	2.29
(-2.0,2.0,0)	0.82	0.84

A further comparison of the average MAE and RMSE values for every point reveals the improvement in estimations over time when considering only the most recent measurements from the experiment. By analyzing the average errors, we can assess the overall performance of the system:

Table 5.16: Comparison of MAE and RMSE for All Estimations and Last 10 Estimations

	MAE (m)	RMSE (m)
All	1.58	1.69
Last 10	1.20	1.22

As we can observe, when considering only the last 10 estimations, the MAE improves to 1.20m and the RMSE improves to 1.22m. This suggests that the system's performance becomes more accurate and stable over time, as the estimations based on the most recent data yield smaller errors compared to the complete dataset.

5.6.2 Using the real distance between an asset and the station

A potential solution to address the issue of inaccurate vector length, which is evident by the high concentration of estimations close to the array (figure 5.20), is to retrieve the real distance between the antenna and the asset. By obtaining the actual distance, we can use this value to determine the length of the vector, instead of simply extending it until it reaches the ground.

This approach would provide a more accurate representation of the position in 3D space, as it takes into account the actual distance between the antenna and the asset. By incorporating the real length into the vector calculation, the estimated points would be more aligned with the expected positions.

In order to accurately detect the distance between the station and the asset, the Nordic Software DM (Distance Measurement) library was utilized [3]. This library leverages the same CTE (Constant Tone Extension) technology used by AoA (Angle of Arrival) to enable precise distance measurements between two Nordic Development Kits (DKs).

Due to time constraints and the schedule of this dissertation, it was not possible to integrate the Angle of Arrival (AoA) and Distance Measurement (DM) code into the same Development Kit (DK). As a result, the final Proof of Work (PoW) setup involved using two separate DKs, one on the asset side and one on the station side, to handle the distance measurements.

This approach allowed for independent development and testing of the AoA and DM functionalities.

Although integrating the AoA and DM code into a single DK would have been ideal, the use of separate DKs was a practical solution given the time limitations. It still enabled the evaluation of the distance measurement capabilities and the exploration of AoA in a controlled environment.

It is important to note that this approach does not impact the overall validity and applicability of the findings presented in this dissertation.

The introduction of distance measurements highlighted an important consideration in the estimation process. Since the system is not designed to identify assets located on different floors, any vector that points below the ground level indicates a potential estimation error. In such cases, we can assume that the estimation is incorrect and requires further handling.

5.6.2.1 Vector Rotation from below the ground level

A solution was developed to handle estimations that pointed below the ground level. The algorithm projects the line formed by the asset's estimated location and the array onto the ground plane. From this projection, a point is found that maintains the specified distance between the asset and the array. working as a rotation of the vector, keeping the 2D direction of the vector the same. See figure 5.24.

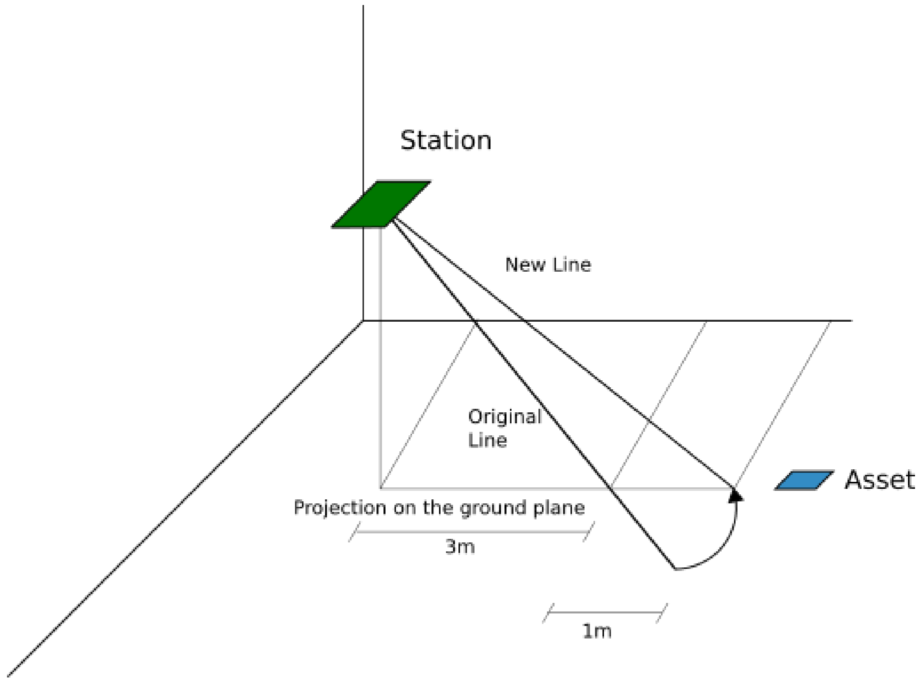

Figure 5.24: Algorithm visualization for dealing with estimations under the ground level

By incorporating the approach of projecting the vector onto the ground when it points below the ground level, several benefits were achieved in terms of estimation accuracy.

Firstly, this approach helped to bring the estimation closer to the real 2D location of the asset. By finding a point on the ground that corresponds to the estimated distance from the station, the estimation was adjusted to align with the 2D direction provided by the angle measurements. This adjustment contributed to reducing the overall estimation error and improving the accuracy of the system.

Secondly, by ensuring that the vector points to a point on the ground, the difference in the Z axis (vertical axis) between the asset and the estimation was minimized. This reduction in the Z axis difference further enhanced the accuracy of the estimated position by aligning it closely with the real-world coordinates of the asset.

If we define the vector as $(x,y,z) = (at, bt, 3 - ct)$ and the size of the original vector as `s`, we can find the vector's projection on the ground by setting the Z value to 0. In this case, we end up with the equation $(x,y,z) = (at, bt, 0)$. We can then find the point on the equation that distances exactly `s` from the station point.

Even though algebraical solutions existed to solve the problem, the approach that was taken was to use a numerical approach, more specifically the **Bisection method** to find the solution to the equation $\sqrt{(at)^2 + (bt)^2 + 3^2} = s$ that finds the distance between the estimation and the station point.

5.6.2.2 Results

By incorporating the rotation algorithm and utilizing the real distance when calculating the final estimations, the system achieved notable improvements in its results compared to the previous approach that relied on a fixed height for calculations.

The tests were made with the same conditions as previously, recording 60 measurements per point.

The rotation algorithm played a crucial role in adjusting the estimations and preventing the previous problem of the points falling short, often close to the station.

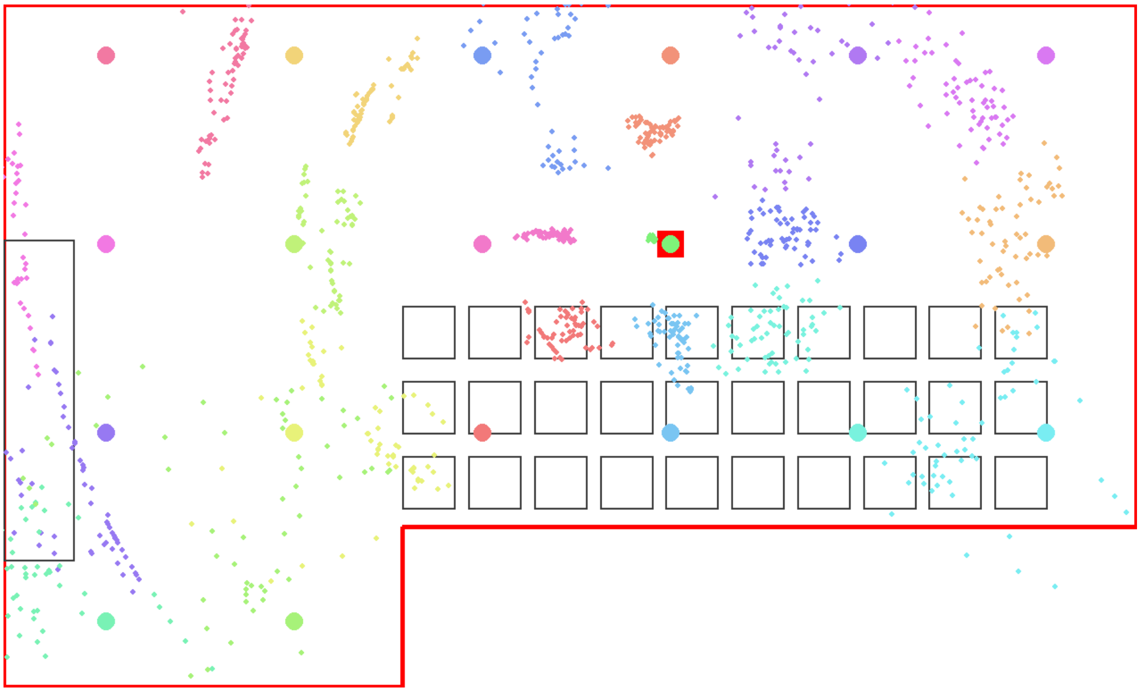

Figure 5.25: Visual representation of the results for using estimated distance for 60 points

Upon analyzing figure 5.25, it is evident that the estimated points are much closer to their respective real positions compared to the previous approach (as shown in figure 5.20).

It is visible also by looking at the metrics that the system's performance improved:

Table 5.17: Error Metrics for the Estimated Distance Approach

Point	MAE (m)	RMSE (m)
(2.0,-2.0,0)	1.57	1.59
(2.0,2.0,0)	1.01	1.1
(2.0,-2.0,0)	0.59	0.62
(6.0,0.0,0)	1.29	1.31
(-2.0,-2.0,0)	1.59	1.62
(-4.0,0.0,0)	0.67	0.71
(6.0,-2.0,0)	1.03	1.09
(0.0,0.0,0)	0.97	0.98
(6.0,2.0,0)	1.41	1.41
(0.0,-2.0,0)	1.05	1.07
(4.0,-2.0,0)	1.1	1.15
(-4.0,2.0,0)	1.05	1.07
(6.0,-4.0,0)	1.11	1.16
(0.0,2.0,0)	0.89	0.89
(-2.0,0.0,0)	1.26	1.28
(4.0,-4.0,0)	1.71	1.94
(2.0,0.0,0)	1.21	1.22
(-4.0,-2.0,0)	1.14	1.18
(4.0,2.0,0)	1.02	1.03
(-2.0,2.0,0)	1.07	1.16

By examining table 5.17, it is evident that the enhanced system's performance has improved compared to the previous approach. Even when considering positions outside the expected zone of good performance, the system demonstrates a remarkable level of accuracy.

Results falling close together and forming visible clusters indicate that the approach employed in the system enables stable estimations. The clustering of results suggests that the system consistently produces estimations that are close to the actual positions of the assets.

Similar to the previous approach, the behavior of the system over time was analyzed to assess its stability and improvement. The expectation was that the estimations would become more stable and the overall error would decrease as more measurements were considered.

To observe this behavior, the last 10 estimations of each point were selected and analyzed. By focusing on the most recent measurements, the aim was to evaluate the system's performance in the current state, which could indicate its overall stability and accuracy.

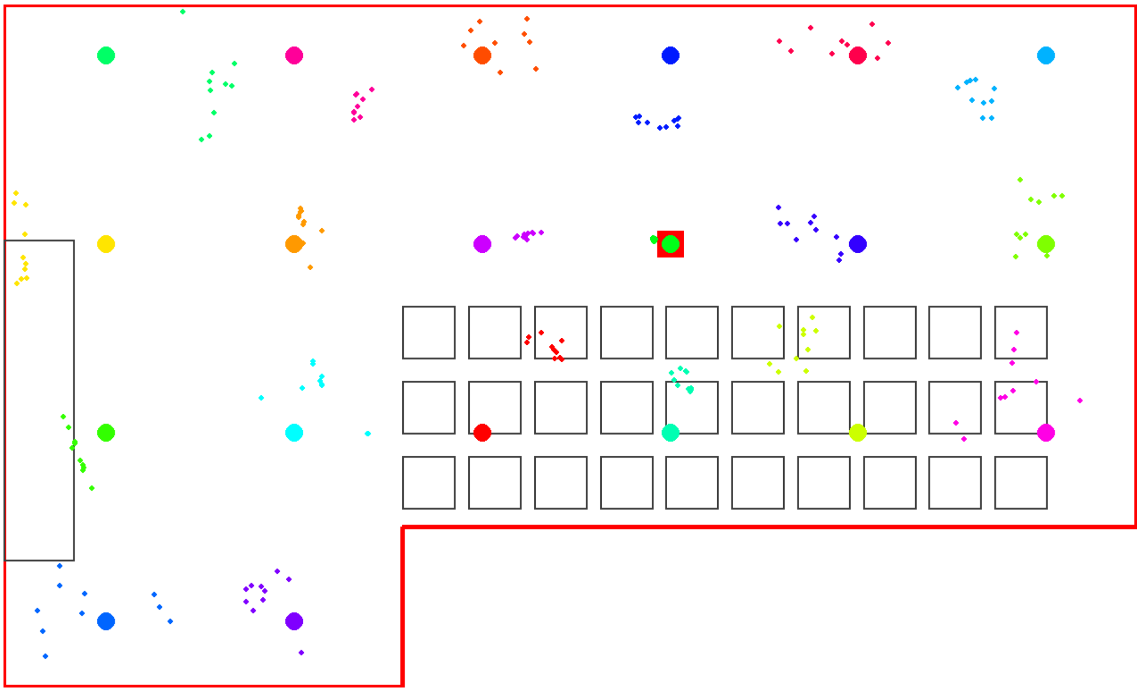

Figure 5.26: Visual representation of the results for using estimated distance for 20 points with last 10 estimations

We can observe that in figure 5.26, it is easily observable to which point each estimation belongs and no overlap exists between estimations from different points. The result shows clear clusters near the real point, and the estimations for points that are further away from the stations are also usable, unlike the previous approach.

The results of the metrics presented in 5.18 are also an improvement over 5.17.

When comparing the results of all estimations with the last 10 estimations of the experiments, it is evident that the values get progressively closer to the real positions as more measurements are considered. This observation aligns with the expectation that the system's performance improves over time as it accumulates more data.

By examining the averaged Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) of all estimations and comparing them with the last 10 estimations (see Table 5.19), we can quantitatively assess the improvement in the system's performance.

Table 5.19: Comparison of MAE and RMSE for All Estimations and Last 10 Estimations using the Distance Approach

	MAE (m)	RMSE (m)
All	1.137	1.179
Last 10	0.788	0.8015

Table 5.18: Error Metrics for Last 10 Measurements

Point	MAE (m)	RMSE (m)
(2.0,-2.0,0)	1.2	1.21
(2.0,2.0,0)	0.36	0.4
(4.0,0.0,0)	0.29	0.3
(6.0,0.0,0)	0.96	0.96
(-2.0,-2.0,0)	1.21	1.23
(-4.0,0.0,0)	0.46	0.48
(6.0,-2.0,0)	0.44	0.44
(0.0,0.0,0)	1.01	1.02
(6.0,2.0,0)	1.24	1.25
(0.0,-2.0,0)	0.7	0.71
(4.0,-2.0,0)	0.65	0.66
(-4.0,2.0,0)	0.88	0.89
(6.0,-4.0,0)	0.6	0.62
(0.0,2.0,0)	0.8	0.8
(-2.0,0.0,0)	1.19	1.2
(4.0,-4.0,0)	0.49	0.5
(2.0,0.0,0)	1.19	1.2
(-4.0,-2.0,0)	0.77	0.8
(4.0,2.0,0)	0.87	0.87
(-2.0,2.0,0)	0.45	0.49

5.6.3 Set Height vs Distance estimation

When comparing the two approaches, it is important to consider their performance, complexity, and limitations.

The Set Height Approach is simpler in terms of implementation as it does not require additional software or calculations. However, its major limitation is that it assumes all estimated positions to be at the same height. This can lead to inaccurate positioning if the assets are not at the specified height. Additionally, this approach showed poor results when estimating positions of assets that are further away from the station.

On the other hand, the Distance Estimation Approach is more complex as it requires additional software, such as the Nordic DM library, to estimate the distance between the asset and the station. This adds an extra layer of complexity to the system. However, this approach demonstrated better results, especially for points where the Set Height Approach was inefficient.

Comparing the errors of both approaches (see table 5.20), it is evident that the Distance Estimation Approach outperforms the Set Height Approach. The use of real distance information in the calculations improves the accuracy of the estimations and reduces errors. This approach takes into account the actual distance between the antenna and the asset, leading to more precise positioning results.

Table 5.20: Comparison of MAE and RMSE between Set Height and Distance Measurement Approaches

	MAE (m)	**RMSE (m)**
Set Height	1.203	1.222
Distance Measurement	0.788	0.802

Considering these factors, the Distance Estimation Approach proves to be superior in terms of accuracy and overall performance, despite its increased complexity compared to the Set Height Approach.

Chapter 6

Discussion

The results and their interpretation were already heavily discussed in the previous chapter (5) as a part of the implementation, since the results of tests were heavily considered when implementing the final system. It is important however to make a final comparison between the values obtained by this dissertation and the results of the State of the Art. Using the values specified on tables 2.1, 2.2, 2.3 and 2.4:

By comparing the values specified in Tables 2.1, 2.2, 2.3 and 2.4 (refer to the respective tables), we can draw meaningful conclusions about the performance of the proposed system in relation to other technologies such as VLC, RFID, WiFi, and BLE without AoA. These comparisons allow us to assess the strengths and limitations of the implemented system and gain insights into its effectiveness.

It is worth noting that the performance of localization systems can vary depending on various factors such as environmental conditions and specific use cases.

Table 6.1: Comparison between Different Methods

Technology	# Anchors	# Tags	Test Dimensions	Accuracy	Method	Ref
VLC	1	4	6m x 6m x 4.2m	RMS error of 6.1cm	Trilateration RSS	[18]
VLC	1	4	10m x 9m x 3.1m	Highest variance error is 0.3m2	Fingerprinting	[39]
VLC	1	5	0.71m x 0.43m x 2.36m	90 th percentile of 10cm	AoA	[22]
RFID	16	-	-	50th at 0.5m	Fingerprinting RSSI	[19]
RFID	-	-	-	0.47m	Fingerprinting RSSI	[30]
WIFI	3	-	43.5m x 22.5m	2.94m at 50%	Fingerprinting RSS	[8]
WIFI	21	-	68.2m x 25.9m	0.6m at 50%	Fingerprinting RSS	[43]
BLE	6	-	6.1m x 12.2m	1.7m	Fingerprinting RSSI	[32]
BLE	3	-	-	1.5m	Trilateration RSSI	[27]
BLE	1	1	6m x 4m x 3m	1.203m	AoA with Set Height	5.6.3
BLE	1	1	10m x 4m x 3m	0.788m	AoA and Distance Measurement	5.6.3

The last two methods in the table 6.1 are the ones described in this dissertation.

By comparing the accuracy results, we can see that the AoA and Distance Measurement approach implemented in this dissertation achieves an accuracy of 0.788m for a test dimension of 10m x 4m x 3m, while the AoA approach achieves an accuracy of 1.203m for a test dimension of 60m x 4m x 3m. These results indicate that the implemented approaches have competitive accuracy compared to the other methods in the table 6.1, having better results than other approaches using BLE technology.

Indeed, considering the specific goals and context of this dissertation, the VLC approach is not suitable due to its requirement of Line of Sight (LoS), which may limit its applicability in real-world environments. The fingerprinting approach, although capable of achieving good results, has limitations such as being time-intensive and sensitive to environmental changes.

In contrast, the AoA approach using BLE technology demonstrates great potential in achieving the goals outlined in the dissertation 1.3. Despite the narrow angle of measurement and susceptibility to RF reflections, the results obtained show promising performance for real-time locations on industrial floors. The use of BLE technology offers advantages such as low-cost hardware, low power consumption, and compatibility with existing infrastructure.

Considering the limitations and strengths of each approach, the AoA approach using BLE technology appears to be a viable and promising solution for real-time location tracking in industrial settings. Further optimizations and refinements can be explored to improve the accuracy and robustness of the system in practical deployments.

Chapter 7

Conclusion

In conclusion, this dissertation presented a comprehensive study on the development of a localization system using an antenna array. The system aimed to accurately estimate the angle of arrival and position of assets in a three-dimensional space. Throughout the research, various techniques and methodologies were explored, and their performance was evaluated through extensive experiments.

The initial phase of the study focused on the implementation and evaluation of different signal processing algorithms for angle estimation. Three approaches, namely Averaging without Filtering, Averaging, and Median, were compared in terms of their mean absolute error (MAE) and root squared mean error (RSME). The results demonstrated the effectiveness of the Median approach with filtering, which exhibited superior performance in terms of accuracy and stability.

To enhance the system's robustness, the antenna array was extended from two to four antennas. This expansion allowed for a broader range of antennas and improved the system's resistance to noise and multipath effects. The performance of the system with four antennas was evaluated, and the results showed a further reduction in the MAE and RSME values compared to the two-antenna configuration.

Furthermore, a 3D localization model was developed to estimate the position of the assets. By utilizing azimuth and altitude angles, the polar coordinates were converted into Cartesian coordinates. The intersection of the vector direction with the floor plane enabled the determination of the asset's position in the three-dimensional space.

The experimental results demonstrated the effectiveness of the proposed system in accurately estimating the angle of arrival and position of assets. The system exhibited responsiveness, stability, and a low error rate, indicating its suitability for practical applications in real-world scenarios.

Future research directions could include investigating the system's performance in dynamic environments with moving assets, exploring advanced signal processing techniques to further improve accuracy, and integrating the localization system with other technologies for enhanced asset tracking and monitoring. Other possible improvement could be the use of the CTE sampling reference period in order to calibrate the system and identify rounds that need to be discarded based on the reference period.

In conclusion, this dissertation contributes to the field of localization systems by providing a comprehensive study on the development and evaluation of an angle-of-arrival based system.

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Appendix A

Images

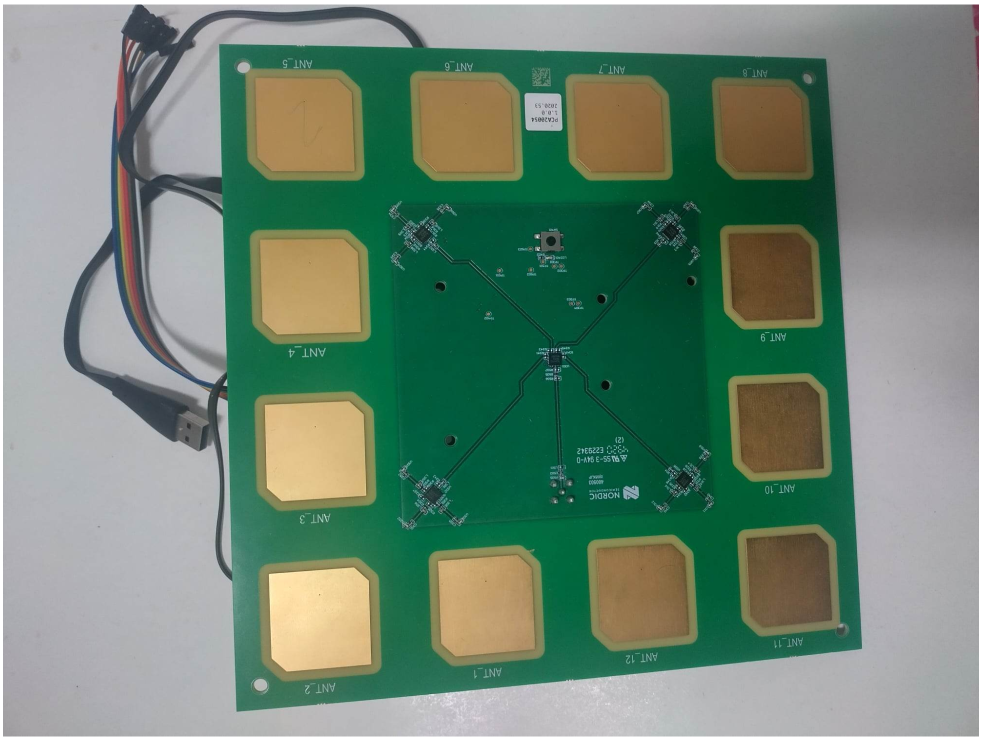

Figure A.1: Array of antennas, base for the solution that will be developed

Appendix B

Photos of the test-bed environment

Appendix C

Experimental Values

Table C.1: First Measurements

Sample Number	Angle Estimation	Angle Estimation with Averaging
0	132.3139719	132.3139719
1	47.33626767	89.8251198
2	56.99078796	78.88034252
3	133.5429994	92.54600674
4	57.03553129	85.44391165
5	58.84884359	81.0114003
6	130.7643062	88.11895829
7	133.3907365	93.77793057
8	58.16870702	89.82135017
9	59.25349386	86.76456454
10	61.26266272	84.44620983
11	131.219497	88.34398376
12	58.91895849	86.08052028
13	58.7705878	84.12981082
14	132.1778062	87.33301051
15	84.36898662	87.14775902
16	87.52825643	87.17014122
17	88.13683147	87.22384623

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
18	88.88367051	87.3112054
19	86.6723816	87.27926421
20	88.86808301	87.35492225
21	88.2593983	87.3960348
22	90.35780301	87.52480733
23	89.76332786	87.61807902
24	86.62045765	87.57817416
25	85.50822419	87.4985607
26	86.56481477	87.46397752
27	86.40793415	87.42626169
28	83.80377163	87.30134824
29	78.43151592	87.00568716
30	84.48696932	86.9244382
31	80.21692996	86.71482856
32	82.91535419	86.59969298
33	81.4226193	86.4474261
34	78.79855554	86.22888694
35	81.51238123	86.0978729
36	82.33109177	85.996068
37	79.09921371	85.81457184
38	83.2479027	85.74875981
39	84.67874945	85.72200955
40	79.86515225	85.57915937
41	63.43367806	85.05188601
42	57.92179508	84.42095366
43	140.0431299	85.68509403
44	138.8106544	86.86566203
45	61.35197045	86.31101657

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
46	59.74658363	85.74581586
47	137.7829122	86.82992204
48	138.2952439	87.88023473
49	61.60953748	87.35482078
50	61.40144045	86.84593097
51	138.3027769	87.8354857
52	59.68845952	87.30440974
53	61.11701859	86.81945805
54	62.2349909	86.37246774
55	97.75915994	86.57580153
56	97.15465354	86.76139542
57	99.1480441	86.97495833
58	99.70797325	87.19077214
59	98.71168106	87.38278729
60	98.74661229	87.5690795
61	96.31398516	87.71012637
62	96.98645593	87.8573697
63	99.5576356	88.04018635
64	96.36811766	88.16830837
65	100.2196389	88.35090429
66	96.87293574	88.47809879
67	109.1742401	88.78245381
68	110.7943463	89.10146674
69	95.64691155	89.1949731
70	50.21095778	88.64590246
71	113.3399672	88.98887558
72	108.8414371	89.26082848
73	35.0005517	88.52758149

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
74	110.175293	88.81621765
75	109.041524	89.0823401
76	110.0743148	89.35496315
77	28.71029579	88.57746741
78	110.4794014	88.85470708
79	108.5638436	89.10107129
80	111.8537637	89.38196872
81	25.67591739	88.60506566
82	132.2754434	89.13121479
83	54.27385734	88.71624625
84	52.4790028	88.28992574
85	128.2165237	88.7541885
86	129.3175427	89.22043395
87	53.82750967	88.81824163
88	50.0855931	88.38304333
89	128.6816967	88.83080615
90	129.3274172	89.27582385
91	53.26568161	88.88440926
92	53.49350086	88.50386186
93	131.7391084	88.96381129
94	132.2273089	89.41921653
95	58.58067933	89.09798177
96	111.3510655	89.327395
97	111.1650356	89.55022807
98	111.7210342	89.77417561
99	32.30910828	89.19952493
100	110.0049951	89.40551969
101	109.4781657	89.60231033

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
102	109.6378886	89.79683051
103	31.77079376	89.23888785
104	112.1946764	89.45751441
105	112.0885707	89.67101494
106	97.01547074	89.73965471
107	32.68329928	89.21135513
108	112.8657978	89.42836836
109	109.1742401	89.60787629
110	29.00580413	89.06191167
111	121.2388262	89.34920555
112	46.37914035	88.96893949
113	118.5393509	89.22832906
114	120.6960566	89.50196147
115	107.4987454	89.65710616
116	41.3782602	89.24446645
117	122.4846465	89.5261629
118	118.1738339	89.76689963
119	43.03012565	89.37742651
120	45.82799608	89.01751386
121	121.9835955	89.28772765
122	122.0846873	89.55436959
123	46.25435451	89.20517592
124	44.48741397	88.84743383
125	106.7711621	88.98968564
126	111.2524067	89.16498266
127	102.1445362	89.26638542
128	19.00761693	88.7217438
129	104.3527647	88.84198242

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
130	107.9157092	88.98758339
131	105.3272476	89.11136873
132	18.28561554	88.57884427
133	106.321004	88.71124844
134	108.5086178	88.85789562
135	106.2393252	88.98570025
136	13.93496436	88.43788466
137	105.7289919	88.56318254
138	107.9619605	88.7027421
139	105.3458588	88.8216215
140	81.63864606	88.77067841
141	80.70151459	88.71385331
142	81.0686862	88.66039061
143	80.33226289	88.60255639
144	80.17559091	88.54443938
145	79.74852373	88.48419339
146	81.35611573	88.43570306
147	80.31360742	88.38082404
148	82.53060592	88.34156083
149	82.0157731	88.29938891
150	82.22450547	88.25915789
151	90.68063105	88.27508864
152	84.16860654	88.24824889
153	80.97287462	88.2010062
154	84.0329015	88.1741152
155	149.2519158	88.56563956
156	70.39615446	88.44991036
157	71.39433009	88.34196365

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
158	152.6955134	88.74670295
159	131.69196	89.01511081
160	71.87632226	88.90865871
161	70.26815584	88.79359387
162	156.5709702	89.209406
163	149.8968056	89.57945112
164	67.68384257	89.44675046
165	67.44630223	89.31421764
166	153.9740922	89.70140252
167	67.51504171	89.56934085
168	69.14028078	89.44845883
169	75.20223201	89.3646575
170	75.36000082	89.28275892
171	77.52994349	89.2144286
172	80.18646943	89.16224386
173	76.49511889	89.0894443
174	76.64252145	89.01831902
175	78.24046468	88.95708121
176	77.00904375	88.88957818
177	76.69685626	88.82107974
178	78.02147453	88.76074675
179	76.91407961	88.69493193
180	74.78431504	88.61807769
181	78.91741691	88.56477736
182	90.21583301	88.57379952
183	63.65072574	88.43834803
184	141.4088433	88.72467504
185	145.1692389	89.02814043

Continued on next page

Table C.1: First Measurements (Continued)

Sample Number	Angle Estimation	Angle Estimation with Averaging
186	63.92488244	88.89389841
187	64.86142972	88.76606613
188	145.208095	89.06470121
189	143.5665293	89.35155293
190	64.9581677	89.22383887
191	74.95108802	89.14950163
192	155.4679314	89.49312044
193	145.1921923	89.78022905
194	87.36223394	89.76782908
195	79.81814652	89.71706539
196	137.7867041	89.96107371
197	70.54259537	89.86300059
198	18.9600761	89.50670449