



KADIR HAS UNIVERSITY  
SCHOOL OF GRADUATE STUDIES  
PROGRAM OF ELECTRONICS ENGINEERING

**THE ENHANCEMENT OF LOCATION  
DETERMINATION IN INDOOR POSITIONING SYSTEMS**

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MASTER OF SCIENCE THESIS

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# **THE ENHANCEMENT OF LOCATION DETERMINATION IN INDOOR POSITIONING SYSTEMS**

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MASTER OF SCIENCE THESIS

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## APPROVAL

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*Üşengeçlikten kurtulmuş bir zihnin başaramayacağı şey yoktur.*

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# THE ENHANCEMENT OF LOCATION DETERMINATION IN INDOOR POSITIONING SYSTEMS

## ABSTRACT

Indoor positioning technologies have advanced significantly in recent years and offer a variety of possible uses. Indoor positioning has an important role in many industries. If give examples of the main sectors that do this indoor positioning: industrial automation, smart home systems, construction, healthcare, and location-based service areas. Technological developments of this sector aim to constantly increase the sensitivity and accuracy of existing indoor positioning techniques. This thesis focuses on reducing position detection error occurring in Non-Line-Of-Sight (NLOS) scenarios in Ultra-Wideband technology by applying the Federated Kalman Filter. It has been demonstrated that using the Federated Kalman Filter in NLOS circumstances greatly reduces position deviation. In this thesis, measurements made indoors location Line-Of-Sight (LOS) and NLOS conditions were analyzed using the Federated-Kalman Filter. The results obtained in this thesis provide a promising basis for future studies in the field of ultra-broadband technology. The results of the thesis underline the potential for improved performance and accuracy to be gained in challenging operational environments. The Federated Kalman Filter showed an average accuracy improvement of approximately 96.64%. After applying the Federated Kalman Filter, the error margin which had previously been as high as 0.30 meters was significantly lowered to 0.0072 meters. Similarly, a comparable increase of approximately 96% was observed in NLOS conditions.

**Keywords:** Ultra-Wide Band, Location Estimation, Non-Line of Sight, Tracking, Positioning, Federated Kalman Filter

# İÇ MEKAN KONUMLANDIRMA SİSTEMLERİNDE KONUM BELİRLEMESİNİN GELİŞTİRİLMESİ

## ÖZET

Son yıllarda, kapalı alan konumlandırma teknolojileri önemli ölçüde gelişmiş ve birçok uygulama alanında büyük potansiyele sahiptir. Kapalı alan konumlandırma belirleme, özellikle akıllı ev sistemleri, endüstriyel otomasyon, inşaat, sağlık ve konum tabanlı hizmetler gibi birçok alanda önemli bir rol oynamaktadır. Bu alandaki teknolojik gelişmeler, mevcut kapalı alan konumlandırma yöntemlerinin doğruluğunu ve hassasiyetini sürekli olarak artırmayı amaçlamaktadır. Bu tez, Federe Kalman Filtresi uygulanarak, Ultra Geniş Bant teknolojisinde görüş hattı dışı (NLOS) senaryoları tarafından oluşan konum sapmasını azaltmaya odaklanmaktadır. Federe Kalman Filtresinin NLOS senaryolarında kullanımı, konum sapmasında dikkate değer bir azalmayı göstermiştir. Bu tez, Federe Kalman Filtresini, kapalı mekân ayarlarında görüş hattı (LOS) ve görüş hattı dışı (NLOS) koşullar altında alınan ölçümleri analiz etmek için kullanmaktadır. Bu çalışmanın bulguları, Ultra Geniş Bant teknolojisi alanında gelecekte yapılacak olan araştırmalar için umut verici bir temel sunarak zorlayıcı çalışma ortamlarında iyileştirilmiş performans ve azaltılmış hata payı ile bu alanın güçlü taraflarını göstermektedir. Federe Kalman Filtresi, ortalama doğruluk iyileştirmesi olarak yaklaşık %96,64'ünü gösterdi. Başlangıçta 0,30 metreye ulaşan hata payı, Federe Kalman Filtresinin entegrasyonu ile 0,0072 metreye önemli ölçüde azaltılmıştır. Benzer şekilde, görüş hattı dışı (NLOS) senaryolarında yaklaşık %96'lık bir iyileştirme gözlemlenmiştir.

**Anahtar Sözcükler:** Ultra Geniş Bant, Konum Tahmini, Görüş Hattı Dışı, Takip, Konumlandırma, Federe Kalman Filtresi

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## LIST OF SYMBOLS

$\Phi(k)$	the system matrix
$\lambda$	the wavelength of the carrier
$G_t$	the antenna gain of the transmitting antenna
$G_r$	the antenna gain of the receiving antenna
$\beta_i$	information sharing coefficients
$\Sigma$	Sum

## LIST OF ACRONYMS AND ABBREVIATIONS

ALC	Active Learning Classroom
AI	Artificial Intelligence
AoA	Angle of Arrival
CNN	Convolutional Neural Network
DS-TWR	Double-Sided Two-Way Ranging
Enc	Encoder
FKF	Federated Kalman Filter
FPE	Final Prediction Error
GPS	Global Positioning System
IR	Infrared
KF	Kalman Filter
LED	Light-Emitting Diode
Li-Fi	Light Fidelity
LBS	Location Based Services
LinSVM	Linear Support Vector Machine
LLSE	Linearized Least-Squares Estimation
LOS	Line-of-Sight
LSTM	Long Short-Term Memory
MWT	Morlet Wave Transform
MLE	Maximum Likelihood Estimation
MLLE	Maximum Likelihood Localization Estimation
NLOS	Non-Line of Sight
RFID	Radio-Frequency Identification

ResNet	Residual Network
RSSI	Received Signal Strength Indicator
SS-TWR	Single-Sided Two-Way Ranging
ToA	Time of Arrival
ToF	Time of Flight
TDoA	Time Difference of Arrival
TWR	Two Way Ranging
UWB	Ultra-Wideband
UWB-EKF	Ultra-Wideband-Extended Kalman Filter
WCE	Weighted Cross-Entropy
Wi-Fi	Wireless Fidelity
WLS-RKF	Weighted Least Squares - Robust Kalman Filter

## 1. INTRODUCTION

The positioning has become an increasingly important issue for humanity in recent days. Because with the developing technology, positioning has become essential in many cases and will continue to come. Because of that, people spend more and more time indoors daily. In the mornings, we are usually in an office or school environment, and in the evenings, we are often in our homes or spending time in malls or cafes. When we are sick, we go to hospitals, another indoor environment. The amount of time people spend outdoors is decreasing, meaning location tracking needs to be improved to direct or track people in these environments. Location tracking is based on estimating the location using at least three readers and one tag, using the distance between each reader and the tag. However, in real life, the distances between the tag and the readers due to the presence of objects need to be formed correctly. These situations where the reader and the tag cannot see each other directly are called Non-Line of Sight (NLOS). In these cases, Ultra-wideband (UWB) technology has resorted to two different ways, such as improving the locations with algorithms to increase the accuracy of the location and creating a location accordingly by understanding whether there is NLOS or not.

Much research has been done to improve NLOS conditions. Some of this research is on UWB technology. The methods used to strengthen NLOS conditions can take different forms. Improvements have been made by replacing the device physically, making hardware changes, or applying filters. Although the number of previous literature studies in this area is minimal, it can be seen that NLOS problems are divided into two groups: NLOS mitigation and NLOS identification.[1]

Improving NLOS conditions means more accurately predicting the location of people in confined spaces. This is very important for the modern world because humanity is spending more time indoors than ever before, which means that the times when we need directions in shopping malls are increasing. In addition, the increase in consumption has caused the products to be followed from the production line in closed areas to the

customer's home. Therefore, improving the position estimation in NLOS situations is very important.

This thesis examined NLOS Situations In UWB with the Federated Kalman Filter (FKF). In the second chapter, the methodology of indoor positioning is presented. The third chapter discusses the calculations involved in positioning, including the differences between Non-Line-Of-Sight (NLOS) and Line-Of-Sight (LOS) propagation. The fourth chapter reviews methods for improving NLOS conditions. This chapter focuses on the use of the FKF structure. In the fifth chapter, we investigate the main findings of our research by carefully summarizing the experimental setup and then proceeding with a comprehensive analysis of the collected data. The final chapter highlights the results obtained from the implementation of the FKF.

## **1.1 Localization**

Localization may seem like a current topic, but it is an important area of research with a history dating back thousands of years. In the early days, observation and awareness of the natural environment provided the basic tools for people to determine their spatial locations. However, the need for more accurate and improved localization, arising from commercial, military, exploration, and travel purposes, has been shaped together with technological and scientific progress.

Since ancient times, people have tried to determine their location by observing stars, the sun, the moon, and other celestial bodies. Sailors tried to estimate their location using phenomena such as the movement of stars and the behavior of birds at sea. During the Renaissance in the first century, sea voyages and geographical discoveries accelerated. For this reason, during this period, geographers and cartographers made significant progress in this field by developing new positioning techniques and maps to prevent ships from being lost. The noteworthy figures like that Piri Reis and Gerardus Mercator made meaningful contributions to localization development. In the second century, marine clocks developed solved the problem of determining the longitude of ships. this development makes by John Harrison. This opened a way to accurately determine the position of ships on long voyages. A revolutionary change in localization technologies

occurred with the introduction of radio waves in the fourth century. Global Positioning System (GPS), Radar and satellite-based positioning systems using radio waves were developed and became widespread during this period. These technologies today play an important role in many areas such as navigation, mapping and logistics.

In conclusion, the evolution of localization throughout history has arisen from the need for human exploration and travel activities and has continuously developed with technological and scientific progress. In the future, it is predicted that more innovation and discovery will contribute to the further development and popularization of localization technologies, especially in indoor areas, as production and transportation become unmanned and autonomous, and as people spend more time indoors.

## **1.2 Positioning Applications**

Many localization applications are already in use in everyday life. In the future, even more will be a part of our lives and become an important point in our lives. The following applications illustrate the place of indoor localization and location-based technology in our daily lives.

### **1.2.1 Hospitals**

Localization technologies play a variety of critical roles in hospital management. First, in terms of patient tracking, these technologies improve patient safety and ensure the efficient use of medical resources by tracking the location of patients and medical equipment. In particular, in intensive care units, the location of a patient can be monitored in real time, and the locations of medical devices can be easily identified. At the same time, positioning-based systems are used for doctors, nurses and other healthcare personnel in terms of personnel management and in order to respond quickly to the urgent needs of patients, manage emergencies more effectively and ensure personnel safety. It is also used to determine the location of devices in the hospital. For example, active surgical tracking is used to track the location of surgeons and surgical equipment at operating rooms and surgical units and to optimize the use of equipment in surgical processes.

Finally, location-based applications for hospital visitors provide easy guidance inside the hospital, making it easier for visitors to reach certain departments or doctor's offices. In this way, confusion in areas such as emergency management and visitor guidance is prevented.

### **1.2.2 Industrial facilities**

In industrial facilities, indoor localization technologies play an important role, especially in controlling production processes. These technologies enable facilities to track the whereabouts of precious assets and materials, assure effective resource usage, and optimize inventory management in relation to asset and material management. They also help avoid losses. Through location-based systems, industrial facilities may track the whereabouts of workers, machinery, and goods on production lines and so boost efficiency through production process tracking. This reduces the possibility of mistakes occurring throughout the production process and facilitates improved production management. Monitoring employee whereabouts is essential for ensuring their safety, particularly in high-risk situations requiring prompt emergency action. In the field of logistics and distribution management, large industrial organizations use indoor location tracking technologies to ensure rapid delivery of goods and materials to their intended destinations and streamline logistics operations. Facilities can use their resources more intelligently and produce more.

### **1.2.3 Mining sites**

Mining is a profession that involves risk and harsh conditions. Mine workers may be exposed to incidents that pose the risk of death and serious injury. Therefore, mine operators must take some precautions to guarantee the safety of mine workers. One extremely useful tool to guarantee mine worker safety is location-based technology. This system can be used to monitor the location and usage of mining equipment. This helps ensure effective use of equipment and prevent accidents. In addition, it tracks the locations of employees in real time and sends warnings to employees, ensuring that they stay away from dangerous places and that in case of emergency, immediate intervention

can be made since their location is instantly known. For example, in order to carry out rescue operations in an emergency situation, the location of the people to be rescued must be known. Tracking the location of the personnel or the personnel's equipment in real time can save his life by knowing his location in the mine. This can help prevent workers from entering hazardous areas and respond quickly to emergencies. Briefly, the following benefits of location-based technologies to mining enterprises can be summarized in three line as follows:

- Worker safety: By tracking the location of workers in real time, mine operators can improve worker safety.
- Efficiency: By tracking the location and use of equipment, mine operators can improve efficiency.
- Cost savings: By preventing accidents and equipment failures, mine operators can save money.

As a result, Location-based solutions are therefore a crucial instrument for guaranteeing worker safety, raising output, and cutting costs in mines.

#### **1.2.4 Navigations**

Positioning system-based navigation technologies are frequently used in various fields. The primary function of navigation apps and gadgets is to provide estimated location information for automobile, Airplane, Ship and pedestrian navigation as well as giving users route instructions to get to their desired destination. In doing so, it usually monitors traffic conditions and suggests users if there is a faster route to their destination. Positioning technologies are critical to ensuring a safe path in maritime, aviation, land excursions and outdoor sports. Particularly in the field of aviation, planes and aircraft are equipped with GPS and other air navigation systems to assist in safe landings and takeoffs. Similarly, GPS systems are a critical point in ships to stay on their travel routes. Geolocation technology also makes route tracking easier for explorers and reduces the likelihood of getting lost during outdoor activities such as hiking. Therefore, navigation

technologies are considered an essential tool for safe, effective, and efficient journeys in daily life and various sectors.

### **1.2.5 Shopping malls**

Location-based technology are being used by shopping malls more and more to control and improve the shopping experience. Customers may be led to crucial sites, such the closest restaurant or restroom at shopping malls, with the use of indoor-based smartphone applications. When customers arrive at the items, businesses may also give them information, such as access to product details and notifications about exclusive sales and promotions. Customers may now enjoy more than just customized experiences thanks to this. It also allows mall stores to attract and retain customers. To ensure security within the shopping center, security measures can be optimized by monitoring visitor flow and preferences. In order to increase the sales of stores, corporate success can be achieved by identifying the places where customers stop most and making in-store arrangements and increasing consumer happiness. In addition to these reasons, shopping center location-based solutions are necessary to improve consumer experience and increase productivity in the retail industry.

### **1.2.6 Vehicle tracking systems**

Vehicle tracking systems help companies use their logistics and transportation operations in the most efficient way by monitoring and directing their vehicles. This is a critical tool for increasing productivity. So the less vehicles are idle, the more money is made. With positioning systems that combine GPS technology with additional technologies, businesses can design routes, monitor the real-time location of their vehicles, learn the vehicle's speed, and track driver behavior. Some of the advantages of tracking vehicles are: It facilitates vehicle maintenance planning, reduces fuel consumption, and increases driver safety, which prevents theft of vehicles or locates them even if they are stolen. also can guarantee on time delivery. Vehicle tracking systems can also help organizations reduce expenses and increase operational efficiency by evaluating fleet data. It also allows

a car to be located or stolen even if it is stolen. Vehicle tracking systems are therefore strategically significant in the logistics and transportation industry.

### **1.2.7 Location based services (LBS)**

Nowadays, location-based services(LBS), are highly essential, especially in the restaurant and food delivery sectors. By giving consumers access to real-time location, these services enable them to swiftly explore and order meal alternatives. Applications for restaurant reservations can benefit from LBS. With a restaurant reservation app, for instance, a user may browse eateries in the area. This enables customers to reserve a table in advance of visiting the restaurant of their choosing. Applications involving food delivery can benefit from LBS as well. Depending on the user's location, food delivery applications might provide a list of the nearby eateries and an estimated time of delivery. LBS has three advantages for eateries and food delivery businesses. First of all, it enables patrons to swiftly peruse and reserve dining establishments. Customers may now swiftly and simply place orders and discover new restaurants and eating alternatives. Second, it makes businesses more efficient by enabling them to study clients and provide more pertinent offers to them. Lastly, it helps companies target consumers with advertisements. Through the analysis of the economic conditions of both the goods being ordered and the location from where the order originated, businesses may enhance the efficacy of their marketing and advertising operations. The two biggest LBS-using restaurant and food delivery applications are Yelp and Foursquare. Users may place orders, read reviews, and access restaurant information with these applications.

### **1.2.8 Sports activities**

Athletes and climbers utilize positioning technology as a tool to track jogging trails, cycling routes, and other routes related to sports. It is also an essential tool for teams in strategy formulation, game analysis, and performance evaluation and optimization for sports teams. Coaches and analysts may track player performances, anticipate injuries, and identify vulnerabilities in both their own team and the opposition's side by using the position data that the players provide. Thanks to GPS-based positioning devices, the

distance traveled and the speed reached by the players during the match can be measured. Thanks to these values, coaches can objectively evaluate the performance and condition of the players. This technology helps referees in some football leagues to determine whether a goal is valid or not. allowing match replays for sports broadcasts and television and allowing in-depth analysis of key moments throughout the Game. For example, the position of the ball played in the 2022 World Cup was determined. In this way, the first goal that put Portugal ahead in the Uruguay-Portugal Match was firstly credited to Cristiano Ronaldo and then to Bruno Fernandes.



## **2. INDOOR POSITIONING**

In today's society, indoor positioning technology is becoming more and more common. With the use of a variety of methods and algorithms, this technology makes it possible to pinpoint one's whereabouts inside restricted areas. While conventional global positioning systems, like GPS, function well in wide spaces, they present a number of difficulties when used indoors, where extreme precision and accuracy are necessary. Finding your position and navigating through tight places may be especially difficult underground. There are various technologies used in indoor positioning. These technologies have different principles also infrastructures and they are used in different application areas.

### **2.1 Indoor Positioning Technologies**

The demand for precise indoor positioning has become increasingly important in rapidly developing modern urban environments, covering a variety of infrastructures such as commercial complexes, healthcare facilities, and corporate centers. Addressing this imperative, a cadre of technologies have emerged as pioneers in indoor positioning. UWB, Camera Systems, Bluetooth, Wireless Fidelity (Wi-Fi), and Radio Frequency Identification (RFID) are important technologies that facilitate the precise determination and guidance of user locations in indoor environments. These technologies, which are used in many areas from mobile applications to industrial automation, collectively enable smarter, more efficient and user-friendly indoor positioning experiences.

#### **2.1.1 Wi-Fi and Bluetooth**

Wi-Fi and Bluetooth are the most commonly used technologies in indoor environments. These technologies enable location determination based on the wireless network infrastructure and signal strength of the devices.[2] Thanks to Wi-Fi and Bluetooth infrastructures, smart devices can detect their indoor location and direct users to their destination. [3]

### **2.1.2 Magnetic field sensing**

Thanks to magnetic sensors, magnetic fields in closed environments can be detected. Location determination is achieved by mapping these magnetic fields and comparing the device's data with these maps. Magnetic field sensing is used for accurate and reliable positioning, especially in indoor environments.[4]

### **2.1.3 Ultrasonic and infrasonic sound waves**

Some indoor positioning systems use sonic sounds. These sounds are ultrasonic and infrasonic sound waves. These waves facilitate communication between fixed sensors or devices within an indoor space, providing location information. Ultrasonic and infrasonic sound waves represent another technology used for high-accuracy positioning in indoor environments.[5],[6]

### **2.1.4 Infrared**

Infrared is a technology that utilizes light waves in the infrared region of the electromagnetic spectrum. This technology is used for location determination and tracking in indoor environments and specialized areas. The method of indoor positioning with infrared fundamentally relies on the transmission and detection of infrared signals. In this method, infrared signals emitted from a source device (e.g., a transmitter) are detected by receiving devices (e.g., sensors or cameras). The timing and strength of the detected signal are used to determine the device's location. The propagation speed and intensity of infrared signals assist in calculating the distance to the signal's source.[7], [3]

### **2.1.5 Radio frequency identification (RFID)**

RFID technologies represent a type of technology that tracks objects using Radio Waves. In this technology, the devices to be tracked can be followed in two different ways: active and passive. Tags in this technology pass through control points, and it is assumed that

the tracked device is near the last read control point. If the tag is active, it continuously sends signals without waiting for any trigger from the control point. In the case of passive tags, a response is generated in response to a signal sent to the tag at control points, and in this way, its location is determined. [3]

### **2.1.6 Ultra wideband (UWB)**

The most remarkable aspect of UWB is its vast bandwidth, which may allow for the delivery of data rates up to Gbps. With this broadband, one may obtain low data rates over long connection lengths or high data speeds indoors and over small distances. Because of this, it is now favored over other communication technologies in applications including personal area networks and wireless UWB [8],[9]. Also UWB technology provides high-accuracy location determination by operating at very low power.

UWB's advantage in bandwidth boosts the dependability of wireless communication. UWB offers a lot of potential, particularly for these kinds of applications where low latency, accurate data transfer, and position determination are necessary. UWB is a bandwidth-related communication technique that makes use of extremely brief time interval pulses. The precise estimation of the pulse's distance from its source may be achieved when there is minimal ambiguity in the arrival timing of these brief pulses. Simple circle intersection techniques may be used to approximate the position of the source by integrating distances measured by various receivers. Consequently, UWB systems may be employed in conjunction with location and communication [9], [3].

### **2.1.7 Optical sensors and camera systems**

In indoor environments, optical sensors and camera systems are another technology used for positioning. These systems determine the location of the devices by detecting markers and labels in the environment. Optical sensors and camera systems are used in mapping and navigation, especially in closed areas.[10],[11]

### **2.1.8 Dead reckoning**

This method is based on using data from motion sensors to estimate the current location. It can be particularly useful in indoor areas and places with weak GPS signals, where reliance on GPS or map data is not possible. Dead reckoning for indoor positioning begins by tracking the movement of the device. Motion sensors usually consist of accelerometers, gyroscopes, and sometimes magnetometers. Accelerometers measure the device's acceleration to help determine the speed and direction of movement. Gyroscopes detect the device's rotational movement and track changes in direction. Magnetometers help determine the direction of the magnetic field. Orientation and speed data are combined with the initial position and time information to make a new position estimate. However, errors can accumulate over time when dead reckoning is used alone. For example, imprecise measurements from accelerometers or rotational speed errors from gyroscopes can lead to deviations in estimates. Therefore, dead reckoning is often combined with other positioning methods. For instance, starting with the initial position and sensor data, the position can then be verified with other methods like Wi-Fi, Bluetooth, or magnetic fields. This reduces error accumulation and leads to more accurate results. [6][12]

### **2.1.9 Pressure sensing**

Pressure sensors placed on the floor provide information about changes on the ground, indicating the presence of something or someone in a room or area, without specifying who or what it is. Users often want to be able to track a specific object from positioning technologies. For this reason, Pressure Sensing technology is not a preferred technology for determining location.

### **2.1.10 Light fidelity (Li-Fi)**

Light Fidelity (Li-Fi) technology is based on data transmission through light signals. Light-Emitting Diode (LED) lights used as light sources emit modulated light signals by rapidly turning on and off, facilitating data transmission. These light signals flicker at

speeds imperceptible to the human eye. The data from the transmitting device is modulated through the turning on and off of the LED lights. The receiving device detects these modulated light signals and decodes the data. The speed of light is extremely high, and Li-Fi technology can achieve high data transmission speeds using these rapid transmission rates. In addition to location information, light signals can also carry other data. This can make the indoor positioning process richer and more detailed.[13], [3]

**Table 2.1 . Indoor Positioning Technologies Comparison**

<b>Technology</b>	<b>Positioning Accuracy</b>	<b>Range</b>	<b>Advantages</b>	<b>Disadvantages</b>	<b>Typical Applications</b>
<b>Li-Fi</b>	1-10 cm	Short-range (indoor)	High accuracy, low interference, secure, energy efficient	Limited range, requires line of sight, not widely adopted	Indoor localization, asset tracking, museums, hospitals
<b>Dead Reckoning</b>	1-5 meters	Variable	Low cost, self-contained, no infrastructure needed	Accumulates error over time, not suitable for large areas	Pedestrian navigation, augmented reality, fitness trackers
<b>Pressure Detection</b>	1-5 meters	Short-range (indoor)	High accuracy in controlled environments, robust to multipath	Sensitive to environmental changes, requires specialized equipment	Indoor navigation, floor detection, elevators
<b>Camera Systems</b>	1-10 cm	Variable	High accuracy, can track multiple objects	Requires camera infrastructure, privacy concerns, performance affected by lighting	Surveillance, security systems, people counting, retail analytics
<b>UWB</b>	10-30 cm	Short-range (indoor)	Very high accuracy, low latency, resistant to interference	Requires specialized hardware and infrastructure, relatively high cost	Industrial automation, high-precision tracking, robotics
<b>RFID</b>	1-10 meters	Short-range (indoor)	Low cost, passive tags, long battery life	Limited range, requires tags on objects, not suitable for real-time tracking	Asset tracking, inventory management, access control

<b>Infrared</b>	1-5 meters	Short-range (indoor)	Low cost, simple setup, no interference from radio waves	Limited range, affected by ambient light, not suitable for outdoor use	Indoor navigation, obstacle detection, people counting
<b>Ultrasonic</b>	1-5 cm	Short-range (indoor)	High accuracy in controlled environments, low cost	Limited range, susceptible to noise, not suitable for outdoor use	Industrial automation, object detection, proximity sensing
<b>Magnetic Field Detection</b>	1-10 meters	Short-range (indoor)	Robust to environmental changes, low cost	Limited range, requires specialized equipment, not widely adopted	Indoor navigation, building automation, asset tracking
<b>Wi-Fi</b>	20-50 meters	Medium-range (indoor & outdoor)	Widely available, existing infrastructure, low cost	Moderate accuracy, susceptible to interference	Indoor location services, navigation apps, asset tracking
<b>Bluetooth</b>	1-10 meters	Short-range (indoor & outdoor)	Widely available, low power consumption, existing infrastructure	Moderate accuracy, susceptible to interference	Proximity detection, mobile payments, beaconing

### 3. POSITIONING CALCULATION

Location Calculation Techniques refer to various methods used to determine the positions of individuals or objects. These techniques can estimate locations using different sensors, algorithms, and data processing methods. Positioning Technologies generally facilitate the establishment of communication distances or the determination of direction. However, without a location calculation technique, this information may not mean much. For this reason, different location calculation techniques are utilized. These techniques can be divided into two main categories measuring distances and calculating positions.

#### 3.1 Measurement Method

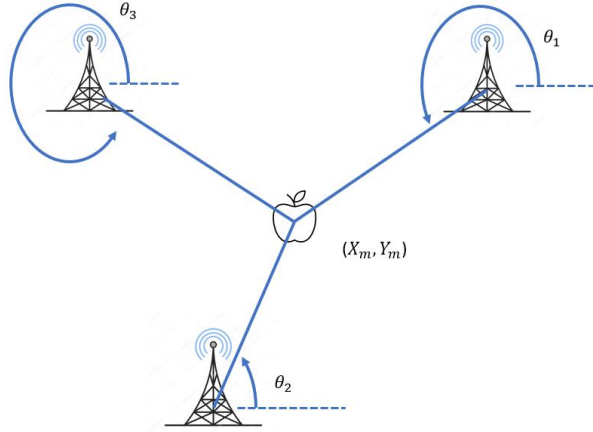
Measurement methods in the context of indoor positioning refer to the techniques and approaches used to gather data and information about the location of objects or users within indoor environments. These methods are crucial for determining the spatial coordinates of devices or individuals, enabling applications such as indoor navigation, context-aware services and asset tracking.

##### 3.1.1 Angle of arrival (AOA)

Angle of Arrival (AOA) refers to the angle and distance calculated through the intersection of grid lines between multiple reference points. This angle and distance are used to estimate the location of the transmitter (tag). AOA works with an Anchor device that measures the angle at which the signal from the tag comes. The Anchor device starts a line by measuring this angle from its location and it is assumed that this line intersects at the location of the target object. The combination of several lines coming from multiple Anchor points places the target object (tag) at the intersection of these lines. For this method, minimum two two angles ( $\theta_1$ ,  $\theta_2$ ) and reference points are used. [3],[14]

The advantage of AOA is that it does not require time synchronization between references, making measurements easier to conduct. However, the drawback is that it needs expensive specialized hardware to implement, making it costly. In summary, AOA

is a method used to estimate the location of objects by measuring angle and distance using multiple reference points.



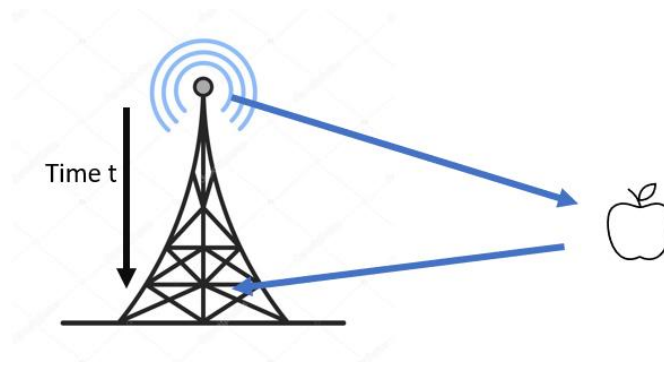
**Figure 3.1** AoA Method

### 3.1.2 Time of flight (ToF)

Time of Flight (ToF) generally refers to the time it takes for a wave to travel from a source to a target and back to a detector. It makes this calculation using the Distance finding (3.1) formula.

$$Distance = Speed \times (t_r - t_e) / 2 \quad (3.1)$$

Signals are assumed to travel at the speed of light, therefore the constant speed of light,  $3 \times 10^8$  m/s is used. This roughly equates to approximately 300,000 km per second. The time taken for a signal to travel from one point to another is calculated as  $(t_r - t_e) / 2$  where  $t_r$  is Time of receiving the response signal,  $t_e$  is Time of sending the pulse. Once these values are known, the distance, referred to as 'Distance', is estimated. [12],[14]



**Figure 3.2** ToF Method

### 3.1.3 Two way ranging (TWR)

An algorithm for two-way ranging is called Two Way Ranging (TWR). Initially, a signal is sent to the anchor via the tag. After receiving the signal, the anchor sends it back to the tag. Lastly, the tag notifies the anchor that the data has been received. By averaging the three periods that radio waves took to travel between the anchor and the tag, the anchor determines the distance between them. ToF is used when performing this operation. TWR Measures the time it takes for a signal to travel from one device to another and back. But ToF Measures the total round-trip time of the signal. TWR can be considered a specific implementation of ToF.

$$D = c \times t_{rt} / 2 \quad (3.2)$$

Where D is Distance between the initiator and the responder, c is Speed of the signal (approximately, the speed of light in space is  $3 \times 10^8$  m/s) and  $t_{rt}$  is Round-trip time, which is the time difference between sending the pulse and receiving the response. There are 2 different TWR measurement techniques

Single-sided Two-Way Ranging (SS-TWR) is a method in which only one device (tag) measures the time difference. The tag measures the difference between its own signal sending time and the arrival time of the response signal it receives from the anchor. This time difference is used to calculate the distance between two devices. [15]

Double-sided Two-Way Ranging (DS-TWR) is a method in which both devices measure the time difference. The tag measures the difference between its own signal sending time

and the arrival time of the response signal it receives from the anchor. Anchor measures the difference between the signal sending time of the tag and the arrival time of the response signal it receives from the tag. These two time differences are used to calculate the distance between two devices.[15]

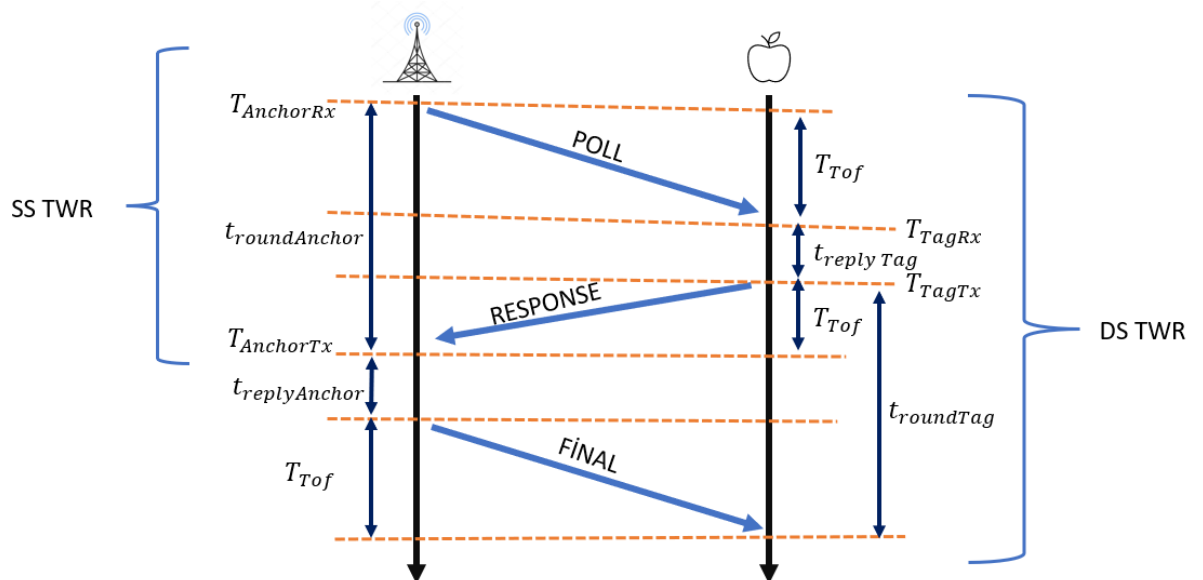
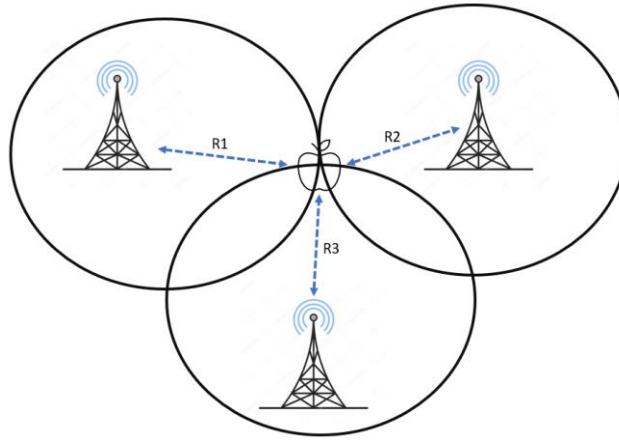


Figure 3.3 TWR Method

### 3.1.4 Time of arrival (ToA)

Time of Arrival (ToA) refers to the time at which a signal or wave reaches a specific location or sensor. Locations can be determined using these times. TOA is sometimes called ToF [12], [14]



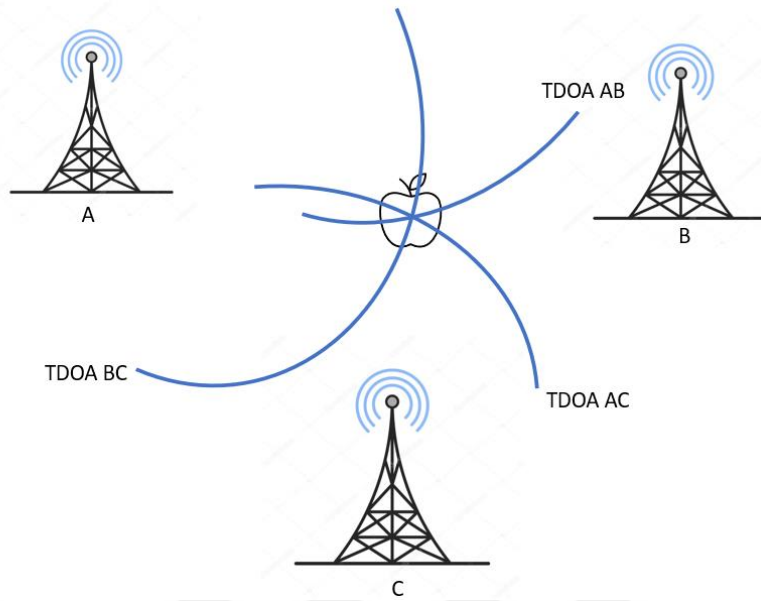
**Figure 3.4** ToA Method

### 3.1.5 Time difference of arrival (TDOA)

Time Difference of Arrival (TDOA) involves estimating distance or location by using the time difference resulting from a signal reaching two different receivers at different times[12]. It has a similar methodology to ToA. However, in TDoA, since the distance between the transmitter and receiver is not used, there is no need for the transmitter to be synchronized with the receiver. Synchronization is only required among all the receivers, as the calculation is based on their time/distance difference.[16] In ToA, inferences are made based on the speed of the signal received and the delay time. In other words, while accurate measurements in ToA or other time-based methods require synchronization between devices[14], this is not necessary in TDoA. Mathematically, it can be expressed as in equation (3.3).

$$D_{12} = \sqrt{(x_1 - x_m)^2 + (y_1 - y_m)^2} - \sqrt{(x_2 - x_m)^2 + (y_2 - y_m)^2} = (t_1 - t_2) \cdot c \quad (3.3)$$

In this equation,  $D_{12}$  refers to the distance between the 1st and 2nd anchors.  $x_1, x_2$  and  $y_1, y_2$  is the location of the Anchor node and  $x_m, y_m$  is the location of Tag node,  $(t_1 - t_2)$  is arrival time differences and  $c$  is speed of light . When calculating the location, it should not be forgotten that the location of the Ancors is known.



**Figure 3.5 TDOA Method**

### 3.1.6 Received signal strength indication (RSSI)

RSSI, an abbreviation for "Received Signal Strength Indicator," is a measure that indicates the strength of a received signal. RSSI shows how strong or weak a signal received from a transmitter is perceived by a receiver. [12] It is usually expressed in decibels. The RSSI approach measures the attenuation of transmitted signals and is used to calculate the decrease or loss of signal strength due to transmission. A correlation is made between the power loss in the received signal and the distance of the transmitter emitting the signal to the receiver. This allows it to be used to estimate the distance between devices. The higher the RSSI, the closer the transmitter is.[2]

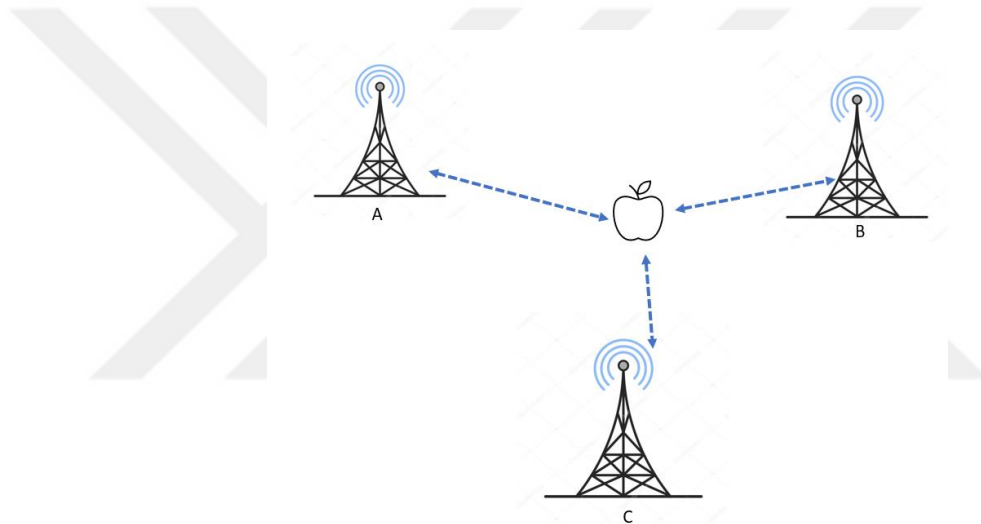
The carrying power of the wireless signal  $P_t$ , the wavelength of the carrier  $\lambda$ , the antenna gain of the antenna transmitting  $G_t$ , the antenna gain of the antenna receiving  $G_r$ , the system loss factor  $L$ , and the received signal strength  $P_r$  is represented in the free space propagation model shown in Equation 3.4 [17].

$$P_r = P_t \frac{G_t G_r \lambda^2}{(4\pi)^2 d^2} \quad (3.4)$$

Another method is the Log-Normal Shading model. This model is valid in situations where obstacles exist. The log-normal shading model is included in Equation 3.5 [19].

$$PL(dB) = 10 \log \frac{P_t}{P_r} = -10 \log \left[ \frac{\lambda^2}{(4\pi)^2 d^2} \right] \quad (3.5)$$

In formula 5 PL(dB): Path loss (dB),  $P_t$ : Sent signal power (watts),  $P_r$ : Received signal power (watts),  $\lambda$ : Carrier wavelength (meters),  $d$ : Distance between sender and receiver (meters)



**Figure 3.6** RSSI Method

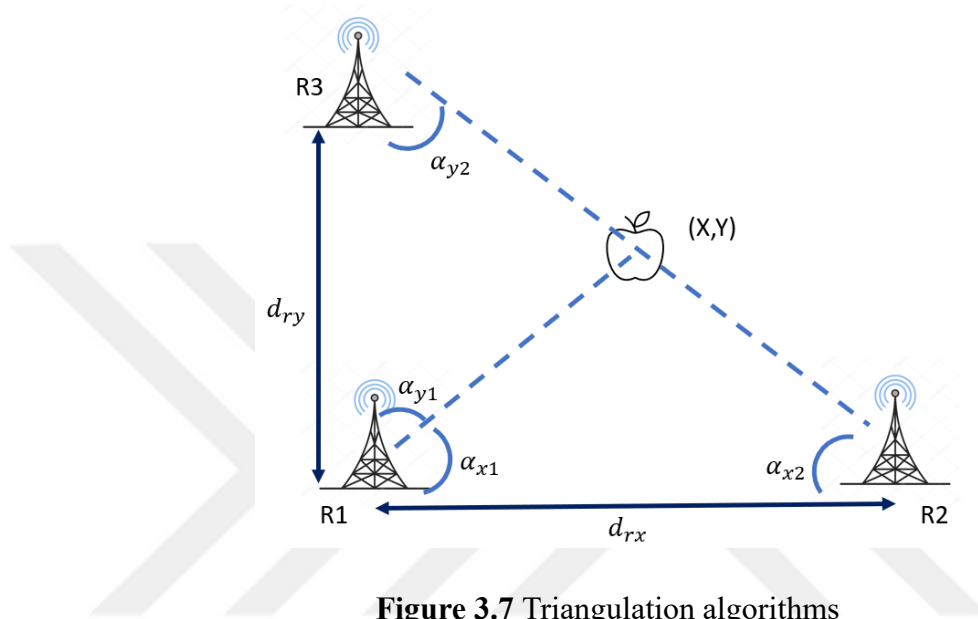
### 3.1.7 Positioning algorithms

Positioning algorithms are computational methods designed to determine the location or position of an object or user within a given space. These algorithms play a critical role in various applications, including navigation systems, location-based services, and tracking solutions. The goal of positioning algorithms is to calculate the coordinates (e.g., latitude, longitude, altitude) or relative position of a target accurately.

Several types of positioning algorithms exist, and their suitability depends on factors such as the available sensors, environmental conditions, and the desired level of accuracy.

### 3.1.8 Triangulation

Triangulation is a calculation method that uses the geometric properties of triangles to estimate the location of a tracked object, taking into account the angles towards the target from two known reference points. This method infers the distance and position of the target relative to these reference points. Example of Calculation Process



**Figure 3.7** Triangulation algorithms

In Figure 3.7,  $R1$  represents the first reference point where access point 1 is located,  $R2$ : is the second reference point where access point 2 is situated, and  $R3$  is the third reference point where access point 3 is located. The calculation of the  $(x, y)$  coordinates, where the Tag is located, using the three-angle method, is carried out using Equation 3.6 and Equation 3.7 [19].

$$x = \frac{d_{ry} \sin(\alpha_{y1}) \sin(\alpha_{y2})}{\sin(\alpha_{y1} + \alpha_{y2})} \quad (3.6)$$

$$y = \frac{d_{rx} \sin(\alpha_{x1}) \sin(\alpha_{x2})}{\sin(\alpha_{x1} + \alpha_{x2})} \quad (3.7)$$

### 3.1.9 Trilateration

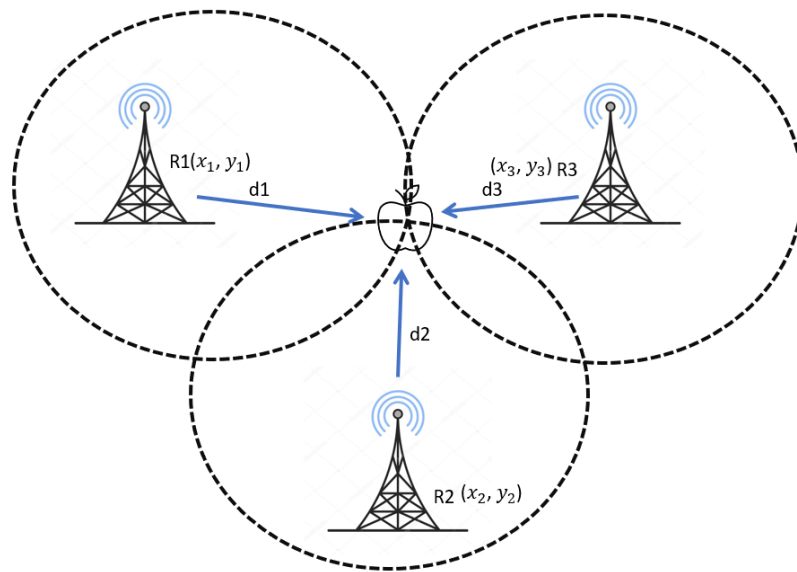
Trilateration is a method used to estimate the location of a target object(tag) using the geometric properties of triangles, such as triangulation [20],[21]. In order to find the location of a target, three reference points whose location is known before are required. Distance measurements relative to three known reference points are used to determine location by calculating the weakness of the signal transmitted [22],[23]. Calculation of location, The position of the target in the relevant  $(x, y)$  plane is calculated using the previously known positions of three reference points  $(x_1, y_1)$ ,  $(x_2, y_2)$ ,  $(x_3, y_3)$ . Performed using Euclidean distance; The calculation of the distance to device  $R1$  ( $d_1$ ) is seen in Equation 3.8, the calculation of the distance to device  $R2$  ( $d_2$ ) is seen in Equation 3.9, and the calculation of the distance to device  $R3$  ( $d_3$ ) is seen in Equation 3.10.

$$d_1^2 = (x_1 - x)^2 + (y_1 - y)^2 \quad (3.8)$$

$$d_2^2 = (x_2 - x)^2 + (y_2 - y)^2 \quad (3.9)$$

$$d_3^2 = (x_3 - x)^2 + (y_3 - y)^2 \quad (3.10)$$

In the positioning process performed using the triangulation method, the signals received from the devices are analyzed with various measurement techniques. They use TOA [24] to measure the time it takes for a signal to reach a receiver from a transmitter. and, TDOA, which is a development of TOA [25]. It can be said.



**Figure 3.8** Trilateration algorithms

### 3.1.10 Proximity

The goal of proximity methods is to determine the exact moment when an item approaches a predetermined point based on data from a sensor built for this purpose. There are two basic approaches to proximity detection. The first technique involves recognizing an object through physical contact using touch sensors, capacitance sensors, and similar technologies. The second method, Using Bluetooth and RFID cards as examples of remote identification technologies that identifies an object when it is within their range. [26].

Unlike trilateration, proximity and triangulation does not provide absolute or relative position estimates; [27], [20] instead, it offers position information based on a grid of antennas with known positions. [20], [24]. When a Tag is in motion, the closest antenna is used for position calculation. (Ibid.) If the device is detected by multiple antennas, the one with the strongest signal is utilized. [27], [24] The position is determined using RSSI, commonly employed in proximity for estimating distances between devices [25]. Proximity is applied in systems using Infrared (IR), RFID, and Bluetooth, requiring minimal calibration effort [20], [28]. However, achieving reliable and extensive coverage necessitates a larger spread of readers, leading to complexity and higher costs.

RSSI value varies due to hardware and radio platform diversity. iOS devices with limited chipsets can accurately represent distance, while Android devices with a wide array may not directly correspond to location due to varying signal strengths. Despite this, leveraging RSSI value in proximity applications remains valuable, as monitoring RSSI value changes can yield meaningful data.

### **3.1.11 Scene analysis and fingerprinting**

In Scene Analysis, location estimation is done regardless of distance or angle. Scene Analysis collects features or information from an observation or scene to estimate the location of an object and then makes the prediction by matching or comparing the collected information with information in an existing database. [20],[24]. This collected information is a unique feature or signature that distinguishes one scene from another and it is also known as a fingerprint (ibid.) i.e. This collected information is called a "fingerprint". It can be done in two stages, offline and online [29]. In the offline phase, it is also called the Training phase or calibration phase. At this stage, signal maps of the area to be determined are created. An environment in a building is examined and grid points are calculated at different locations in different parts of the building. Each grid point has a list of RSSI values for visible access points at the location [29]. Additionally, the relevant location information and signal strengths at different locations are collected for location estimation purposes [20]. In the online phase, this phase is also named positioning phase. The signal values of a mobile (Tag) within the structure are instantly cross-checked with the signal map on the server previously learned by the classification algorithm in the offline phase, and the most probable location of the object is calculated [20].

### **3.2 Relation Of Positioning Algorithms And Measurement Methods**

Positioning algorithms and measurement methods are closely related components within the broader context of location-based systems. While measurement methods focus on acquiring data about the physical characteristics of signals or objects in a given space, positioning algorithms use this data to determine the location or position of an object. In essence, measurement methods provide the raw data, and positioning algorithms process

that data to derive meaningful position information. The choice of measurement method and positioning algorithm depends on the specific requirements of the application, the characteristics of the environment, and the desired level of accuracy.

### **3.3 Non-Line-of-Sight and Line-of-Sight Conditions**

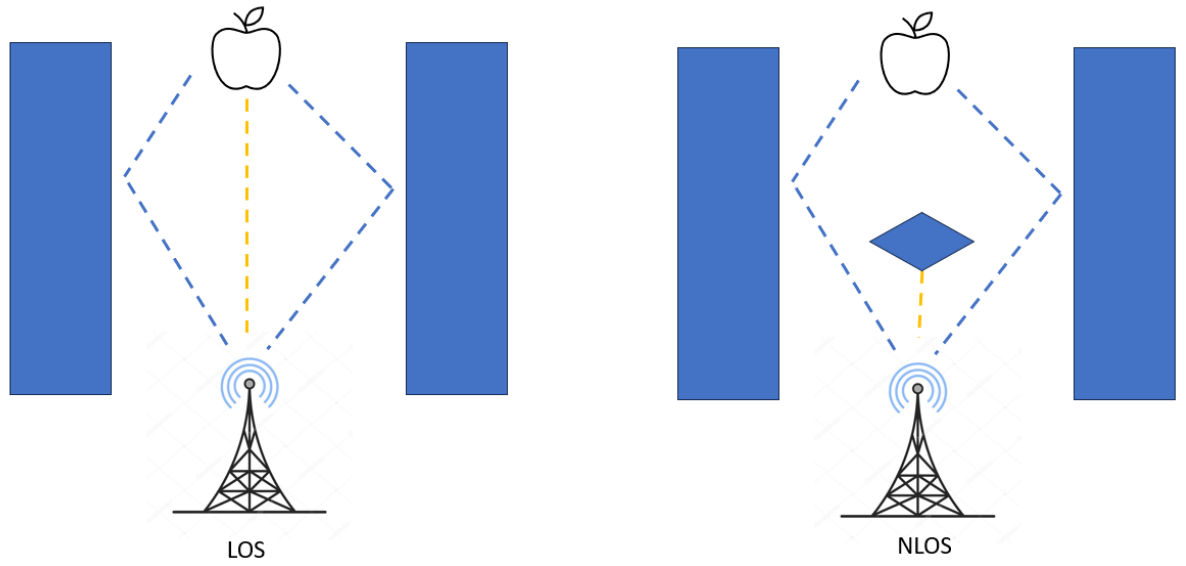
Non-Line-of-Sight (NLOS) and Line-of-Sight (LOS) are important terms in wireless communication and communication technologies, used to determine whether a communication link will be effective. [3]

#### **3.3.1 Line-of-sight (LOS)**

This can be briefly defined as the ability of devices to see each other without any obstacles in between. The most important condition for an LOS connection is the absence of any obstacles between the receiver and the transmitter. The two devices must be in direct visual contact. This allows radio waves to propagate freely. To establish visual contact, mounting antennas at sufficient heights can make NLOS conditions less likely.

#### **3.3.2 Non-line-of-sight (NLOS)**

This can be briefly defined as the inability of devices to see each other directly. Under NLOS conditions, the direct line of sight between the transmitter and the receiver is blocked or interrupted. This can be due to obstacles like buildings, mountains, forests, or surface reflections. Radio waves are either blocked or reflected by these obstacles, making it difficult to establish a direct LOS connection. Under NLOS conditions, the signal is typically scattered or diffused over surfaces. Therefore, the signal strength is lower, and transmission can experience more attenuation. Additionally, the diffusion over surfaces causes phenomena like reflection and multipath effects. These effects are common under NLOS conditions. Radio waves can reflect off obstacles and follow different paths, leading to signal confusion and degradation.



**Figure 3.9** LOS/NLOS Conditions

## **4. POSITION ESTIMATION METHODS FOR LOCATION IMPROVEMENT**

### **4.1 Literature Review**

NLOS states are used when the conversation between the device and the tag is not direct, so the most fundamental change to improve these situations is to change the environment or location of the sensors [30],[31]. Still, in real life, we can't always put the devices in the imagined places. Because we can't prevent the tag from hiding behind something within the distance of the device, it is better to improve the NLOS states. It was made by using structures that used many methods. These methods are Optimization Algorithms, Clustering and Filtering Techniques, NLOS identification methods [32]-[36] and NLOS error mitigation methods.

Several studies have been conducted on improving UWB positioning based on the optimization algorithm. One of the approaches used for enhancing indoor positioning accuracy with ultra-wideband sensors is the TOF calculation combined with the Big Bang-Big Crunch optimization method. The results showed a significant improvement of 27.5% in positioning accuracy [37].

Several studies have shown NLOS identification methods. Cheng et al. [38] showed that NLOS state identification can be made in NLOS scenarios using Maximum Likelihood Localization Estimation (MLLE) and a two-layer Kalman filter[39]. The Kalman filter has demonstrated in other studies that it can do this using the help of Artificial Intelligence (AI). For example, Among the five different structures of Convolutional Neural Network (CNN), including Linear Support Vector Machine(LinSVM), Radial Basis Function Support Vector Machine (RbfSVM), Fully Convolutional Network (FCN), Residual Network (ResNet), and Encoder (Enc). FCN, ResNet, and Enc have been shown to have the best accuracy. [40] or Expectation Maximization for Gaussian Mixture Models" to classify LOS and NLOS components. The experiment was conducted using simulation, and the results show that LOS and NLOS signals can be organized with an accuracy of 86.50% [41]. A method using Morlet wave transform(MWT) and CNN is proposed to differentiate LOS and NLOS. According to the simulation findings, the MWT-CNN approach offers 100% accuracy in office environments. [42] if CNN is used to discover

and extract features automatically, Long Short-Term Memory (LSTM) is used for classification. The performance of this method has been analyzed by comparing different settings, and the results have shown that CNN-LSTM achieves the best classification performance. The hyperbolic positioning algorithm improves location accuracy [43]. The approximate positioning algorithm using five lines gave results 4.8 cm more accurate than the algorithms using three or four lines according to static and dynamic positioning tests. Using four lines gives results 20.1cm more accurate than the three lines algorithm. Therefore, it is recommended to use the approximate positioning algorithm using five lines [44].

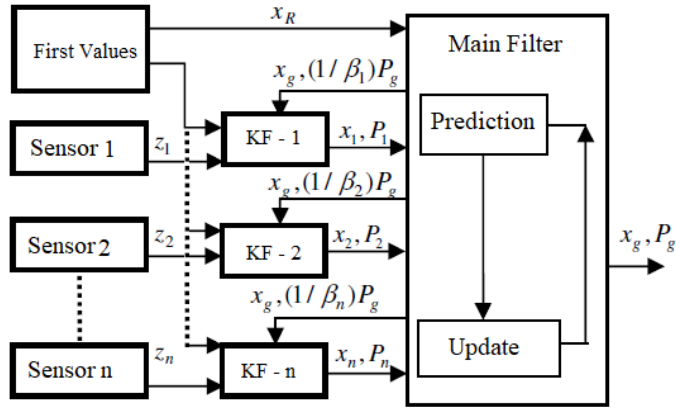
Several studies have utilized clustering and filtering techniques in UWB positioning. The Weighted Least Squares - Robust Kalman Filter (WLS-RKF) method was used with the Kalman filter in studies to improve NLOS conditions [45], and improvement was observed. In the study of Poulose et al. [46], Final Prediction Error (FPE), Weighted Cross-Entropy (WCE), and Linearized Least-Squares Estimation (LLSE) algorithms were compared, and it was seen that LLSE was more successful than the others. Again, Poulose et al. compared LLSE, WCE, Maximum Likelihood Estimation (MLE), and Ultra-Wideband-Extended Kalman Filter (UWB-EKF) methods and found that the UWB-EKF positioning algorithm was better than the LLSE algorithm. [47] In another study by Taoyun Zhou and Yun Cheng, the Fang, Chan, and Taylor algorithms were analyzed in non-line-of-sight (NLOS) conditions. Using comparative simulation analysis, it was found that the Chan algorithm had the best performance independent of the number of anchors in the presence of Gauss noise. In contrast, the Taylor algorithm had the second-best performance, and the Fang algorithm had the worst. Additionally, when the number of anchors reached a specific value, the number of anchors was no longer significant for the Chan and Taylor algorithms[48]. In a different study, Arsan et al. proposed a methodology that combines K-means clustering and Kalman filtering techniques to enhance UWB positioning accuracy. The K-means clustering algorithm was used to group the received UWB signals into different clusters, allowing for more. [49]

## **4.2 Kalman Filter (KF)**

The Kalman filter is an algorithm designed to optimally estimate the state of a system using information obtained from noisy and uncertain measurements. Particularly when faced with noisy measurements, this filter processes such measurements to produce more accurate and reliable estimates. Providing a fundamental approach for linear systems, this filter operates through a process that includes fusion of data from a sensor, and stages of prediction and update. Recognized as one of the most important inventions of the 20th century, the Kalman filter is widely used in many fields, especially in engineering and navigation systems. It is a filter that minimizes prediction error among existing filters by taking uncertainties into account.[50]

## **4.3 Federated Kalman Filter (FKF)**

The Federated Kalman Filter (FKF) is a balancing and prediction approach that uses information from several local systems to produce overall predictions [51]. Federation is the process of combining several techniques into a single filter structure. Distributed systems without a centralized control point use the Federated Kalman Filter. Each local system runs its own Kalman filter and conducts its own measurements. These neighborhood filters provide neighborhood forecasts based on their own system dynamics and measurement information. The Federated Kalman Filter uses a communication protocol to make it easier for the local filters to collaborate and share information. The local filters can exchange and update prediction data with one another thanks to this protocol. Therefore, by combining data from other systems, each local filter may produce overall forecasts that are more accurate. The structure of the Federated Kalman Filter is like the Figure 4.1 and its basic steps are:



**Figure 4.1** Structure of the Federated Kalman Filter

### 4.3.1 Initialization of filters and setting initial values

Initialization of Local and Master Filters, The initial state estimate and error covariance matrix are initialized to 0 or the previously calculated value.

### 4.3.2 Update and information sharing

First, the primary purpose of the FKF is to combine the forecasts to improve the accuracy and reliability of local forecasts. How this fusion process is performed can be expressed mathematically.

Initially, system and measurement equations for models generating data from existing sensors are defined:

$$x(k + 1) = \Phi(k)x(k) + w(k) \quad (4.1)$$

Equation (4.1) relates the state at the next time step (  $x(k + 1)$  ) with the current state ( $\Phi(k)x(k)$ ) and system noise ( $w(k)$ ) indicating uncertainties in the model,  $\Phi(k)$  is the system matrix, defining how the state evolves.

$$z_i(k) = H_i(k)x(k) + v_i(k) \quad (4.2)$$

Equation (4.2) shows how the measurement of the  $i^{\text{th}}$  sensor ( $z_i(k)$ ), the current state ( $x(k)$ ) and the measurement noise ( $v_i(k)$ ) are related.

Subsequently, how local estimates (predictions from each sensor) are combined with the global estimate is determined.

$$\sum_{i=1}^N \beta_i = 1 \quad (4.3)$$

Equation (4.3) states that the sum of all information sharing coefficients ( $\beta_i$ ) equals 1, meaning information is entirely shared among all local filters. In this thesis, equal coefficients are used for each sensor. Since we used two sensors in this study and these sensor devices have similar features so we take the  $\beta_i = 0.5$

$$P_i^{-1}(k-1|k-1) = \beta_i P_g^{-1}(k-1|k-1) \quad (4.4)$$

Equation (4.4) indicates that the inverse of each local filter's error covariance matrix ( $P_i^{-1}$ ), is proportionally adjusted with the inverse of the global error covariance matrix ( $P_g^{-1}$ ), and the coefficient  $\beta_i$ . The covariance matrix represents the uncertainty of the estimated position. The smaller the P value, the higher the confidence level in the Kalman filter's initial prediction.

$$Q_i^{-1}(k-1) = \beta_i Q_g^{-1}(k-1) \quad (4.5)$$

Similarly, Equation (4.5) adjusts the inverse of each local filter's process noise matrix ( $Q_i^{-1}$ ) proportionally with the inverse of the global process noise matrix ( $Q_g^{-1}$ ) and the coefficient  $\beta_i$ . The process noise signifies the uncertainties in the model. A lower Q value indicates a more stable system and a slower adaptation of the prediction.

$$\hat{x}_i(k-1|k-1) = \hat{x}_g(k-1|k-1) \quad (4.6)$$

Equation (4.6) states that the initial prediction in each local filter ( $\hat{x}_i$ ), is the same as the global prediction ( $\hat{x}_g$ ), meaning local filters are initiated with the global prediction.

### 4.3.3 Application of kalman filter equations

This information restructures local systems, and Kalman filtering equations are applied. In other words, predictions and updates of local filters begin. Updates are conducted as follows:

Each sensor is assigned a unique Kalman filter, allowing all filters to operate in parallel and generate their state estimation ( $\hat{x}_i$ ) Equation (4.7) and error covariance matrix ( $P_i$ ) Equation (4.8).

$$\hat{x}_i(k|k-1) = \Phi(k-1)\hat{x}_i(k-1|k-1) \quad (4.7)$$

$$P_i(k|k-1) = \Phi(k-1)P_i(k-1|k-1)\Phi^T(k-1) + Q_i(k-1) \quad (4.8)$$

Where Equation (4.8) and Equation (4.7),  $\Phi(k-1)$  is the system matrix,  $Q_i(k-1)$  is the process noise covariance matrix. In this study, Q was chosen as a 4x4 corner matrix with a value of 0.0003.

Then, the produced state estimation ( $\hat{x}_i$ ) Equation (4.10) and error covariance matrix ( $P_i$ ) Equation (4.11) are updated with the Kalman gain ( $K_i$ ) Equation (4.9).

$$K_i(k) = P_i(k|k-1)H_i^T(k) \times [H_i(k)P_i(k|k-1)H_i^T(k) + R_i(k)]^{-1} \quad (4.9)$$

$$\hat{x}_i(k|k) = \hat{x}_i(k|k-1) + K_i(k)[z_i(k) - H_i(k)\hat{x}_i(k|k-1)] \quad (4.10)$$

$$P_i(k|k) = [P_i^{-1}(k|k-1) + H_i^T(k)R_i^{-1}(k)H_i(k)]^{-1} \quad (4.11)$$

where Equation (4.9), Equation (4.10) and Equation (4.11), H is the measurement matrix, R is the noise covariance matrix and  $z_i(k)$  is the measurement vector. In this study, R was chosen as a 2x2 corner matrix with a value of 1.178

The gain determines how much of the difference between the estimated state and the actual measurement should be added to the prediction. If the gain is low, the measurement has little impact on the prediction. Conversely, a high gain means the measurement heavily influences the prediction. A lower R-value signifies more reliable measurements [50].

#### 4.3.4 Optimal combination of local estimates

Selecting appropriate information-sharing coefficients is critical in applying FKF. These coefficients determine how local predictions are combined with global predictions.

The global prediction is obtained by combining local predictions:

$$P_g^{-1}(k|k) = \sum_{i=1}^N P_i^{-1}(k|k) \quad (4.12)$$

$$\hat{x}_g(k|k) = P_g(k|k) \sum_{i=1}^N P_i^{-1}(k|k) \hat{x}_i(k|k) \quad (4.13)$$

where  $P_g(k|k)$  is the global error covariance matrix can be seen equation (4.12),  $\hat{x}_g(k|k)$  is the global state estimation can be seen equation (4.13), and  $N$  is the number of sensors. Using a federated filter, the two-dimensional

The position of the Tag, which is fixed on the coordinate plane, was tried to be estimated with model. system and measurement equations are given by (4.14) and (4.15).

$$\begin{bmatrix} p_k^x \\ v_k^x \\ p_k^y \\ v_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} p_{k-1}^x \\ v_{k-1}^x \\ p_{k-1}^y \\ v_{k-1}^y \end{bmatrix} \quad (4.14)$$

$$z(k) = \begin{bmatrix} p_k^x \\ p_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_k^x \\ v_k^x \\ p_k^y \\ v_k^y \end{bmatrix} + v_i(k) \quad (4.15)$$

It is important to note that while federated filtering results are globally optimal, the solutions obtained from individual local filters may be suboptimal due to the upper bounds imposed on their covariance matrices. Amplifying the noise covariance can degrade the accuracy of local estimates and fault detectability. Therefore, a fault in a subsystem that goes undetected before the fusion process can contaminate the global system and affect the fault-free local filters. To improve fault tolerance, it is recommended not to use the reset mode of the federated filter, but this may result in the global solution being no longer optimal [52],[53].

The federated filtering technique's use of information sharing has the following benefits:

- 1) Enhanced measurement data throughput by concurrent local filter operation and internal data compression.
- 2) Improved system fault tolerance by maintaining numerous component solutions to increase fault detection and recovery capabilities.
- 3) By employing theoretically sound estimate techniques, cascaded filter operations are more accurate and stable [54].

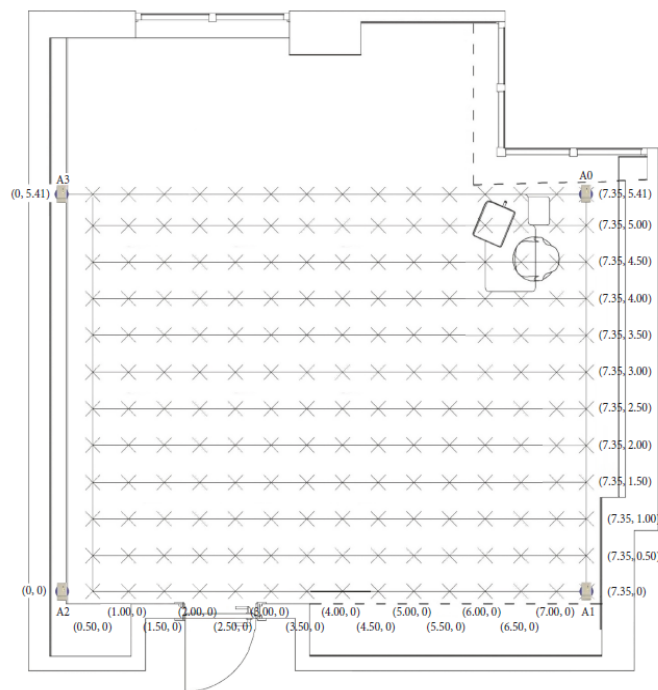
#### **4.4 Differences Between Kalman and Federated Kalman Filters**

The Federated Kalman Filter is an approach that integrates data from multiple sensors. It is specifically designed for merging and coordinating data from several sensors, making it suitable for situations where different sensors may have different characteristics and accuracies. The Kalman filter, on the other hand, is used to filter data from a single sensor or data source. It operates on a single measurement model and a single process model.

The Federated Kalman Filter often shows superior performance compared to the traditional Kalman Filter, particularly due to its ability to work with multiple sensors and assign different weight coefficients to each sensor. This capability effectively reduces error states through a robust feedback and update system. These features allow FKF to achieve more precise results, especially in environments where sensor integration is involved or where there is a high likelihood of errors.

## 5. EXPERIMENT

In this thesis, real data has been used. These data were collected in the Active Learning Classroom (ALC) at Kadir Has University. An area of 7.35 m x 5.41 m in the classroom was available for the experiment. In the four corners of the classroom, there are devices used for distance measurement, referred to as Anchors (indicated as A0, A1, A2, and A3 in Figure 5.1).



**Figure 5.1** Testbed area of 7.35m × 5.41m

The devices are positioned at a distance of 2.85 m from the ceiling. The classroom is designed as an environment with a floor divided into quadrangles. The floor of the environment is marked at intervals of 0.50 m. Using these marked points, there are 10 fixed points where data were collected. By connecting these points, a butterfly-shaped route was defined (Figure 5.2).



**Figure 5.2** Scenario for the  $7.35\text{m} \times 5.41\text{m}$  Testbed area.

The marked floor facilitated the determination of the actual locations of the fixed points. This allowed for the observation of differences between measured values and actual values. During the data collection process, 4 receivers and 2 transmitters were used. The receiver devices were placed at a fixed height of 2.85m in the four corners of the room, as indicated in Figure 5.1 as A0, A1, A2, and A3. The Decawave MDEK1001 UWB development kit, shown in Figure 5.3 [55], was used to conduct this experiment, serving both as a receiver and a transmitter. The data were collected in scenarios of NLOS and LOS, involving multiple devices operating side by side and individually.



**Figure 5.3** Decawave MDEK1001 UWB Sensor.

## 5.1 Data Collection and the Success of the Data

The data was collected under two distinct conditions during the data collection process: LOS and NLOS. Initially, each tag device was operated individually, and data was collected at each specific point. Subsequently, to assess whether the concurrent operation of the devices influenced location accuracy, both tag devices were operated simultaneously at the same location, and data was gathered. In the NLOS data collection scenario, in contrast to the LOS scenario, the devices were placed in the same pocket of a garment to ensure that they were subject to NLOS conditions in the presence of the human body. The collected data were analyzed in the subsequent phase to calculate error conditions for both scenarios, where the tag devices were operated both individually and in pairs while at each specific point. Although data was collected more than once at each point, the work on the last collected data is shown. Tags were left fixed at each point and data were collected from fixed points. The collected data contains X and Y information.



**Figure 5.4** Tag pairs at each specific point

The formula used in this analysis represents a method used to evaluate the difference between actual values and measured values. This formula is based on the concept of Euclidean distance and is used to calculate the differences between the coordinates of an actual point in two-dimensional space and the coordinates of a measured point. Mathematically, it can be seen in formula (5.1).

$$Error = \sqrt{((X_{actual} - X_{measured})^2 + ((Y_{actual} - Y_{measured})^2)} \quad (5.1)$$

Here,  $X_{actual}$  value and  $Y_{actual}$  value represent the coordinates of the actual values, while  $X_{measured}$  and  $Y_{measured}$  represent the coordinates of the calculated values. After squaring these differences and summing them, the square root of the total value is taken. This result is used to determine how close or far apart two points are from each other. This error analysis method is typically used when comparing predictions or measurements to actual values. The obtained result indicates the magnitude of the difference between real and measured values. Lower results indicate that the measured values are closer to the actual values, while higher results indicate larger errors. Subsequently, the average of these error values is calculated for each point.

The recovery rate is a measure of how much a value has changed relative to its initial value. It compares the final value with the initial value and calculates the ratio of this difference to the initial value. Therefore, the recovery rate can be either positive or negative. This rate is expressed as a percentage. the formula can be seen in (5.2).

$$Improvement\ rate = \left( \frac{Last\ Value - First\ Value}{First\ Value} \right) \times 100 \quad (5.2)$$

In this formula, the "Final Value" represents the value after the process, while the "Initial Value" represents the starting value.

The values after applying Kalman filter and Federation Kalman filter to the data collected by running them individually and in pairs while in motion in LOS and NLOS situations give the results as shown in the Tables 5.1, 5.2, 5.3 and 5.4 below. The unit of errors is the meter.

**Table 5.1** In cases where the tags are individually and LOS conditions are present, error scenarios.

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
Tag 1	0.1525	0.1495	0.2059	0.1021	0.2947	0.3835	0.3468	0.3693	0.1906	0.1200	0.2315
Tag 2	0.1520	0.1213	0.2396	0.1224	0.3115	0.3182	0.3093	0.2667	0.1237	0.1669	0.2132

**Table 5.2.** In cases where the tags are individually and NLOS conditions are present, error scenarios.

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
Tag 1	2.7576	4.9666	5.1663	4.8009	5.8701	4.6540	3.1989	4.5464	5.2367	2.4930	4.3690
Tag 2	2.0264	4.3047	5.5194	3.1821	4.5827	1.6564	3.8367	4.9599	3.9500	3.0357	3.7054

**Table 5.3** In cases where the tags are pairs and LOS conditions are present, error scenarios.

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
Tag 1	0.2591	0.2950	0.2701	0.2984	0.3050	0.2716	0.2879	0.2958	0.3453	0.3234	0.2952
Tag 2	0.1729	0.1719	0.2947	0.1729	0.3255	0.4627	0.3296	0.4337	0.1474	0.1793	0.2691

**Table 5.4** In cases where the tags are pairs and NLOS conditions are present, error scenarios.

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
Tag 1	4.7535	7.7296	3.0798	4.5937	5.3731	8.1867	4.0007	4.4737	6.4654	2.0129	5.0669
Tag 2	2.8704	8.0547	3.2606	3.9518	5.6892	7.2822	2.9155	2.5592	2.8404	3.0468	4.2471

## 5.2 Applying The Federated Kalman Filter To The Data

In LOS environment studies, it was observed that there was an average improvement of approximately 96.64% following the application of the FKF. In Table 5.5 and 5.6 the impact of FKF on tags in LOS conditions is demonstrated.

**Table 5.5** The tags are individually and LOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<i>Tag1</i>	0.0050	0.0050	0.0094	0.0033	0.0095	0.0124	0.0110	0.0121	0.0056	0.0038	0.0077
<i>Tag2</i>	0.0051	0.0050	0.0075	0.0049	0.0105	0.0101	0.0103	0.0085	0.0042	0.0060	0.0072

**Table 5.6** The tags are pairs and LOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<i>Tag1</i>	0.0083	0.0062	0.0071	0.0044	0.0092	0.0135	0.0121	0.0142	0.0082	0.0088	0.0092
<i>Tag2</i>	0.0059	0.0053	0.0076	0.0039	0.0116	0.0135	0.0103	0.0141	0.0037	0.0067	0.0083

In NLOS conditions, after the application of the FKF in the studies, an average improvement of approximately 96% was observed. This means that the error margin, which was approximately 5 meters, was reduced to 0.12 meters. In Table 5.7 and 5.8, the impact of FKF on tags in NLOS conditions is demonstrated.

**Table 5.7** The tags are individually and NLOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<i>Tag1</i>	0.0936	0.1618	0.1784	0.1557	0.1941	0.1489	0.1069	0.1364	0.1737	0.0807	0.1430
<i>Tag2</i>	0.0644	0.1393	0.1936	0.1011	0.1471	0.0495	0.1242	0.1574	0.1409	0.0955	0.1213

**Table 5.8** The tags are pairs and NLOS conditions are present, error scenarios after the application of FKF

ID	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8	Point 9	Point 10	Total Error
<i>Tag1</i>	0.1570	0.2456	0.0944	0.1583	0.1769	0.2634	0.1269	0.1518	0.2170	0.0652	0.1657
<i>Tag2</i>	0.0847	0.2708	0.1006	0.1277	0.1853	0.2389	0.0720	0.0758	0.0943	0.1008	0.1351

Furthermore, it was observed that in scenarios where multiple mobile devices were present in environments accommodating both conditions, the error rate was higher. The results of the experiment, evident in tables 5.8, 5.6, 5.4 and 5.3 showed that the devices performed worst when operated in pairs. These tables revealed that paired devices had a higher average error rate compared to those operated individually.

### 5.3 Applying the Kalman Filter to Data

When only the Kalman Filter is applied in NLOS situations, it has been observed that the error situations are worse compared to the Federated Kalman Filter. The Federated Kalman Filter has shown an improvement of 18.78-19.26% in separate NLOS situations, and 19.05-19.57% in dual situations, compared to the Kalman Filter. In LOS situations, compared to the Kalman Filter, an improvement of 19.79-19.10% was seen in separate operations, and 11.96-21.69% in combined operations

In LOS conditions, the KF performance is superior compared to NLOS conditions. The values in Tables 5.11 and 5.12 are smaller than those in Tables 5.9 and 5.10, indicating fewer errors. When considering tags in pairs, the KF performance is worse compared to when they are considered individually. The values in Tables 5.10 and 5.12 are larger than those in Tables 5.9 and 5.11

**Table 5.9** The tags are individually and NLOS conditions are present, error scenarios after the application of KF

ID	Point1	Point2	Point3	Point4	Point5	Point6	Point7	Point8	Point9	Point10	Total Error
<i>Tag1</i>	0.1142	0.2011	0.2146	0.1943	0.2408	0.1864	0.1312	0.1730	0.2162	0.1001	0.1772
<i>Tag2</i>	0.0794	0.1732	0.2350	0.1260	0.1829	0.0588	0.1563	0.1975	0.1663	0.1188	0.1494

**Table 5.10** The tags are pairs and NLOS conditions are present, error scenarios after the application of KF

ID	Point1	Point2	Point3	Point4	Point5	Point6	Point7	Point8	Point9	Point10	Total Error
<i>Tag1</i>	0.1964	0.3074	0.1110	0.1902	0.2176	0.3275	0.1574	0.1924	0.2666	0.0812	0.2048
<i>Tag2</i>	0.1056	0.3318	0.1282	0.1572	0.2304	0.2958	0.0957	0.0962	0.1168	0.1236	0.1681

**Table 5.11** The tags are individually and LOS conditions are present, error scenarios after the application of KF

ID	Point1	Point2	Point3	Point4	Point5	Point6	Point7	Point8	Point9	Point10	Total Error
<i>Tag1</i>	0.0062	0.0063	0.0118	0.0040	0.0118	0.0155	0.0137	0.0151	0.0070	0.0047	0.0096
<i>Tag2</i>	0.0062	0.0061	0.0094	0.0060	0.0132	0.0126	0.0128	0.0106	0.0053	0.0073	0.0089

**Table 5.12** The tags are pairs and LOS conditions are present, error scenarios after the application of KF

<b>ID</b>	<b>Point1</b>	<b>Point2</b>	<b>Point3</b>	<b>Point4</b>	<b>Point5</b>	<b>Point6</b>	<b>Point7</b>	<b>Point8</b>	<b>Point9</b>	<b>Point10</b>	<b>Total Error</b>
<i>Tag1</i>	0.0103	0.0075	0.0041	0.0034	0.0131	0.0197	0.0144	0.0138	0.0099	0.0070	0.0103
<i>Tag2</i>	0.0069	0.0068	0.0118	0.0069	0.0131	0.0119	0.0133	0.0175	0.0059	0.0072	0.0101



## 6. RESULT

In thesis at Kadir Has University's Active Learning Classroom, In order to enhance the precision of UWB-based indoor positioning sensors under Non-Line-Of-Sight conditions, the focus of this manuscript is directed towards the utilization of the Federated Kalman Filter. The Federated Kalman Filter is designed to refine location predictions by amalgamating information sourced from various local systems. Notably, the Federated Kalman Filter substantiates an enhancement in location accuracy beyond a specified threshold, as delineated in the data presented within the article. For example, the application of the Federated Kalman Filter results in a reduction of the accuracy range for Non-Line-Of-Sight data to a diminished value, such as 0.12 meters.

in other state, In experiments conducted within Line-of-Sight environments, the Federated Kalman Filter demonstrated an average accuracy improvement of approximately 96.64%. The error margin, initially reaching 0.30 meters, is substantially mitigated to 0.0072 meters with the incorporation of Federated Kalman Filter. Analogously, a comparable enhancement of approximately 96% was observed in Non-Line-Of-Sight scenarios, presenting an approximate 19% advancement over the Kalman Filter within Non-Line-Of-Sight configurations. The Federated Kalman Filter outperforms the standard Kalman Filter, primarily attributed to its adeptness in operating with multiple sensors and allocating distinct weighting coefficients to each sensor. This characteristic, facilitated by a robust feedback and update mechanism, effectively diminishes error states. These attributes empower the Federated Kalman Filter to yield more precise outcomes, particularly in settings characterized by substantial error probability or intricate sensor integration.

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Bachelor's Degree Education: Kadir Has University (2021-2024)

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## Work Experience

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Turkey Technology Team Foundation 12/2019-03/2020

Alarge Alıç Ağacı Mak. Elekt. Ar-Ge 06/2019-07/2019

KemiQ 3D Printers & Solutions 02/2018-03/2018

Türk Telekomünikasyon Comp. 06/2018-07/2018