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Innovations in Indoor Positioning Systems (IPS)

Edited by Albert Sabban

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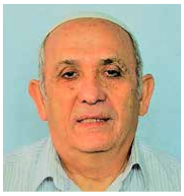
Meet the editor



Dr. Albert Sabban holds a Ph.D. in Electrical and Computer Engineering from the Faculty of Electrical and Computer Engineering at the University of Colorado at Boulder, USA (1991) and an MBA from the Faculty of Management at Haifa University in Israel (2005). He holds a BSc and MSc (Magna Cum Laude) from Tel Aviv University in Israel. He is a senior lecturer and researcher at Israel's electrical and computer engineering colleges. From 2007 to 2010, Dr. Sabban was a radio frequency and antenna specialist at biomedical hi-tech companies, where he designed wearable compact systems for medical systems. In 1976, he joined Rafael Advanced Defense Systems Ltd., Israel, where he worked as a senior researcher, group leader, and project leader in the electromagnetics department until 2007. He has published more than 100 research papers and holds several patents. He has written and edited over ten books and book chapters on wearable systems, antennas, and green electronics technologies for communication and medical systems. He is the author of a book on electromagnetics and microwave theory for graduate students and a book on wideband microwave technologies for communication and medical applications.

Contents

Preface

This book presents innovations in indoor positioning systems (IPS), a field that has experienced continuous growth over the past decade. Significant advances in wireless communication and electronic systems have contributed significantly to the development of advanced IPS technologies. An indoor positioning system is a network designed to continuously and in real-time determine the position of people or objects in rooms, buildings, or other indoor environments. IPS has broad applications in commercial industries, medical centres, military networks, retail, and inventory tracking.

An introductory chapter presents the basic concepts and topics of IPS. The book also provides a comparative analysis and review of IPS technologies. This review covers various technologies used in IPS development, such as Wi-Fi systems, Bluetooth low energy (BLE) technology, radio frequency identification (RFID), vision-based systems, inertial measurement units, and sensors. Readers will gain insights into the foundational theory, IPS system architecture and modules, limitations, innovations, and future trends in this rapidly evolving field.

IPS systems employing multiple technologies are designed and implemented to provide accurate positioning information for objects and individuals in indoor environments. Applications include locating objects, tracking people within buildings, healthcare monitoring, navigation assistance for visually impaired persons, emergency response operations, and military uses. Several algorithms and techniques are used to ensure precise tracking and localization within indoor spaces.

Artificial Intelligence (AI) further enhances IPS by improving the detection and positioning of individuals and objects in indoor settings. Employing AI and data science advancements, IPS can achieve excellent accuracy and exhibit good adaptability to dynamic environments and human behaviours. AI enables IPS systems to detect, interpret, and predict movement patterns, adapting in real-time to environmental changes.

This book also explores advanced localization techniques for unmanned aerial vehicles (UAVs), a field that has seen remarkable progress in the last decade. Additionally, the book discusses several indoor positioning strategies, including Global Positioning Systems (GPS), Visible Light Communication (VLC), and vision-based methods. The integration of sensors and the strategic use of buildings as reference points enhance localization accuracy. The importance of sensor fusion and artificial intelligence in improving the precision and efficiency of UAV navigation is presented in this book. The book examines the role of sensor fusion and AI in enhancing the precision and efficiency of UAV navigation.

Challenges such as signal attenuation caused by construction materials and multipath propagation, which introduce uncontrollable positioning errors, are also addressed.

Multipath effects, particularly in IPS systems utilizing RF technologies, remain a significant source of error. The book emphasizes the importance of accuracy in IPS, which can achieve precision up to 2 cm, though greater accuracy often involves increased complexity and cost.

Emerging technologies like MIC (Microwave Integrated Circuits), MMIC (Monolithic Microwave Integrated Circuits), and LTCC (Low-Temperature Co-Fired Ceramic) are discussed for developing RF modules and systems for IPS. These technologies benefit the design of compact and efficient RF devices, including transmitters, receivers, and antennas. Advanced antenna designs, such as microstrip mono-pulse antennas and metamaterials, are employed to find accurate position and direction in IPS and radar systems.

The book provides an overview of the major technologies, techniques, and modules used to ensure accurate indoor positioning. These include cellular phones, radio waves, Wi-Fi, Bluetooth, smart devices, light, magnetic fields, acoustic signals, and behavioural analytics. IPS uses different technologies such as distance measurement, smartphone integration, and tagging to achieve its objectives.

We hope this book will be a valuable resource for researchers, engineers, and project managers involved in developing and manufacturing IPS. The information presented aims to inspire further innovation and application in this field.

Acknowledgements are extended to all the authors who contributed to this volume.

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Section 1

Introduction to Indoor Positioning Systems

Chapter 1

Introductory Chapter: Indoor Positioning Systems (IPS)

Albert Sabban

1. Introduction

Indoor positioning system (IPS) is a network of devices used to locate people or objects, especially inside rooms and building, see Ref. [1]. An IPS system consists of two different elements, an anchors and location tags. Anchors are modules placed in the building. Tags are carried by persons or objects whose location should be detected.

GPS and other satellite technologies cannot function with good precision inside apartments, buildings, medical centers, airports, parking garages, and underground locations. Several variety of technologies, techniques, and devices are used to provide indoor positioning, such as cellular phones, radio waves, Wi-Fi, Bluetooth, smart devices, light, magnetic fields, acoustic signals, and behavioral analytics are all used in IPS systems. IPS can achieve position accuracy up to 2 cm. IPS uses different technologies, including distance measurement, smart phones, Wi-Fi, Bluetooth, smart devices, and tags. IPS has broad applications in commercial applications, medical centers, military networks and applications, retail, and inventory tracking industries. There are several commercial systems on the market. Due to the signal attenuation caused by construction materials, satellite-based systems are not effective as indoor positioning systems. Moreover, reflections from the ground and buildings cause multi-path propagation results in uncontrollable positioning errors. Multi-path effects are causing positioning errors to IPS systems, which employ RF technologies.

2. Types of indoor positioning systems

2.1 Radio frequency (RF) technologies

Several IPS systems are based on RF technologies [1–11]. Several IPS systems use the advantages of RF technologies that are already deployed, such as wireless communication, Wi-Fi networks, Bluetooth, and smartphones. The cost of deployment of RF IPS systems is reduced drastically by using available RF modules. RF IPS systems can also provide larger coverage. RF signals can traverse obstacles; they can function in real-world environment where obstacles are unavoidable.

2.2 Radio frequency identification (RFID)

RFID uses RF fields to identify and track tags attached to people or devices, see Ref. [10]. These systems use RFID tags and readers. Readers transmit signals that are identified by tags. Tags send back an ID information as a respond to the request of the reader. RF RFID systems send and receive RF signals from 125 KHz to 5.8 GHz. RFID devices may be passive, active, or semi-passive. The power needed to passive tags to transmit the data is obtained from the reader's signals. Passive tags may store a few kb of memory, and they are cheap. The reader should very close to the tag around 1 meter from the tag to get the data.

Semi-passive RFIDs have a battery to power the tag. The antenna and other devices are the same as in the passive RFID system. In this case, a better working range is achieved. Active RFIDs have efficient smart antennas that can provide a larger range, up to 100 m. These tags can also store more information. The cost of active RFID system is much higher. RFID systems do not provide tracking information, and many times they are combined with other technologies that can provide positioning.

2.3 Inertial measurement unit (IMU)

Inertial systems are small modules that inform about the relative movement of the tag. They consist of several sensors such as magnetometer, accelerometer, and gyroscope. The direction and orientation of movement of the tag may be detected by these sensors. They combination of these sensors may provide a good prediction of the relative motion with regard to the previous location. Algorithms named Dead Reckoning use this information collected by all available sensors. These IPS devices do not use anchors in the environment. The accuracy of this IPS devices is poor, and the accumulated error over a period of time is few meters after few seconds.

2.4 Bluetooth and Wi-fi technologies

IPS devices may employ EIFI and Bluetooth and Wi-Fi networks to locate persons and tags. The advantage of Bluetooth and WiFi Wireless Fidelity, networks is that they use the infrastructure of Wi-Fi and Bluetooth networks that are available in cellular phones, smartphones, and smart wearable sensors. Installation and infrastructure of these devices is easier and very cheap than other devices. The operating concept of this technology uses the Received Signal Strength (RSS). By measuring the RSS of the tag to multiple Wi-Fi access points, it is possible to estimate the position of the cellular phone. The main disadvantage of these devices is that RF Wi-Fi signals are attenuated in the presence of metals, walls, moving people, and other obstacles. The signal strength decreases in the presence of walls and IPS device accuracy decrease. The accuracy obtained with these IPS systems can be around 1-2 m.

2.5 Infrared light

Infrared light systems used infrared light signals, the same as TV remote control device. An unobstructed Line of Sight (LOS) between the anchor and the tag is required. These devices are very reliable as room detectors. Light cannot pass walls. A tag cannot detect light from an anchor that is not in the same room. Many anchors should be installed to achieve precise localization because the low strength and quality of the signal is required to calculate the position from several anchors.

2.6 Ultra-wideband IPS systems, UWB

UWB is a RF technology for short-range IPS systems. UWB communication has a strong multipath resistance and to some extent penetrability for building material, which may be important for indoor tracking, localization, and distance estimation. These IPS devices can penetrate glass, concrete, and wood; this is very useful in buildings and rooms where line of sight is not possible. Wide bandwidths provide a good time resolution and better accuracy. These devices have better distance estimation and positioning. The accuracy of UWB IPS devices up to date is the best of IPS devices with errors around 0.3 to 0.5 m.

There are some disadvantages for UBW IPS systems. The technology is not available to smartphone users in buildings. To prevent interferences between other RF signals and devices, there are legal restrictions on the frequency band of IPS systems. The allowed frequency band is from 3.1 to 10.6GHz. The transmitted power level is limited. Due to these facts, the operation range of UWB IPS systems is around 100 m.

3. Features and trade-off in developing IPS systems

The major features of IPS Systems are frequency band of the RF IPS systems, accuracy, area coverage, number of anchors used, and cost.

3.1 Accuracy

The accuracy of the distance between the estimated position and the true position is the most important feature for IPS systems. The complexity and cost of the IPS system is significantly higher for accurate IPS networks. When accurate positioning is not important, simpler and low-cost technologies are employed.

3.2 Coverage and scalability

Coverage is the second major feature of IPS systems. The coverage of IPS devices ranges from devices that can cover apartments, a single room, several rooms, warehouses, malls, hospitals, and healthcare centers. Coverage is the zone where the location data is available. There is a trade-off between coverage and accuracy. Technologies with larger coverage typically imply smaller accuracy of the IPS system. The ability to cover larger areas by using more anchors, access points, or card readers define scalability. It is very important that IPS devices may locate several persons and objects at the same time.

3.3 Adaptation to environment conditions

The ability of the IPS devices to adapt to the environment is crucial to achieve good accuracy of the IPS system. Changes in the environment conditions may affect the electrical performance of the IPS system.

3.4 IPS system cost

The cost of an IPS system include development costs, manufacturing expenses, operational expenses, and maintenance costs during the lifetime of the IPS devices. Several IPS systems can use the existing infrastructure and networks. However, others need fixed installation. Installation and calibration process is costly in time.

4. Very small X band monopulse direction finding transceiver

The RF head uses a monopulse patch array to transmit and receive electromagnetic X band waves. The electromagnetic waves are down converted to 60 MHz. Electromagnetic and optical direction-finding systems may be assembled in the same RF Head.

4.1 RF head description

The transceiver modules and assembly are presented in **Figure 1**. The transmitting power amplifier can transmit 60 W CW power or 400 W peak power. A circulator and a limiter protect the sum link and the transceiver from high-power received signals. The limiter is connected to a digital attenuator with 0 to 20 dB attenuation level. The output port of the digital attenuator is connected to a LNA, low-noise amplifier, with 26 dB gain and 1.2 dB noise figure. The SUM port is connected to an IRM, Image Rejected Mixer, through a 10 dB digital attenuator (0 or 10 dB) and a band-pass filter. The difference, Δ,(ΔAz, ΔEl) antenna output ports are connected through a Limiter to a SP3T switch. The difference (ΔAz, ΔEl) links are identical to the sum channel. The same RF modules are used in the sum and difference channels. The guard input port is also connected to the SP3T switch *via* limiter. The RF signal is down conversion to 60 MHz IF signal by 10.64 GHz LO signal. The local oscillator signal, LO, to the IRM mixers of the transmitting and receiving channels is provided *via* a power divider. BIT, Built-In-Test, and calibration are performed by injecting a RF signal to the BIT port. To conclude the RF head has five ports, Azimuth difference and elevation difference, sum, Guard, and BIT.

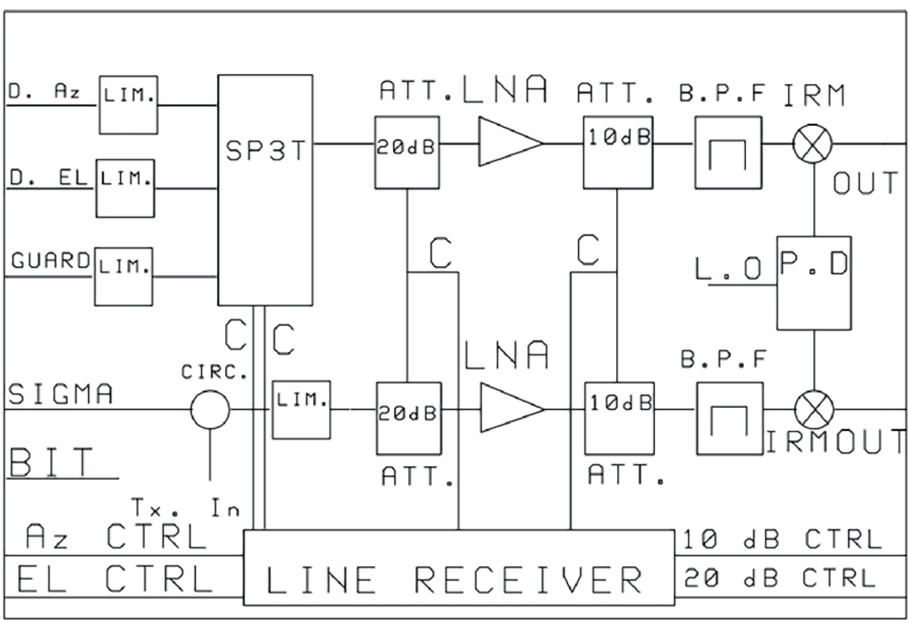

Figure 1.
Block diagram of a compact X band direction finding transceiver.

4.2 X band direction finding transceiver specifications

The X band direction finding Transceiver Specifications is given in **Table 1**. The gain of sum link is around 11 dB. The gain of the difference channels (ΔAz, ΔEl) is around 10 dB. The noise figure of the difference channel is around 5 dB. The noise figure of the sum channel is around 5 dB.

Parameter	Specifications
1. Frequencies	
RF FREQ	10,500 - 10,900 MHz
IF FREQ	60 MHz
2. Tx input	
Peak power	400 Watt max.
Tx. Average power	60 Watt max.
Duty factor	15% max.
PRF	2 to 220 KHz
Pulse width	0.1 to 15 μSec.
3. N.F N.F at, room temp. +25°C	
Σ channel	NF = 4.8 dB
Δ channel	NF = 4.8 dB
guard channel	5.8 dB max.
4. RF to IF Gain	@ 25°C @ 10,600 MHz
Σ channel	9–12 dB
Δ channel	9-12 dB
gain change vs. freq. @ 25°C	2 dB max.
Gain change vs. temp.	3 dB max.
RF to IF Gain Guard	9–11.8 dB
Amplitude matching	+0.5 dB
Phase matching	+8 deg.
5. Isolation	
Sum to Δ	20 dB min.
Between Δ	20 dB min.
Guard to Σ	30.0 dB max.
6. 1 dB C.P.	25°C @ 0 dB att.
Σ channel	-8 dBm min.
Δ channel	–9.6 dBm min.
25°C @ 30 dB att.	+11.8 dBm min
7. IP3	25°C @ 0 dB att.
7. IP3	25°C @ 0 dB att.
Σ channel	–5.8 dBm min.

Parameter	Specifications
Δ channel	-8 dBm min.
@ 30 dB att.	+13 dBm min.
8. Recovery time	
Recovery time	200 nsec.
9. VSWR	
All ports	1.6: 1 max.
Parameter	Specification
10. Circulator isolation	
Circulator isolation	19Db min.
11.Channels power handling	Limiter requirement
10,550- 10,850 MHz:	
Pulse width	15 μsec. Max.
Duty factor	15% max.
Av. Power	5 Watt max.
Peak Power	40 Watt max.
2000-18000Mhz	
cw power	1 Watt max.
12 switches and attenuators	
Rise/fall time	50nSec.
Switching speed	100nSec.
13.Attenuators Value	
20Db att., 10Db att.	+ 2.5 dB
14.IRM	20 dB min.
15. LO input	
Freq. 10,490-10,790 MHz	
power level	10 to 15 dBm
16.Frequency Response, Fixed L.O	Filter requirement
-3Db points	10.7 + 0.75GHz
rejection at +1200 MHz rejection at +2400 MHz	20 dB min. 30 dB min.
17. Switch on time	300nSec. Max.
18. DC Power	12 W

Table 1.
The X band direction finding transceiver specifications.

4.3 X band direction finding transceiver evaluation

In **Figure 2** noise figure and gain budget at the output of the difference link (ΔAz, ΔEl) are shown. The difference channels (ΔAz, ΔEl) gain are around 11 ± 0.3 dB and the difference link noise figure is around 4.3 ± 0.3 dB. In **Figure 3**, noise figure and

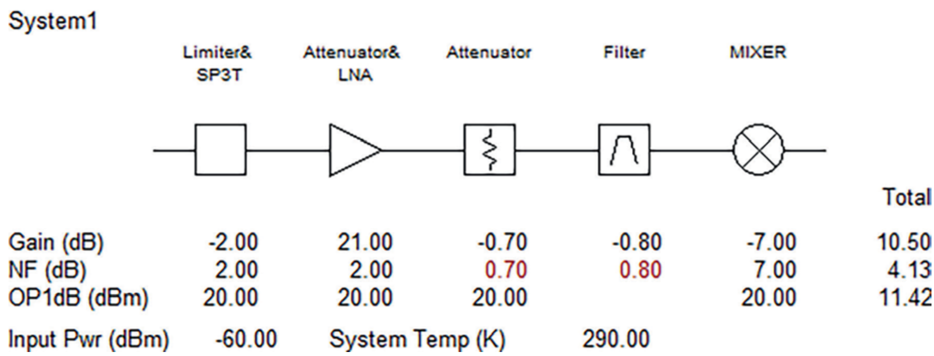

Figure 2.
Gain and noise figure budget at the output of the difference channels.

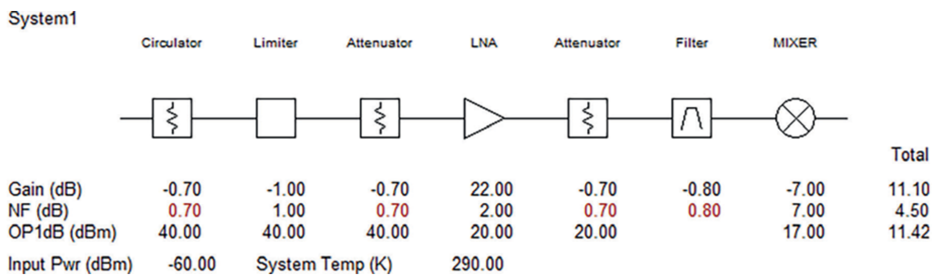

Figure 3.
Gain and noise figure at the output of the sum channel.

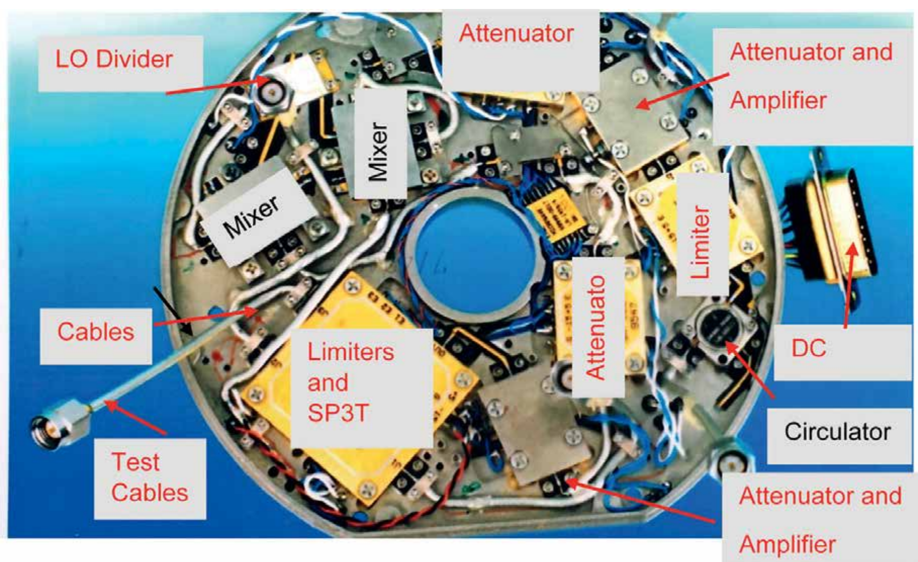

Figure 4.
Photo of the measured X band direction finding transceiver.

gain budget at the output of the sum link are shown in **Figure 3**. The sum link gain is around 12 ± 0.5 dB and the sum link noise figure is around 4.2 ± 0.5 dB. The small transceiver photo and modules are shown in **Figure 4**.

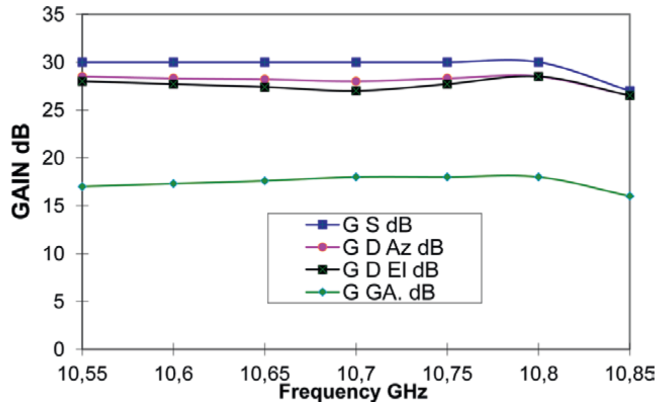

Figure 5.
Measured gain of the X band direction finding transceiver.

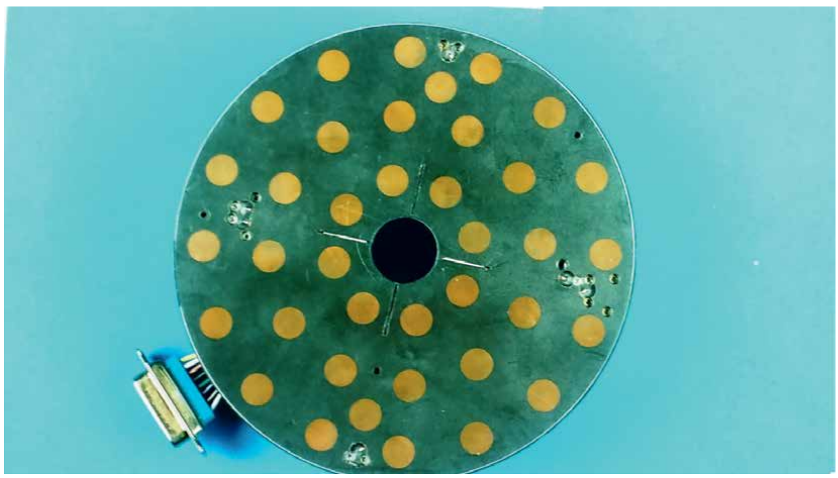

Figure 6.
Photo of the integrated transceiver with the microstrip antenna array.

Figure 5 presents the transceiver, with the patch array, measured gain of the sun, guard, and difference links. The sum channel gain is around 29.5 ± 1 dB. The difference channel gain is around 28 dB. The guard channel gain is around 17.5 ± 0.5 dB. In **Figure 6** a photo of the transceiver with the patch-stacked monopulse array is presented. The monopulse circular patch antenna array is etched on a substrate with dielectric constant of 2.2. The antenna is a stacked double-layer patch antenna. The antenna feed network is printed on the first layer with 0.5 mm thickness. The microstrip circular radiators are printed on the second layer, see **Figure 6**. The antenna array thickness is around 1 mm.

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Section 2

Indoor Positioning Systems and Technologies

Chapter 2

A Comparative Analysis and Review of Indoor Positioning Systems and Technologies

Owen Casha

Abstract

This chapter presents a comparative analysis and review of indoor positioning systems, both from an algorithm and a technology point of view. It sheds light on the evolving landscape of location-based services within confined spaces. The review encompasses a diverse range of technologies employed in indoor positioning systems, including Wi-Fi-based systems, Bluetooth low-energy solutions, radio frequency identification technologies, ultra-wideband, inertial measurement units, visual-based systems, and sensor fusion approaches amongst many others. By summarising a multitude of research findings and technological advancements, the chapter offers insights into the strengths, limitations, and emerging trends within the field. Furthermore, it critically assesses the performance metrics of various indoor positioning systems, thus providing a comprehensive guide for researchers, developers, and practitioners. The comparative analysis delves into the practical implications of these systems, by considering factors such as design and deployment cost, power efficiency, and adaptability to different indoor environments. The main types of signal acquisition and position estimation techniques used in indoor positioning systems are discussed, while providing the advantages and disadvantages of each approach. This chapter aims to contribute to the advancement of indoor positioning technology, by offering valuable perspectives for future research directions and practical applications.

Keywords: location-based services, literature survey, communication protocols, algorithms, adaptability, sensing

1. Introduction

An indoor positioning system (IPS) is a system that continuously and in real time determines the position of a person or an object in an indoor environment [1]. This system is designed to work within the confines of a building or a structure while relying on various technologies, algorithms, and techniques to accurately track and locate targets. In recent years, there has been a growing interest in IPS research and development [2]. Various IPSs have been designed to provide accurate information about the position of a person or an object inside a building [3]. These systems have various applications, ranging from warehouse management, healthcare tracking, navigation assistance for blind individuals, and emergency response operations [2, 4, 5]. The evolution of IPS has paved the way for the development of indoor location-based services (LBS), where applications are built around the position estimation of an object or a person [6]. Geofencing, asset tracking, and targeted advertising are just a few examples of LBS that can be enhanced by the implementation of IPS. These services utilise the precise location data provided by IPS to offer a personalised experience, improve operational efficiency, and optimise resource management [2, 7]. Although a number of literature review articles have already been published [2, 3, 6–12], this work aims to present an updated and complete overview together with a comparative analysis of IPS, focusing on both the algorithms and the technologies. This review aims to shed light on the evolving landscape of LBS within confined spaces, considering a diverse range of IPS technologies, including Wi-Fi-based systems, Bluetooth low-energy solutions, radio frequency identification (RFID) technologies, ultra-wideband (UWB), inertial measurement units, visual-based systems, and sensor fusion approaches, amongst others.

While outdoor positioning systems (OPSs), such as the global position system (GPS), are widely used for LBS in open and outdoor environments, they are not suitable for indoor use. This is primarily due to the limitations of signal penetration and accuracy in indoor spaces [2]. OPSs rely on satellite signals to determine the location of a person or an object. However, when these signals enter the indoor environments, they often experience signal degradation or complete blockage due to the presence of walls, ceilings, and other physical obstructions. This can result in inaccurate and unreliable positioning information within indoor settings. Therefore, IPS has emerged as a separate field, focusing on developing technologies and algorithms that can accurately locate objects or persons within confined spaces. In contrast, IPS is specifically designed to overcome these challenges by utilising alternative technologies that are better suited for enclosed spaces. These technologies can provide more precise and reliable indoor location information. One or more technologies can be employed to compensate for the limitation of a single technology.

Understanding the distinct differences between outdoor and indoor positioning systems is crucial for developing effective and accurate LBS, which are tailored to specific environments. By leveraging the strengths of indoor positioning technologies, businesses and organisations can optimise operational efficiency, enhance safety measures, and improve the user experience within indoor spaces [3]. The review presented in this chapter summarises a multitude of research findings and technological advancements, providing insights into the strengths, limitations, and emerging trends within the field of IPS. Employing a combination of sophisticated sensors with wireless communication has introduced new applications, which can simplify the daily activities of human beings, increase independence, and improve the quality of life [13]. IPS has gained significant attention due to their potential to revolutionise various industries and improve the overall user experience within confined spaces [9].

In addition to the introductory section, this chapter is divided as follows. Section 2 discusses the need for IPS and its targeted applications, while highlighting the challenges and opportunities. In addition, Section 2 lists the performance metrics that are used to characterise and compare different IPSs in a fair way. Section 3 delves into the five main types of signal acquisition techniques and algorithms, while providing the advantages and disadvantages of each approach. Section 4 discusses different position estimation techniques such as triangulation, trilateration, finger printing, and vision analysis. Section 5 presents and compares the various technologies employed in IPS. Finally, Section 6 discusses the potential research directions and future applications of IPS and Section 7 provides a few concluding remarks.

2. Indoor positioning systems

In order to obtain the physical position of an object or a person, two phases are involved in an IPS: the signal acquisition phase and the position estimation phase, as shown in **Figure 1**. In the first phase, the communication system attached to the object, or a person transmits and receives signals to and from a number of reference nodes placed at known locations within the indoor environment [14]. A particular property of these signals, such as the signal strength or the time-of-flight, is then measured and used in the position estimation phase to calculate the target's coordinates. There are several types of signals that can be utilised for indoor positioning, each with its own strengths, limitations, and properties [10] as will be discussed in Section 5. In addition, since signal measurement in practical systems is only accurate to a certain degree, various algorithms and techniques are employed to improve the accuracy and reliability of IPS [6], including optimisation-based statistical techniques that filter out measurement errors and noise.

The need for IPS arises from the numerous applications and the benefits it offers in a variety of industries and scenarios [7]. These applications range from private home use, such as tracking items and as an aid for the elderly or disabled individuals, to public buildings where IPS helps visually impaired individuals to navigate indoors, track people in crowded places, and enhance security measures [7]. IPS also plays a crucial role in medical environments, where they can be used for tracking patients, preventing the theft of expensive equipment, and aiding doctors and nurses in their daily tasks [7]. Furthermore, IPSs are increasingly being adopted in industries such as manufacturing, robotics, and automation. Applications such as robotic guidance, smart factories, and cooperative robotics are quite common. The emergence of smartphones has further accelerated the demand for IPS. Smartphones have become ubiquitous and are equipped with various technologies such as Wi-Fi and Bluetooth radios, which can be utilised for indoor positioning [2]. Furthermore, the rapid growth of e-commerce and online shopping has created a need for accurate IPS in retail environments [3]. IPS has the potential to revolutionise the retail industry by providing personalised shopping experiences, targeted advertisements, and efficient inventory management [2].

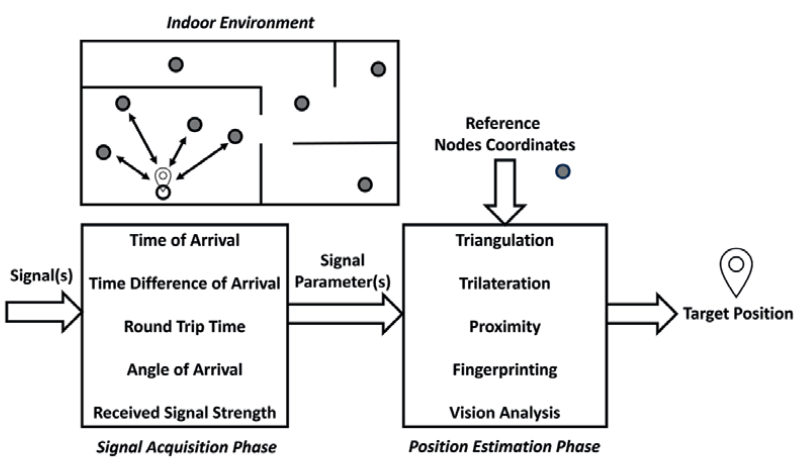

Figure 1.
Signal acquisition and position estimation in indoor positioning systems.

2.1 Challenges and opportunities

IPSs face unique challenges compared to OPS, since they feature unique characteristics that are different from those of OPS. The primary challenge faced by IPS is the presence of obstacles and signal interference [2]. The presence of signal reflections and multipath propagation in indoor environments can lead to signal distortion and destructive interference, affecting the accuracy and the reliability of the position estimation. Indoor positioning applications often require a higher accuracy and precision in comparison with OPS applications, to efficiently handle small areas and existing obstacles. The presence of walls, furniture, and other physical structures can obstruct or weaken signals, leading to signal loss and degradation [6]. Additionally, electromagnetic interference generated by other electronic devices and wireless networks in proximity can complicate the positioning process. Various techniques and algorithms have been developed, to overcome these challenges and improve the accuracy and reliability of IPS [15]. These techniques and algorithms involve signal measurement, signal processing, and fusion of multiple signals [3]. Furthermore, the limited availability of line-of-sight (LOS) signal propagation, like in the case of GPS, impacts the performance of IPS.

Nonetheless, there are several characteristics within indoor environments that facilitate positioning [2]. In an indoor environment, a person or an object moves at a relatively slower speed with respect to an outdoor scenario. In addition, a small area facilitates the position monitoring due to a predetermined infrastructure together with small variations in ambient parameters such as temperature, humidity, and air circulation. In indoor environments, signals from technologies like Wi-Fi, Bluetooth, and RFID can reflect off surfaces such as walls, floors, and ceilings. While this can create challenges in signal measurement and analysis, it also provides opportunities for triangulation and signal enhancement, leading to more precise location determination [12].

Indoor environments often have a fixed infrastructure which aids the strategic placement of access points, beacons, and RFID readers for enhanced network connectivity or operational purposes. These infrastructure elements can be used by IPS to establish reference points and enhance location accuracy [16]. Compared to outdoor spaces, indoor environments offer a more controlled setting, allowing for the optimisation of signal propagation and reception. This control can be instrumental in minimising signal interference and improving the overall performance of indoor positioning systems [10, 12, 15]. IPS can be integrated with building management systems, security systems, or smart environment technologies. This provides holistic functionalities that enable efficient resource utilisation, enhanced security measures, and the seamless coordination of various indoor processes [7, 12]. IPS can also be integrated with Internet of Things (IoT) devices and sensors within indoor environments, enabling the collection of real-time data for various applications such as smart homes, healthcare monitoring, asset tracking, and energy [17]. Indoor environments generally have reliable power sources and network connectivity, providing a stable infrastructure for the deployment and operation of IPS. This accessibility facilitates the continuous operation of positioning systems with minimal downtime [7, 17]. Understanding these characteristics can aid in the development and the deployment of IPS which are tailored to specific indoor environments. Ultimately accuracy, reliability, and effectiveness are enhanced, thus leading IPS to support a wide range of applications and scenarios.

2.2 Performance metrics

In this section, different performance metrics of IPS are presented and discussed. Performance metrics play a crucial role in assessing the suitability of a system before designing or deploying it for a particular application. Such metrics are used to characterise and compare different IPSs in a fair way and provide insights into their strengths and limitations.

2.2.1 Accuracy and precision

Accuracy refers to the closeness of the measured positions to the true positions. The accuracy of an IPS is the mean Euclidean distance between the estimated position and the true position [3, 10]. It is essential to ensure that the location data provided by the IPS is reliable and can be used for critical applications such as emergency response or asset tracking. Accuracy is still an open challenge for researchers in this field [3]. Precision is the consistency or repeatability of the position measurements. High precision implies that the system can consistently determine the same position for an object or person in multiple measurements. This is crucial for applications that require fine-grained location information and reliable tracking such as indoor navigation and augmented reality (AR) [18].

2.2.2 Availability and reliability

Availability refers to the percentage of time that the system is operational and can provide accurate location information. Availability is generally classified into three different levels: low availability (less than 95%), regular availability (more than 99%), and high availability (more than 99.9%) [19]. It is essential for applications that require continuous and uninterrupted positioning, such as real-time asset tracking and emergency response systems. Availability can be limited by both random factors such as communication congestion and periodic factors such as routine maintenance. Reliability measures the consistency of the system in providing accurate results over time. A reliable IPS ensures that the location data remains consistent and trustworthy even with changes in environmental conditions or user mobility.

2.2.3 Latency

Latency is another important metric for IPS, representing the time delay between the instant when a position measurement is requested and the instant when the result is available. Low latency is crucial for time-sensitive applications, such as interactive LBS and real-time tracking, where immediate responsiveness is essential for excellent user experience and operational efficiency [12].

2.2.4 Coverage area

The coverage area indicates the physical space within which the IPS can provide accurate location information. Each IPS has its own coverage area, which can vary from a small room to an entire building [3]. Nonetheless, designing an IPS that features a coverage of more than 60 metres is still very challenging. The coverage range depends on the technology used and the infrastructure in place [6]. For example, Wi-Fi-based systems generally have a coverage range of up to 30 meters, while RFID technologies may have shorter ranges of around 5 meters. Hence, short-range technology such as RFID may be suitable for localised applications, while long-range technologies like Wi-Fi can provide coverage for larger areas [3]. Thus, short-range technology needs more devices to cover a given area in comparison with long-range technology.

2.2.5 Scalability, complexity, and robustness

Scalability refers to the ability of the system to accommodate an increasing number of tracked objects or users without compromising performance. A scalable IPS should maintain its accuracy and reliability, as the number of tracked entities grows. This ensures its suitability for diverse environments and applications. Scalability also refers to the ability of the system to expand its coverage area or range by adding more infrastructure components or devices [20, 21]. Complexity, on the other hand, refers to the intricacy and sophistication of the IPS. A complex system may require advanced algorithms, multiple sensors, and a robust infrastructure to operate effectively. Thus, complexity can be attributed to the algorithmic implementation, whether it is distributed or centralised, the hardware requirements of the IPS including the computational platform and peripheral devices, and the overall operation factors such as installation and maintenance [22]. Robustness is another important aspect influencing the complexity of an IPS and refers to the ability to handle variations and external factors that may affect the performance of an IPS [3]. In relation to this, the adaptiveness of an IPS refers to its capability to adjust to dynamic environmental conditions, such as changes in signal interference, infrastructure layout, or user mobility patterns. An adaptive system can optimise its performance and accuracy by dynamically adapting its algorithms, signal processing techniques, or infrastructure configuration in response to varying conditions. This ensures reliable and robust operation in real-world indoor environments [6].

2.2.6 Power consumption and efficiency

Power consumption and efficiency are significant considerations for IPS, especially for battery-powered devices and energy-efficient infrastructure. Minimising power consumption while maintaining high-performance levels is essential for prolonging the operational lifespan of devices and minimising maintenance needs such as battery replacement. Furthermore, power-efficient IPS can also have a positive impact on environmental sustainability by reducing energy consumption.

2.2.7 Cost effectiveness

Cost effectiveness is an important factor to consider when evaluating IPS. It involves assessing the balance between the cost of implementing and maintaining the system and the benefits it provides in terms of improved operational efficiency, enhanced user experience, and overall value to the organisation or end users. Factors such as initial setup costs, infrastructure requirements, maintenance expenses, and potential return-on investment need to be considered when determining the cost-effectiveness of an IPS for a specific application [6, 23, 24]. The cost of an IPS can be evaluated across different dimensions including financial, time, space, and energy [2]. Furthermore, the cost effectiveness of an IPS can also be influenced by factors such as scalability and complexity [3]. Certain IPS employs passive RFID tags that are more cost-effective due to their low-energy consumption and simple implementation, while others reuse existing infrastructure such as Wi-Fi networks, making them more cost-effective compared to systems that require the installation of dedicated hardware.

2.2.8 Privacy, security, and user experience

Privacy, security, and user experience are increasingly becoming significant considerations in the design and deployment of IPS [23]. Privacy concerns arise from the collection and use of location data, especially in scenarios where individuals or assets are being tracked. It is important for IPS to implement privacy-preserving measures and comply with relevant regulations to ensure the protection of sensitive location information against intrusion, theft, or misuse [24]. User experience encompasses the ease of use, accuracy, and the overall value of the LBS provided by the IPS. A positive user experience is essential for the widespread acceptance and adoption of IPS, making it a crucial performance metric. Furthermore, to improve the user experience, IPS should aim to provide real-time and seamless positioning information in a non-intrusive way, while maintaining a high level of security and privacy.

3. Signal acquisition techniques and algorithms

This section discusses the main types of signal acquisition techniques and algorithms while providing the advantages and disadvantages of each approach. These techniques can be generally divided into three categories: time-based acquisition, angle-based acquisition, and received signal strength acquisition.

3.1 Time-of-arrival

Time-of-arrival (TOA) or time-of-flight (TOF) is a signal acquisition technique that measures the time it takes for a signal to travel from the transmitter node to the receiver or target node. This technique relies on accurately measuring the time delay t_d between the transmission and the reception of the signal, to determine the distance d between the nodes, by knowing *a priori* the corresponding signal propagation velocity v_p [25, 26].

$$d = t_d \times v_p \tag{1}$$

This information can then be used to triangulate the position of the target node. The advantages of TOA include its high accuracy and precision in determining the distance between nodes. While TOA-based techniques are based on a simple principle (Eq. 1), they can be sensitive to factors such as signal reflections and multipath effects, which can introduce errors in the distance measurements. In order to mitigate the impact of these factors, TOA techniques require synchronisation between the transmitter and the receiver nodes [27]. A well-synchronised clock is crucial for accurate TOA measurements. The work [28] presented fundamental bounds for an ideal and multipath environment while highlighting the main sources of error for

TOA ranging. TOA is often used with UWB technology, which utilises pulses of short duration to filter out signal reflections and improve overall performance. Another disadvantage is its high computational cost, due to the need for high-resolution time measurements and complex calculations to determine the distances between nodes. TOA-based algorithms have been used to locate objects or devices in various applications [26]. An underground coal mine worker localisation system was designed using this technique together with UWB technology to track the position of workers for safety purposes [9]. A novel UWB-based navigation system for mobile robot tracking was presented in Ref. [29].

3.2 Time difference-of-arrival

Time difference-of-arrival (TDOA) relies on measuring the difference in arrival times between two different types of signals transmitted from the transmitting node to the receiver node [27]. By comparing the time difference between the arrivals of these signals at the receiver, the transmitting node location can be deduced by using Eq. (2):

$$t_{d1} - t_{d2} = \frac{d}{v_{p1}} - \frac{d}{v_{p2}} \tag{2}$$

where v_{p1} and v_{p2} are the propagation velocities of the two different signals and t_{d1} and t_{d2} are the time delays taken by the two respective signals to travel a distance d between the transmitting node and the receiving node. Another approach to TDOA-based algorithms is based on measuring the TDOA of a single signal sent by an object or person and received by three or more receivers [30]. Each difference of arrival time produces a hyperbolic curve on which the target location lies. One needs prior information to eliminate the position ambiguity caused by the intersection of multiple hyperbolic curves [31]. The advantage of TDOA-based techniques is their ability to provide accurate positioning measurements, even in environments with severe multipath fading [27]. For instance, multi-carrier signals can be used to reduce the performance degradation due to multipath propagation within indoor environments [32, 33]. The localisation accuracy of TDOA-based techniques is highly dependent on the synchronisation of the clocks at the receiver nodes. Nonetheless, precise synchronisation between the target and the base station is not required as in TOA [9, 34]. One limitation is the need for multiple receivers to accurately measure the time difference of arrival. Furthermore, TDOA-based algorithms require significant bandwidth due to the need for multiple receivers to share data and cooperate in determining the location of the transmitter [35]. TDOA-based algorithms have also been combined with other techniques to enhance the accuracy of IPS as reported in Refs. [36, 37]. Apart from using RF technologies, TDOA can also be employed in visible light communication systems as proposed in Ref. [38].

3.3 Round trip time

Even though TOA and TDOA are employed in many IPS, they are still limited by strict synchronisation requirements [39] which increase the deployment and the maintenance costs to guarantee adequate accuracy. Round trip time (RTT) is another technique which measures the time t_{RTT} taken by a signal to travel from a transmitting node to a receiving node and back again. RTT was proposed as an alternative technique to mitigate the synchronisation problem of TOA [40, 41]. In RTT, the distance d is calculated using Eq. (3):

$$d = \frac{(t_{RTT} - \delta t) \times v_p}{2} \tag{3}$$

where δt is the processing time incurred by the hardware within the receiving node and v_p is the signal velocity of propagation. In RTT, only one node measures the transmitted and arrival time instead of using two local clocks in both the transmitting and receiving nodes as in TOA. Nonetheless, RTT increases the computational time complexity of the system to $O(n^2)$, where the complexity of this approach rises quadratically as the number of nodes n increases. The system requires n iterations to determine the target node position *via* message relaying with the other nodes. Time measurements are also impacted by several uncertainty factors including the phase noise or the jitter of the clock [8]. Given the limitations of RTT, the issue of synchronisation in time-based approaches deserves further investigation since RTT solves it only to a certain extent, while factoring in other considerations and restrictions in the implementation.

3.4 Angle-of-arrival

Angle-of-arrival (AOA)-based methods make use of the nodes' capability to measure the angle of arrival of signals [1, 2, 9, 42]. This information is used to determine the position of an object, where LOS conditions are present. Only two beacons are required to estimate the position in a two-dimensional (2D) plane, while three or more beacons are needed for three-dimensional (3D) positioning or in case one needs to improve the accuracy. The AOA technique estimates the position of an object or a person by comparing either the signal amplitude or the carrier-phase across multiple antennas. The target's receiver position can be estimated *via* the intersection of the angle line from each signal source. Since the transmitter timing information is encoded in this signal, the receiver does not need to maintain synchronisation with the clock of any beacon [3]. On the other hand, directional antennas [43] or antenna arrays are needed, thus increasing the cost. AOA is affected by multipath or non-line-of-sight (NLOS) propagation and reflections, which can lead to inaccuracies in the estimated position since the direction of signal arrival is altered. AOA accuracy is also influenced by the range, and the antenna array geometry has a major impact in the estimation algorithm [44]. Due to these limitations, AOA techniques are often combined with other techniques such as TDOA [45] or adopt a cooperative approach. Such approach integrates pairwise AOA information amongst all sensor nodes rather than relying solely on anchor nodes [46].

3.5 Received signal strength

Received signal strength (RSS)-based methods rely on measuring the strength of radio signals received from beacons or access points to estimate the distance between the target object and the reference points [9]. The distance is inversely proportional to the signal strength and is measured based on the attenuation due to the signal propagation by using an empirical mathematical model [8]. This model depends on the number of obstacles, attenuation factors, and routing factors. RSS localisation either employs a propagation model algorithm or a fingerprinting algorithm [47]. RSS is simpler to use when compared to AOA or TDOA. It does not need dedicated hardware at the mobile station, apart from a wireless network interface card [3], and RSS algorithms tend to involve less communication traffic. This provides an improved channel access control and position accuracy [9]. RSS-based methods do not require synchronisation but need at least three reference nodes for a 2D space and at least four reference nodes for a 3D space. LOS propagation is preferred since signal attenuation is affected by obstacles and multipath propagation, which can distort the signal strength and lead to inaccuracies in the estimated position [48]. Moreover, the accuracy of RSS-based methods is highly dependent on the environment in which they are deployed, making it hard to establish an accurate propagation model [3, 9], especially in dynamic scenarios.

4. Indoor position estimation techniques

The position estimation in IPS involves determining the location of a target object or a person based on the measurements obtained through the various techniques discussed in Section 3 [8]. This process employs various mathematical algorithms and techniques which can be categorised into different approaches, including trilateration, triangulation, fingerprinting, proximity sensing, and vision analysis [3]. Statistical techniques such as maximum likelihood estimation (MLE) are often used to improve and augment the accuracy in a noisy environment [8], particularly in the context of trilateration-based positioning [49]. MLE is also used to limit the problem of synchronisation by predicting uncertain bias parameters in the time domain [50, 51].

4.1 Trilateration

Trilateration determines the location of a target T by measuring its distance from at least three reference points as shown in **Figure 2**.

The distances are typically determined using techniques such as TOA, TDOA, or RSS. The trilateration algorithm then uses these distance measurements to calculate the coordinates of the target in a 2D or 3D space. By knowing *a priori*, the coordinates of the reference nodes RN_1, RN_2, and RN_3, and estimating the corresponding distance from each reference node to the target node (d_1, d_2, and d_3), one can obtain the following three circle equations (Eq. 4):

$$\begin{aligned}
(x_1 - x)^2 + (y_1 - y)^2 &= d_1^2 \\
(x_2 - x)^2 + (y_2 - y)^2 &= d_2^2 \\
(x_3 - x)^2 + (y_3 - y)^2 &= d_3^2
\end{aligned} \tag{4}$$

which provide the unknown coordinates of the target *(x,y)* by finding the intersection of the three circles [8]. The work in Ref. [52] showed that by considering

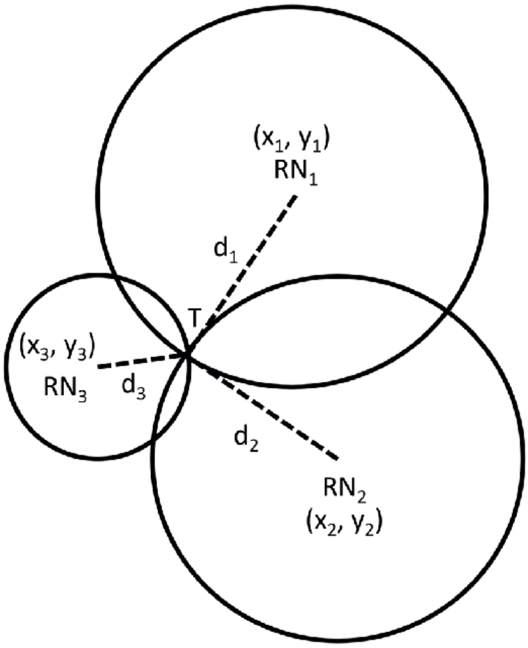

Figure 2.
Visualisation of the trilateration-based position estimation for a 2D space.

the layout of the three reference nodes, one can improve localisation performance, particularly if RN_1, RN_2, and RN_3 are placed on the vertices of equilateral triangles. In addition, by considering the influence of the noise on the measurements and using different confidence coefficients for the nodes, it is possible to further improve the quality of the trilateration [53].

4.2 Triangulation

Triangulation is based on measuring angles, by using AOA techniques instead of measuring distances as in trilateration, to determine the position of an object relative to multiple reference points as shown in **Figure 3**.

Compared to trilateration, only two reference nodes (RN_1 and RN_2) are required in a 2D space triangulation instead of three reference nodes. The intersection of a pair of angle direction lines given by Eq. (5):

$$\frac{y-y_1}{x-x_1}=\tan(\theta_1) \qquad \frac{y_2-y}{x_2-x}=\tan(\theta_2) \tag{5}$$

is used to determine the coordinates of the target position *(x,y) via* the geometric properties of triangles and predetermined coordinates of the reference nodes (x_1, y_1) and (x_2, y_2), after measuring angles θ_1 and θ_2 [20, 54]. Triangulation can be transformed to trilateration, because the distance between the nodes is related to the angles between them [8].

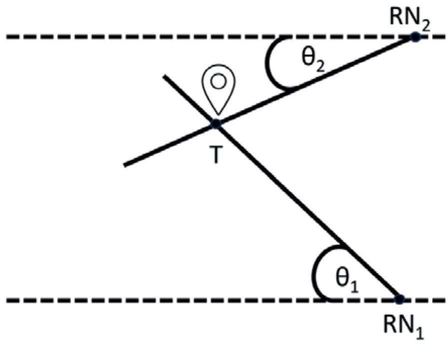

Figure 3.
Visualisation of the triangulation-based position estimation for a 2D space.

4.3 Proximity location sensing

Proximity location sensing is a technique that estimates the location of a target object with respect to a known position or area, by using a particular physical phenomenon [55]. Several detectors are placed at predetermined locations.

Proximity sensing relies on either the detection of physical contact or the use of radio sensors with a limited range or automatic identification systems [54]. Physical contact can be detected using sensors such as pressure sensors, inductive sensors, capacitive field sensors, or touch sensors. Proximity sensing can be alternatively implemented by continuously monitoring wireless access points (Wi-Fi, Bluetooth, or cellular) and detect the presence of a mobile device when it gets into range. One can also infer the location of a mobile object by using automatic identification systems such as point-of-sale terminals, computer login registries, or land-line telephone records [3]. If these devices have a known location and are accessed by the mobile object by either scanning a RFID label or interrogating a tag, one can get its location. Advantages of proximity location sensing include its simplicity and low cost, whereas its disadvantages include limited range, the inability to provide precise location information, and user dependability.

4.4 Fingerprinting

Fingerprinting relies on the matching of signal characteristics, such as RSS, at different locations within an indoor environment either using deterministic or using probabilistic algorithms. Prior to its deployment, a database of signal strength measurements at various known locations within the indoor environment is created, during the so-called training or offline phase. The construction of a radio map is carried out by sub-dividing the area into cells by using a floor plan. RSS values of radio signals at different positions are measured for a finite amount of time [3, 20, 55, 56]. Subsequently, while operating in the online stage, the system uses the currently observed RSS values and compares them to those stored in the database to identify the location of the target object based on its measured signal strength [12]. Advantages of fingerprinting include its ability to provide highly accurate and precise location information, especially in environments where signal propagation characteristics are well modelled and stable. It can also accommodate various environmental factors, such NLOS propagation, which can affect other localisation methods. However, fingerprinting also has some limitations. Creating, maintaining, and updating the fingerprint database can be labour-intensive, resource-intensive, and time-consuming, especially in dynamic environments where signal propagation characteristics may change. For instance, the RSS values can be easily affected by reflection, scattering, or diffraction propagation phenomena [15, 56].

4.5 Vision analysis

Vision analysis uses cameras or vision sensors to capture images or video footage of the indoor environment and then analysing them to estimate the position of a target object. Real time images captured by one or multiple cameras fixed within the IPS tracking area are processed using computer vision algorithms. These can detect and track objects based on their visual features such as colour, shape, or texture. The observed target images are compared against a database of known images or patterns. Vision positioning techniques can also provide useful location context information employed by LBS [55].

5. Indoor positioning technologies

This section provides an overview of some of the commonly used IPS technologies, while highlighting their respective strengths and limitations. When selecting the appropriate technology for a particular application, it is important to consider the performance metrics discussed in Section 2.2 to achieve the best trade-off between complexity, cost, and performance. In addition, complementary technologies can be used to take advantage of their distinctive advantages and compensate for any limitations [3, 9]. IPS technologies can be classified according to different criteria. These criteria include the type of sensors used, whether IPSs are networked-based or not, whether they require existing hardware located in the building or are self-contained and the physical medium used to determine the position of a target [3].

5.1 Radio frequency identification (RFID)

RFID uses radio waves to automatically identify objects or people in large systems [2]. RFID-based IPS rely on small tags that can be attached to objects or worn by individuals [3]. These passive or active tags contain unique identification information and can be read by RFID readers placed throughout the indoor environment [2]. RFID tags consist of a microchip and an antenna, whereas the RFID reader consists of an antenna, transceiver, power supply, a processor, and an interface to a dedicated server [3]. The main advantage of RFID is that it may penetrate through solid non-metallic objects and does not require LOS propagation. On the other hand, the communication is not intrinsically secure and consumes more power than infrared (IR) devices. In a RFID system, signals can be affected by their antennas, its positioning coverage is generally small, and it is not easy to integrate it in other systems [3]. RFID makes use of proximity and RSS measurement techniques.

5.2 Mobile phone networks

Mobile phone networks such as Global System for Mobile Communications (GSM) have become popular for indoor positioning because they are widely accessible worldwide and have a high rate of usage [9]. This approach relies on the existing infrastructure of base station towers and the signals transmitted between the mobile devices and these towers is used to determine their indoor position. The main advantages of using phone networks are their ubiquity and the fact that they operate on specific licenced bands, thus eliminating the chance of interference from other communication devices [57]. They are also capable of providing coverage in both indoor and outdoor spaces. By analysing the RSS and timing information from multiple towers, these systems can estimate the position of a mobile device within an indoor environment. However, there are some limitations to using phone networks for indoor positioning. The accuracy of mobile phone-based IPS can vary depending on factors such as signal interference, building materials, and the density of the surrounding structures [9, 15]. Additionally, phone networks are primarily designed for communication rather than precise location determination, which can impact the accuracy of indoor positioning.

5.3 Wireless personal area networks - ZigBee and Bluetooth

ZigBee technology is a short-distance and low data rate (around 250 kbps) wireless personal area network (WPAN) standard operating on the IEEE 802.15.4 specification providing network, security, and application support services [3]. ZigBee technology is attractive due to its low power consumption and cost efficiency. ZigBee devices are small and consist of a microcontroller and a multichannel two-way radio. These systems typically involve the deployment of ZigBee anchor nodes throughout the indoor environment, which communicate with mobile devices and exchange information to determine the position by either using RSS [58, 59] or phase shift measurements [3]. Several studies have explored the use of ZigBee technology for indoor positioning [10, 12, 59]. ZigBee-based systems face some challenges including limited range and coverage, as ZigBee signals have a relatively short-range and can be obstructed by walls [9].

Furthermore, Zigbee-based systems may experience interference from other wireless communication systems operating in the same frequency range, resulting in reduced accuracy, since they operate in the unlicensed industrial, scientific, and medical (ISM) radio bands. ZigBee nodes can either be implemented as a full function device (FFD) or a reduced function device (RFD) [3]. A FFD implements the full protocol set and acts as a network coordinator. On the other hand, RFDs are devices capable to implement a minimal version of the protocol [58, 60].

Bluetooth low energy (BLE) technology, also known as Bluetooth Smart, has gained popularity for IPS due to its low power consumption and wide availability and does not require LOS propagation. It uses proximity or RSS techniques to estimate the position of a target [9]. BLE technology operates on the 2.4 GHz ISM band and offers a range of up to 10 meters [20]. While similarly to ZigBee, it utilises a network of beacon nodes placed throughout the indoor environment, it differs from ZigBee since the Bluetooth standard is a proprietary format, and its gross bit rate is around 1 Mbps. Bluetooth requires a good number of relatively expensive receiving cells and that the target must host a microcontroller that supports Bluetooth radio. ZigBee is better suited for larger networks since it is more scalable and secure, but with trade-offs such as limited range and slower data transfer rate. On the other hand, Bluetooth is suitable for smaller networks and high-speed data transfers.

5.4 Wireless local area network (WLAN)

The IEEE 802.11 WLAN standard is a widely used technology for wireless communication in indoor environments. It provides a means of communication between devices using radio waves at a frequency of 2.4 GHz or 5 GHz and can support high-speed data transfer up to around 100 Mbps. The use of WLAN for indoor positioning is primarily based on the principle that the RSS of WLAN access points can be used to estimate the distance between a target and an access point [57] with a typical accuracy of 3 m to 30 m with an update rate of few seconds [20]. This information can then be used in combination with trilateration or fingerprinting techniques to determine the position of the device within the indoor space. On the other hand, AOA, TDOA, and TOA are more difficult to apply for WLAN IPS, due to the complexity of time delay and angular measurements [3]. An empirical model and a theoretical analysis on Wi-Fi-based indoor positioning and communication are presented in Ref. [12]. An algorithm that integrates indoor target positioning and communication based on Wi-Fi signals is reported to exploit the complexity and the high cost of developing the algorithm across more than one application. WLAN does not require LOS propagation, it is almost readily available in many built environments and most existing mobile devices are equipped with WLAN connectivity. WLAN IPS requires simple and low-cost equipment. The main disadvantage with using WLAN fingerprinting systems is the need to frequently recalculating the predefined RSS map. This is particularly true in dynamic environments with people or objects constantly moving around [57]. In addition, this technology provides a low accuracy and suffers from a lack of effective signal usage [12].

5.5 Ultra-wideband (UWB)

Ultra-wideband (UWB) is an emerging and promising IPS technology as reported in Ref. [11]. It offers several advantages over other technologies, such as high accuracy, precise ranging capabilities, and robustness in multipath environments. Due to its high performance, a common application for UWB is in indoor navigation aids for the visually impaired persons [4, 5]. UWB employs a communication channel that spreads information out over a wide portion of the frequency spectrum with a bandwidth greater than 500 MHz [3]. This allows UWB transmitters to transmit large amounts of data (up to 100 Mbps) while consuming low energy. The use of UWB technology for indoor positioning can be based on a wide range of signal estimation techniques including TOA, TDOA, AOA, RSS, and hybrid algorithms [11]. UWB has been found to provide accuracy in the range of tens of centimetres, making it one of the most accurate indoor positioning technologies available. Additionally, UWB can penetrate obstacles such as walls and objects, making it suitable for indoor environments, where LOS communication may not always be possible. If it is properly designed, UWB does not interfere with existing RF systems. The main disadvantages of UWB technology are the high cost of the equipment [3] and that signal interference can be caused by metallic and liquid materials present in the indoor environment [20].

5.6 Infrared (IR)

Infrared radiation can be used to transmit data between different devices [61]. It is typically used for short-range communication and requires LOS propagation.

Direct IR, such as Infrared Data Association (IrDA), uses point-to-point ad hoc data transmission for very low-power communication which reaches a maximum data rate of around 16 Mbps [9]. On the other hand, diffuse IR features stronger signals than direct IR; therefore, it has a longer range up to around 12 metres. Diffuse IR uses wide angle light emitting diodes (LED) that emit signals in many directions, allowing for one-to-many connections, and does not require direct LOS between devices [9]. The main advantage of IR technology is its ability to provide a secure communication, since IR signals cannot penetrate through walls, and thus, they cannot be easily intercepted or tampered with. This ensures the privacy and the security of data transmission. Disadvantages of direct IR technology are its limited range since it is easily blocked by obstacles and requires LOS communication, making it suitable only in small spaces [3]. On the other hand, diffuse IR systems suffer from a degraded performance in locations having fluorescent lighting or direct sunlight, which create interference even though the transmitted data is modulated. Proximity, TDOA, and AOA techniques are frequently used with this technology.

5.7 Visible light communication (VLC)

Visible light communication (VLC) is a short-range wireless technology, where the visible spectrum emitted by LED is modulated to transmit data at a very high data rate [10, 38]. Each LED emits a different encoded flicker which is specific for a particular location or area and can be coherently detected by a receiver, located on the target *via* a photodiode sensor. This IPS technology employs the readily available lighting infrastructure within a building, thus facilitating its deployment. VLC-based IPSs have the capability to provide a resolution in the centimetre range [10, 14]. A theoretical accuracy analysis on a VLC-based IPS using RSS was presented in Ref. [62]. VLC positioning can be used in RF sensitive areas such as hospitals. TDOA and RSS techniques are frequently used with this technology [38, 63]. While the simulation results presented in the literature are quite promising [62], experimental data show that VLC positioning has several challenges including inter-cell interference, multipath reflection, limited range, the need of LOS communication, and the reduction of the calculation time [14]. In addition, the localisation accuracy is dependent on the ambient light noise, time measurement, and the mobility of the target [14].

5.8 Image-based technology

Image-based technologies or optical methods utilise visual information from cameras or sensors to determine indoor positioning. These technologies often rely on computer vision algorithms to extract features from images and use them to estimate the position of a target [3]. Upon identifying these features, 3D maps are generated by comparing and mapping the captured images to a predefined set of reference images with known locations. Three dimensional maps create a highly detailed and searchable database of the environment. The database is then used by the system to determine the position and the orientation of the device, by using localisation algorithms which match the captured images to the visual cues in the database. The performance attained depends a lot on the type of camera or sensor used, the lighting conditions, and the extracted information obtained from the images [3]. Image-based technologies have gained increasing attention in the field of IPS since they are relatively cheaper when compared to UWB and ultrasonic technologies and are easily deployed [9]. Nonetheless, this technology requires LOS, and its coverage is generally restricted to one room or area [3].

These systems can be categorised into two main types: camera-based systems and sensor-based systems. Camera-based systems have been widely reported in literature [60, 64–66], where different types of cameras are used including smart phone cameras, omni-directional cameras, and 3D cameras. The movement of the camera, located on a target, with respect to a fixed scenario is often used to determine the target's location. On the other hand, sensor-based systems use static sensors such as depth sensors or laser rangefinders to capture the 3D information about the environment to locate moving targets [3].

5.9 Ultrasonic

Ultrasonic technology makes use of ultrasound waves, featuring a frequency above 20 kHz to estimate the relative distance between different objects. An ultrasonic transmitter emits ultrasonic waves into the surrounding environment, which propagates through the air or other media as a series of compressions and rarefactions [57]. While ultrasonic waves do not require LOS propagation conditions and do not interfere with electromagnetic waves, they may suffer from attenuation due to obstacles and are not able to efficiently penetrate solid walls. In fact, when ultrasonic waves encounter an object or surface, they are reflected towards the sensor, due to the difference in the acoustic impedance between the transmitting medium and the object. These systems employ TOA signal acquisition of ultrasonic pulses travelling from the emitters to the receivers. They can estimate the target's position through multilateration using three or more fixed receivers [67]. Ultrasonic positioning systems have a relatively short range, making them suitable only for certain indoor environments [9, 57]. This technology is not very efficient in terms of scalability, as the increase in number of simultaneous transceivers in an environment affects system performance due to increased interference [2].

5.10 Dead reckoning

Dead reckoning is a technique used to estimate the position of an object or a person *via* tracking, based on its previous position and the data obtained from inertial measurement sensors such as accelerometers, gyroscopes, and magnetometers. Since these sensors are readily available in mobile devices such as smart phones [68], dead reckoning is very cost effective as it requires no additional hardware or fingerprinting. The major issues with this technique are that inertial measurements provide position information relative to a known starting point [3] and the sensors used often suffer from drifting. This means that over time, the estimated position becomes less accurate as errors accumulate. Nonetheless, by frequently updating the absolute position, these errors can be contained within certain bounds [69]. In addition, with the use of sensor fusion, where inputs from multiple inertial sensors are integrated using techniques such as Kalman filtering [70], provides an improved accuracy and error reduction [71]. Dead reckoning can also be combined with other positioning technologies such as Wi-Fi, Bluetooth, and UWB to improve accuracy and reduce drift.

6. Future research directions

As IPS continues to evolve, there is a growing need for a robust infrastructure to support their operation. This includes the installation of access points, beacons, sensors, and other necessary hardware throughout indoor spaces to ensure comprehensive coverage and accurate positioning. Additionally, advancements in signal processing techniques, such as complex signal analysis and optimisation algorithms, have allowed for a more accurate and reliable indoor positioning. Many IPSs now use a combination of different technologies to enhance accuracy and reliability. Examples include combining Wi-Fi-based systems with Bluetooth low-energy or RFID technologies or integrating visual-based systems with sensor fusion approaches [72]. There are other promising future advancements and research directions on which to embark on. These developments are expected to further enhance the accuracy, reliability, and overall capabilities of indoor positioning technology. The following is a summary of several emerging trends in the field.

There is an increasing focus on developing indoor mapping and navigation solutions alongside IPS. These solutions provide users with detailed maps of indoor spaces and offer step-by-step navigation guidance, like GPS navigation in outdoor environments [9]. Another future advancement is the integration of AR technology [17]. By combining indoor positioning data with AR capabilities, users can experience enhanced LBS that provide interactive and immersive experiences within indoor environments. AR overlays can offer real-time information about nearby points of interest or interactive navigation guidance through visual cues and markers overlaid on the user's portable or wearable device [2, 73]. This seamless integration of AR and indoor positioning is anticipated to revolutionise various sectors, including retail, hospitality, and entertainment [73].

Future advancements in IPS may also focus on improving multi-user support. By developing systems that can accurately track and manage the locations of multiple users or objects simultaneously, indoor positioning technology can be applied to various collaborative and interactive applications. These include group navigation, location-based gaming, or indoor social networking platforms [57].

The synergy between IPS and the smart building infrastructure is an avenue for significant advancement. As smart buildings increasingly incorporate IoT devices, environmental sensors, and automation systems, the integration of indoor positioning technology can enable context-aware applications, person-alised environmental controls, and seamless interactions between occupants and the built environment. This convergence is projected to pave the way for truly intelligent and adaptive indoor spaces [17]. By integrating environmental sensors to detect factors such as air quality, temperature, or humidity, indoor positioning technology can provide users with valuable environmental data, thus going beyond the provision of location information. This expansion of functionality could support applications ranging from indoor environmental monitoring to personalised location-based recommendations based on environmental conditions [57].

In order to address growing concerns about data privacy and security, future IPSs are expected to implement advanced privacy-preserving techniques. This includes the use of secure and anonymised data collection methods, robust encryption mechanisms, and transparent user consent frameworks to ensure the responsible handling of location data. By prioritising privacy protection, IPS can earn greater trust and acceptance by the users and the regulatory bodies [9]. The ethical and legal implications of collecting and processing location data cannot be overlooked. Striking a balance between providing valuable LBS and respecting user privacy rights requires ongoing attention and adherence to the evolving regulatory frameworks and the industry best practices. Standardisation and interoperability remain crucial factors for the widespread adoption of IPS. As the industry continues to innovate and introduce new technologies, the establishment of standardised protocols and frameworks will facilitate seamless integration and interoperability between different IPSs, promoting a cohesive and efficient ecosystem for indoor LBS [17].

Another anticipated advancement is the integration of sensor fusion and edge computing in IPS [57]. Edge computing is an emerging technology that brings data processing and analysis closer to the source of data generation. This reduces latency and improves real-time decision-making [74]. By combining sensor fusion techniques with edge computing, IPS can take advantage of the power of a variety of sensors, such as accelerometers, gyroscopes, and magnetometers. By combining data from multiple sensors such as cameras, inertial measurement units, and wireless signals, IPS can achieve higher accuracy and robustness in challenging indoor environments. Additionally, the use of edge computing allows for real-time processing and analysis of sensor data, reducing latency and improving overall system responsiveness.

Machine learning algorithms are increasingly being used in IPS to improve accuracy and adaptability. These algorithms learn from the data collected from various sensors and devices, allowing the system to make informed and accurate location estimations [67]. The integration of artificial intelligence (AI) and predictive analytics into IPS represents a significant future direction. By employing AI algorithms and predictive analytics, IPS can also anticipate user movement patterns, predict crowd dynamics, and optimise resource allocation within indoor spaces. This predictive capability can lead to more efficient space utilisation, enhanced safety measures, and improved overall user experiences [75]. With the ongoing evolution of wireless communication technologies, the emergence of 6G networks is expected to revolutionise IPS [13, 76]. These networks promise ultra-low latency, high data rates, and seamless connectivity. These features will significantly enhance the real-time performance and the reliability of indoor positioning solutions [75]. This technological leap is expected to open new possibilities for immersive location-based experiences and advanced indoor navigation applications.

7. Conclusion

This chapter presented a comparative review of the state-of-the-art IPS. It aimed to contribute to the advancement of indoor positioning technology by providing a complete account on the currently available technologies and algorithms. The review encompassed a diverse range of technologies employed in IPS, including Wi-Fi-based systems, Bluetooth low-energy solutions, RFID technologies, UWB, and VLC amongst many others. In addition, the main types of signal acquisition and position estimation techniques used in IPS were discussed and compared. A focus on the evolution of LBS within confined spaces was also presented. The performance of an IPS is highly impacted by the selection of the technology, methodology, and algorithms. The comparative analysis delved into the practical implications of these systems, by considering factors such as design and deployment cost, accuracy, power efficiency, and adaptability to different indoor environments. An appropriate solution to attain specific attributes is strongly related to the given application. Indoor positioning remains an ongoing research field due to the challenges encountered in indoor environments and the necessity for greater accuracy. Hybrid positioning methods are promising for the future, as they seek to blend various approaches to enhance performance. While considerable progress was made in the recent years, there are still several open issues that need to be addressed including multi-user support, improving energy efficiency, cost reduction, signal coverage, data privacy and security, and full integration with IoT systems, amongst many others. In addition, this chapter offered valuable perspectives for future research directions and novel practical applications. The integration and adoption of technologies such as AR, edge computing and 6G mobile networks, is expected to provide a substantial advancement in IPS. These technologies are expected to enhance the accuracy, reliability, and overall performance of IPS. In addition, they will provide new applications and an improved user experience that goes beyond the provision of location information.

Dedication

To my beloved wife, Charmaine, whose unwavering love and support is my beacon through life's turbulent seas. Your presence is a constant source of joy and strength, and I am eternally grateful for the incredible journey we share together.

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Chapter 3

Indoor and Outdoor Localization for UAVs

Yawen Xiao, Guanchong Niu, Chung Shue Chen, Liang Mao and Peipei Zhu

Abstract

This chapter investigates advanced localization techniques for unmanned aerial vehicles (UAVs), focusing on the challenges and solutions associated with both indoor and outdoor environments. By examining a range of positioning strategies, including the global positioning system (GPS), visible light communication (VLC), and vision-based methods, this chapter presents a comprehensive overview of the current state and future potential of UAV localization. The integration of various sensors and the strategic use of landmarks as reference points are explored to enhance localization accuracy. Moreover, two pioneering prototypes that are designed to mitigate the limitations identified in current technologies are introduced for case study. A modularization approach for VLC systems and an empirical method for vision-based distance estimation employing multi-scale QR codes. This chapter also highlights the role of sensor fusion and artificial intelligence in improving the precision and efficiency of UAV navigation. Through proof-of-concept experiments utilizing photodiodes (PDs), inertial measurement units (IMUs), and cameras, we demonstrate the practical applicability and effectiveness of the discussed methodologies. Finally, we study the practical applicability and effectiveness of the discussed systems and their experimental results. Our investigations illustrate significant superiority in UAV localization technologies, paving the way for expanded applications across diverse industries and complex operational scenarios.

Keywords: UAVs, indoor positioning, VLC, vision-based localization, cooperative system

1. Introduction

In recent years, the utilization of unmanned aerial vehicles (UAVs) has witnessed a significant increase across various industries. From aerial photography and surveillance to package delivery and infrastructure inspection, the applications of UAVs are expanding rapidly such as surveillance [1], express delivery [2, 3], and precision agriculture [4]. Undoubtedly, accurate and efficient localization of UAVs is important for these applications to be successful. This chapter aims to explore the UAV localization scenarios, examining diverse positioning techniques and the integration of various sensors to enhance localization accuracy.

At present, the application scenarios of UAVs are mainly outdoors. However, actually, UAVs can also be used in practical indoor environments such as hospitals, greenhouse, manufacturing factories, and nuclear power plants. With the advantages of high mobility and low cost, UAVs have a wide range of applications, including indoor mapping and measurements [5], where a UAV-enabled indoor channel modeling system was proposed. However, considerable research efforts on indoor positioning and navigation (IPIN) systems are still required to materialize the benefits promised by UAVs in practice.

1.1 Indoor and outdoor positioning techniques and evolution

Positioning techniques play a crucial role in determining the location of UAVs as shown in **Figure 1**. Traditional methods, such as the global positioning system (GPS) [6], have been widely used for 3-D localization purposes. GPS provides accurate positioning information by utilizing a network of satellites. However, GPS signals can be affected by factors such as signal loss in urban environments, multipath effects, and interference [7], where the autonomous navigation is considered in the GPS-denied environments. To overcome these limitations, alternative positioning techniques have emerged.

One such technique is visible light communication (VLC) [8], which utilizes the visible light spectrum for communication and positioning. VLC leverages the existing infrastructure of lighting systems to transmit data, allowing UAVs to determine their position based on light signals received from beacons or light fixtures. VLC offers advantages such as high accuracy, low latency, and immunity to electromagnetic interference, making it a promising solution for UAV localization [9].

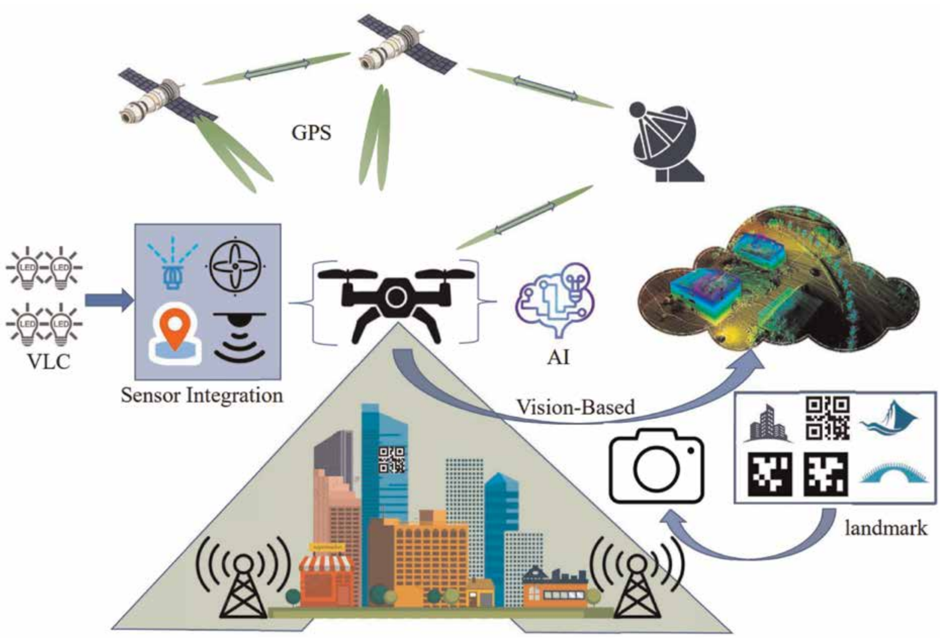

Figure 1.
Different scenarios for UAV localization.

Another positioning technique that has gained traction in recent years is vision-based approaches [10–12]. Vision-based localization relies on cameras mounted on UAVs to capture images of the surrounding environment, using algorithms to extract features and match them with preexisting maps or reference images. This technique enables UAVs to determine their position by analyzing visual cues such as landmarks [13], quick-response (QR) codes [14], or distinctive features of the environment. Vision-based approaches provide a high level of accuracy and can operate in both indoor and outdoor environments, making them versatile for various UAV applications.

In addition, acoustic positioning techniques [15], utilizing sound waves for localization, have emerged as a viable option for environments where optical and radio frequency signals are unreliable. By emitting sound waves and analyzing their reflections or the time it takes for them to reach multiple sensors, UAVs can triangulate their position with a high degree of accuracy. This method is particularly useful in underwater or indoor environments where traditional signals may be obstructed [16].

1.2 Sensor integration and cooperative localization

In addition to exploring different positioning techniques, this chapter also focuses on the integration of various sensors, such as inertial measurement unit (IMU) [17] and magnetometer [18], to facilitate cooperative localization. Cooperative localization involves the collaboration of multiple UAVs to enhance localization accuracy. In Ref. [19], a novel algorithm with robust velocity update was proposed to localize the UAVs by integrating IMU, magnetometer, barometer, and mass-flow. In addition, Y. Zhao, et al. [20] introduced a method for UAV position and power joint optimization in space-air integrated network. By sharing sensor data and exchanging information, UAVs can collectively solve the localization problem as a signal processing task. This approach reduces the reliance on a single sensor and improves the overall accuracy and reliability of localization.

Artificial intelligence (AI) plays a significant role in enhancing the capabilities of positioning systems [21]. AI algorithms can process data from various sensors in real time, predicting and compensating for potential errors in positioning information. This proactive approach allows for dynamic adjustments to the UAV's navigation system, ensuring more stable and accurate flight paths [22]. Recent advancements in vision-based positioning have seen the incorporation of machine learning algorithms to improve feature detection and matching processes. Deep learning models are particularly effective in analyzing complex images and extracting relevant features for more accurate localization. These models can adapt to various lighting conditions and environmental changes, enhancing the versatility of vision-based positioning [23].

Moreover, this chapter investigates the strategic integration of landmarks, which are characterized by their precisely known positions, to improve the localization process [24]. These landmarks act as unique reference points that UAVs can utilize to enhance the precision of their localization efforts. By leveraging landmarks whose positions are accurately known, UAVs can match their derived locations against a confirmed ground truth. Such comparison helps in identifying and amending inaccuracies in the UAV's estimated locations, markedly enhancing the precision of their localization [25].

The utilization of such landmarks introduces an extra dimension of exactitude to UAV localization by providing fixed points of reference in an otherwise dynamic environment. This method is particularly beneficial in areas where GPS signals are unreliable or in scenarios where UAVs operate in densely built-up or complex environments. The incorporation of landmarks into the localization framework not only bolsters the reliability of the positioning system but also enhances its resilience to common localization challenges, such as signal interference and multipath distortion.

1.3 Prototype testing

To advance the implementation of these methodologies and concepts, a comprehensive research and development initiative has been undertaken. This encompasses a thorough exploration of both the theoretical frameworks and practical aspects pertinent to UAV localization. This chapter is characterized by providing an in-depth review of the existing literature. The objective is to investigate the advantages and limitations inherent in various positioning strategies and the integration of different sensors. In the subsequent phase of our research, we will develop and introduce two distinct prototypes for the case study: a VLC-based system and a vision-based cooperative system for UAV localization. These prototypes are designed to empirically demonstrate the effectiveness and operational viability of our proposed systems. Through rigorous testing and evaluation, we aim to demonstrate viable solutions for accurate navigation and positioning in GPS-denied scenarios.

2. Prototype 1: VLC-based indoor localization and navigation for UAVs

To address the challenges for global navigation satellite system (GNSS)-denied indoor scenarios, a few IPIN schemes have been proposed to break the limitation of traditional GNSS-based outdoor algorithms, such as shadow matching algorithm and LiDAR digital elevation model (DEM)-aided algorithm [26]. In conventional robotic studies, simultaneous localization and mapping (SLAM) technology based on a LiDAR or camera has been widely investigated for IPIN service for the GNSS-denied scenarios. However, the robustness and accuracy of vision-based methods cannot be guaranteed, especially for the environment with repeated or similar patterns, while the 3D LiDAR is usually too large and expensive for a UAV [27]. Therefore, an IPIN algorithm, which is based on the difference in horizontal and vertical 2D magnetic field intensity (MFI) measurements, was proposed in [28]. However, the results in [28] have shown that the accuracy is highly dependent on the quality of the magnetic field fingerprint, which is often unstable. A 3D indoor positioning algorithm for UAVs was developed with spread spectrum ultrasound and time-of-flight (ToF) cameras in [8]. However, the interference caused by non-line-of-sight (NLoS) transmissions is noticeable.

The development of micro-electromechanical systems technology makes it possible that small low-cost inertial measurement unit (IMU) can be easily implemented on a UAV [29]. Despite that the IMU synchronous output of acceleration and attitude data can be used to provide precise 3D navigation during a short period, the IMU data may accumulate non-negligible drift errors. To settle this problem, ultra-wideband (UWB)-based scheme is an alternative solution. The bandwidth of UWB enables high-precision ToF measurements in wireless communication. In Ref. [30], UWB and IMU data are fused to improve the positioning quality of UAVs in starting and landing scenarios. However, apart from their expensive hardware cost, UWB-based systems are known to severely interfere with other wireless systems that share the same radio frequencies.

The rapid development of smart equipment has led to the growth of indoor positioning and navigation systems, with unmanned aerial vehicles (UAVs) being a prominent example. While UAVs are typically associated with outdoor applications, they also have the potential for practical indoor use in settings such as hospitals, greenhouses, manufacturing factories, and nuclear power plants. With their mobility and cost-effectiveness, UAVs offer a wide range of applications, including indoor mapping and measurements.

To overcome the challenges of GNSS-denied indoor scenarios, researchers have proposed various indoor positioning schemes. These schemes aim to go beyond traditional outdoor algorithms and address the limitations of vision-based methods and expensive LiDAR technology. For instance, an algorithm based on the difference in horizontal and vertical 2D magnetic field intensity (MFI) measurements has been explored. However, the accuracy of this approach is often dependent on unstable magnetic field fingerprints.

Another approach involves the use of spread spectrum ultrasound and time-of-flight (ToF) cameras for 3D indoor positioning. However, non-line-of-sight (NLoS) transmissions can cause interference in this method. Additionally, the development of micro-electromechanical systems technology has made it possible to implement low-cost inertial measurement units (IMUs) on UAVs. While IMUs can provide precise 3D navigation for short periods, they may accumulate drift errors over time.

To address these challenges, the use of ultra-wideband (UWB) technology has been considered. UWB enables high-precision time-of-flight measurements in wireless communication. By fusing UWB and IMU data, the positioning quality of UAVs can be improved, particularly in starting and landing scenarios. However, UWB-based systems can be expensive and may interfere with other wireless systems operating on the same radio frequencies.

In recent years, VLC-based localization has emerged as an attractive option. This technology utilizes conventional light-emitting diodes (LEDs) and photodiodes (PDs) or optical cameras to achieve high positioning accuracy at a low cost. One approach involves using an optical camera to estimate distances between LEDs and the camera based on the relative positions of received pixels in captured photos. However, this method relies on a complex VLC channel model, requiring accurate prior knowledge of the relationship between irradiance and incidence angles.

To overcome this challenge, a fingerprint-based algorithm using machine learning techniques will be developed. This algorithm eliminates the need for a channel model but does require the construction of a fingerprint database as a tradeoff, which can be labor-intensive for large indoor buildings.

In this section, we will introduce a VLC-based IPIN system that enhances localization by integrating IMU data as shown in **Figure 2**. Utilizing dynamic time warping (DTW) alongside the Kalman filter, this system offers precise indoor navigation by merging the spatial accuracy of VLC with the motion insights from IMU sensors.

VLC technology provides exact positioning through light signals, while the IMU offers continuous motion data. The challenge of IMU drift is addressed by employing DTW for aligning IMU sequences with VLC positions, improving accuracy. The Kalman filter then seamlessly fuses these data streams, optimizing real-time position estimates by reducing noise and uncertainties. This dual-algorithm approach ensures a robust and accurate VLC-based IPIN system, setting a new standard for efficient indoor UAV navigation without GPS.

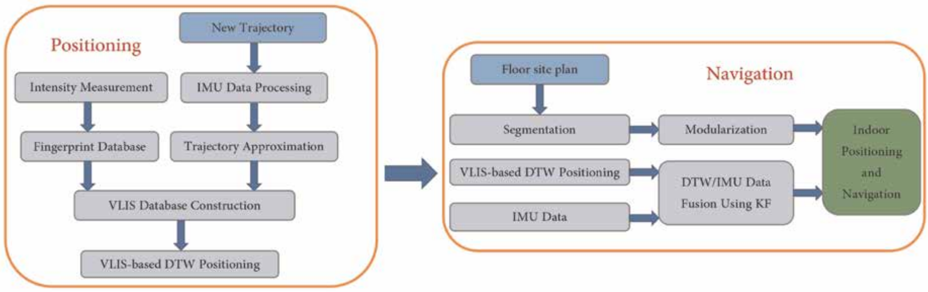

Figure 2.
Proposed VILS/IMU data fusion algorithm [31].

2.1 Positioning by the fusion of VILS and IMU data

This section outlines the development of a robust indoor positioning system through the integration of visible light indoor localization system (VILS) and inertial measurement unit (IMU) data. Given the inherent instability of light intensity fingerprints caused by stochastic drift, the approach combines these two data sources to establish a more stable and reliable positioning method.

2.1.1 Displacement calculation by IMU

To accurately process IMU data, we first establish an appropriate coordinate system. Acceleration data from the IMU is transformed from the body to a global coordinate system using the transformation matrix $\boldsymbol{R}$, defined as:

$$\boldsymbol{R} = \begin{bmatrix} c_\gamma c_\psi + s_\gamma s_\psi s_\theta & -c_\gamma s_\psi + s_\gamma c_\psi s_\theta & -s_\gamma c_\theta \\ s_\psi c_\theta & c_\psi c_\theta & s_\theta \\ s_\gamma c_\psi + c_\gamma s_\psi s_\theta & -s_\gamma s_\psi - c_\gamma c_\psi s_\theta & c_\gamma c_\theta \end{bmatrix}, \tag{1}$$

where $c_\alpha = \cos(\alpha)$, $s_\alpha = \sin(\alpha)$, and γ, θ, and ϕ represent the roll, pitch, and yaw angles, respectively.

The global coordinate acceleration $\boldsymbol{a}_g$ is then given by:

$$\boldsymbol{a}_g = \boldsymbol{R}\boldsymbol{a}_b + \boldsymbol{G}, \tag{2}$$

with $\boldsymbol{a}_b$ as the body-referenced accelerations and $\boldsymbol{G} = [0, 0, -g]^T$ representing gravitational acceleration.

The position at time t is estimated by summing the displacements over time, as shown in:

$$\boldsymbol{x}_t = \boldsymbol{x}_{t-1} + \sum_{k=0}^{K} \left[v_k \Delta T + \frac{1}{2} \boldsymbol{a}_g^{(k)} \Delta T^2 \right], \tag{3}$$

where ΔT is the sampling interval, and v_k is the velocity at the k-th sample.

2.2 2D positioning based on DTW matching

For 2D positioning, we divide the space into squares of size $\lambda \times \lambda$ to create a fingerprint database. Each square's light intensity, as measured by a PD during TDMA transmission, constitutes a unique fingerprint.

2.2.1 Input trajectory

An arbitrary trajectory is divided into N sampling positions, $\boldsymbol{X} = [\boldsymbol{x}_0, \cdots, \boldsymbol{x}_N]$, with $\boldsymbol{x}_0 = [0, 0]^T$ assumed as the starting point for simplicity. This segmentation allows for accurate calculation of relative displacement over short intervals, mitigating IMU error accumulation.

2.2.2 Training dataset

The DTW algorithm necessitates a predefined fingerprint sequence. We can categorize the trajectory space into squares, limiting the range to a manageable width W and length L. The total number of required fingerprints is $N_W \times N_L$, calculated as:

$$N_W = \lceil W/\lambda \rceil, \quad N_L = \lceil L/\lambda \rceil. \tag{4}$$

The fingerprint dataset, $\boldsymbol{I}$, and corresponding position set, $\boldsymbol{P}$, are then utilized to approximate the trajectory as a sequence within the database. By comparing the input VLIS $\boldsymbol{I}^*$ to the training database $\mathcal{T}$ using DTW, one would identify the most similar trajectory, enabling precise positioning.

This methodology leverages the strengths of both VILS for spatial accuracy and IMU data for motion tracking, resulting in a robust system capable of overcoming the challenges posed by stochastic drift in light intensity measurements for indoor positioning.

Then, the fingerprint VLIS set can be represented as.

$$\boldsymbol{I} = \begin{bmatrix} I_{00} & I_{01} & \cdots & I_{0N_L} \\ \vdots & \vdots & \ddots & \vdots \\ I_{N_W 0} & I_{N_W 1} & \cdots & I_{N_W N_L} \end{bmatrix}, \tag{5}$$

with a corresponding position set.

$$\boldsymbol{P} = \begin{bmatrix} \boldsymbol{p}_{00} & \boldsymbol{p}_{01} & \cdots & \boldsymbol{p}_{0N_L} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{p}_{N_W 0} & \boldsymbol{p}_{N_W 1} & \cdots & \boldsymbol{p}_{N_W N_L} \end{bmatrix}. \tag{6}$$

Thus, the trajectory can be approximated as a sequence in the fingerprint database:

$$\boldsymbol{x}_n^* = \operatorname{argmin}_{\substack{i = 0,1,\cdots,N_W, \\ j = 0,1,\cdots,N_L}} \|\boldsymbol{P}_{ij} - \boldsymbol{x}_n\|_2, \quad \text{for} \quad n = 0, 1, \cdots N. \tag{7}$$

As shown in **Figure 3**, the input approximated VLIS $\boldsymbol{I}^*$ is the intensity sequence corresponding to the position sequence $\boldsymbol{X}^* = \left[\boldsymbol{x}_0^*, \boldsymbol{x}_1^*, \cdots, \boldsymbol{x}_N^*\right]$. Subsequently, the

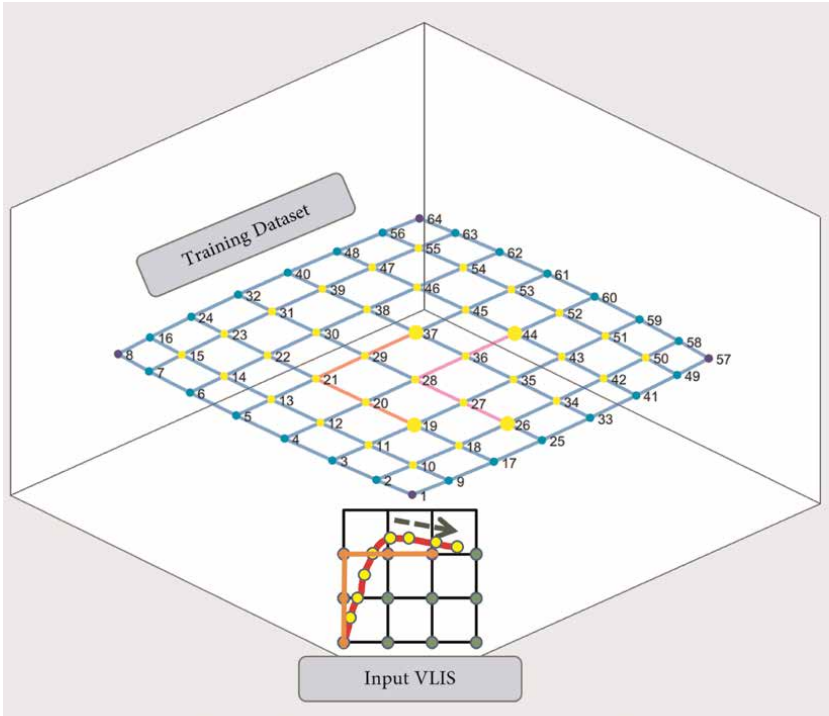

Figure 3.
Trajectory approximation and training data generation [31].

training database $\mathcal{T}$ is constructed based on the structure of $\boldsymbol{X}^*$. For instance, the red and pink trajectory sequences depicted in **Figure 3**, that is, the sequence with index [19–21, 26–29, 32, 33] are the two VLIS sets in $\mathcal{T}$. In this way, a pretrained fingerprint database $\mathcal{T}$ can be constructed directly. By calculating the DTW scores for $\boldsymbol{X}^*$ and $\mathcal{T}$, the similarity score can be derived before the position is determined by the sequence with the smallest score.

2.2.3 Implementation

In fingerprint-based positioning algorithms, a significant challenge lies in the necessity to collect extensive fingerprints across the deployment area. Achieving higher levels of positioning accuracy requires even more exhaustive data collection, a task that often proves impractical due to its substantial workload. Unlike traditional positioning methods that rely on UWB or magnetic fields, VLIS offers a unique advantage for modularization. This is because light intensity is adjustable, and LED placement can be meticulously planned and executed.

Inspired by this advantage, segmenting the floor space into distinct types of modules is recommended. By adopting this strategy, it becomes possible to limit fingerprint measurement to these predefined modules, substantially reducing the overall data collection efforts. This modular approach not only streamlines the setup process but also offers a practical solution to the challenges traditionally associated with fingerprint-based localization, enabling efficient and scalable deployment in diverse environments.

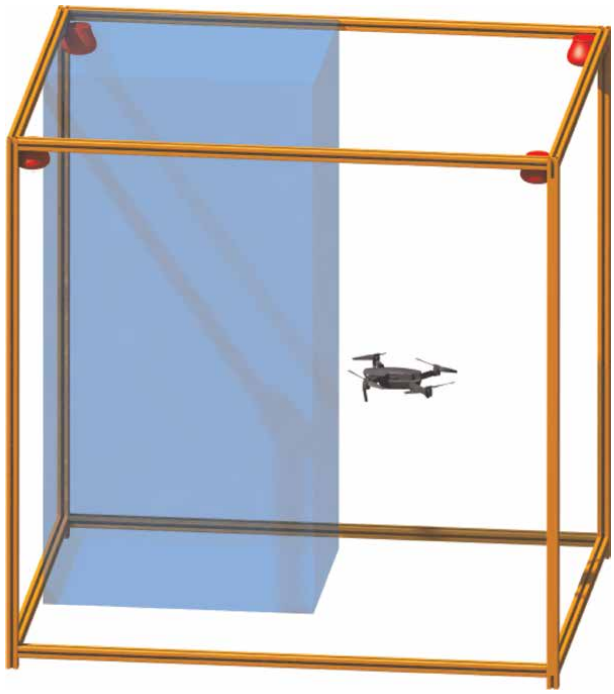

Figure 4.
Fingerprint measurement for a 3D module.

In this study, a standard symmetric module to streamline the process of collecting fingerprint data is introduced, as illustrated in **Figure 4**. This module simplifies the measurement process by utilizing the symmetrical arrangement of four LEDs. By measuring the fingerprint data within the blue quadrant, we can extrapolate the data for the remaining quadrants through data processing, eliminating the need for additional measurements.

Further, simplification is achieved by modularizing the floor layout, as depicted in **Figure 5**. By leveraging the uniformity across the floor plan, we can systematically organize the space into predefined modules. This modular approach allows for precise localization within the floor site by identifying the boundaries of each module.

The implementation of this model significantly enhances the system's efficiency and accuracy. Key navigational nodes are identified at the edges of each module, serving as critical points for navigation. As an object crosses from one module to another, its movement is accurately tracked, facilitating seamless navigation. This methodological innovation not only reduces the complexity of the measurement process but also augments the precision of indoor positioning and navigation.

2.3 Data fusion using discrete kalman filter for UAV indoor localization

In this study, we address the limitations of dynamic time warping (DTW) in terms of its update frequency, which is constrained by the time required for visible light indoor localization system (VLIS) measurements. Although inertial measurement unit (IMU) data can be updated more frequently, it is prone to accumulative errors. To mitigate these issues, we introduce a data fusion algorithm that integrates VLIS and IMU data using a discrete Kalman filter (KF).

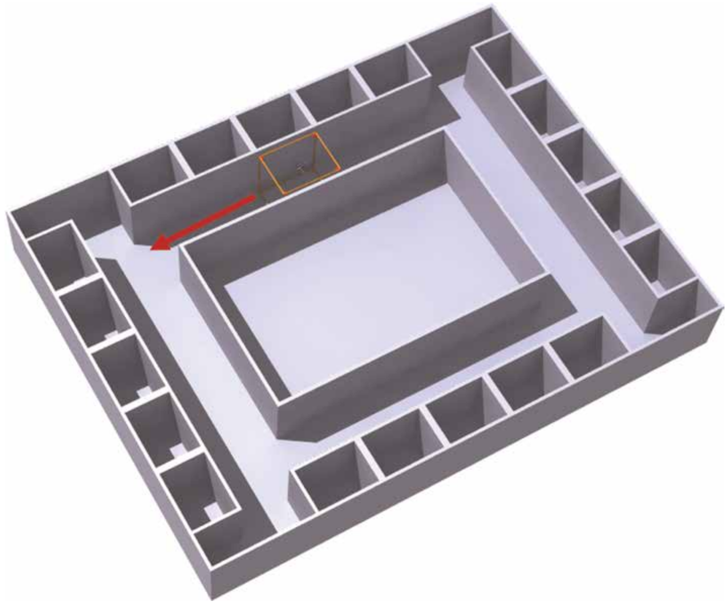

Figure 5.
Navigation scheme in a floor site.

2.3.1 Discrete kalman filter

The KF is proposed for dynamic systems to perform state estimation by exploiting sensor measurements. A typical KF can be described using the following discrete-time state space model:

$$\begin{aligned} \boldsymbol{s}_{t+1} &= \boldsymbol{A}\boldsymbol{s}_t + \boldsymbol{B}\boldsymbol{R}_t\boldsymbol{u}_t + \boldsymbol{\beta}, \\ \boldsymbol{p}_t &= \boldsymbol{C}\boldsymbol{s}_t + \boldsymbol{\omega}, \end{aligned} \tag{8}$$

where $\boldsymbol{s}_t = \left[x_t, y_t, z_t, v_{x,t}, v_{y,t}, v_{z,t}\right]^T$ is the state vector. At time instant t, the input parameter $\boldsymbol{u}_t = \left[a_{x,t}, a_{y,t}, a_{z,t}\right]^T$ is the acceleration at x, y, and z-axis of the global coordinate system, respectively, while the output result $\boldsymbol{p}_t = \left[x_t, y_t, z_t\right]^T$ represents the 3D aerial position coordinates of an object in a global Cartesian coordinate system. The three-dimensional rotation matrix $\boldsymbol{R}_t$ is $\boldsymbol{R}$ represented by Eq. (1) at the t-th time instant to estimate the user's propagated position in the global coordinate. Finally, $\boldsymbol{\beta}$ and $\boldsymbol{\omega}$ are the Gaussian noise with zero mean separately.

The transition matrix $\boldsymbol{A} \in \mathbb{R}^{6\times6}$, control matrix $\boldsymbol{B} \in \mathbb{R}^{6\times3}$, and the output matrix $\boldsymbol{C} \in \mathbb{R}^{3\times6}$ can be represented as.

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{I}_3 & \Delta T\boldsymbol{I}_3 \\ \boldsymbol{0}_3 & \boldsymbol{I}_3 \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} \frac{1}{2}\Delta T^2\boldsymbol{I}_3 \\ \Delta T\boldsymbol{I}_3 \end{bmatrix}, \boldsymbol{C} = \begin{bmatrix} \boldsymbol{I}_3 \\ \boldsymbol{0}_3 \end{bmatrix}^T, \tag{9}$$

where $\boldsymbol{I}_3 \in \mathbb{R}^{3\times3}$ is an identity matrix and $\boldsymbol{0}_3 \in \mathbb{R}^{3\times3}$ is a zero matrix.

2.3.2 VLIS/IMU data fusion using discrete kalman filter

As the VLIS is utilized to infer the position of the UAV, we can get the position estimated by the DTW algorithm once a VLIS is measured at instant t. The trajectory corresponding to the end of the trajectory with matched VLIS is considered as the most reliable position denoted by $\boldsymbol{p}_t$. Since the sampling frequency of IMU is much larger than the fingerprint matching, IMU can be used to estimate the position more frequently. As a result, we can use the KF to realize a better accuracy.

Correspondingly, the state space model of IMU for KF in Eq. (8) can be used to derive the VLIS/IMU fusion algorithm. The detailed formulation of position estimation based on KF is listed as follows:

$$\hat{\boldsymbol{s}}_{t|t-1} = \boldsymbol{A}\hat{\boldsymbol{s}}_{t-1|t-1}, \tag{10}$$

$$\boldsymbol{\Sigma}_{t|t-1} = \boldsymbol{A}\boldsymbol{\Sigma}_{t-1|t-1}\boldsymbol{A}^T + \boldsymbol{Q}, \tag{11}$$

$$\boldsymbol{e}_t = \boldsymbol{p}_t - \boldsymbol{C}\hat{\boldsymbol{s}}_{t|t-1}, \tag{12}$$

$$\boldsymbol{E}_t = \boldsymbol{C}\boldsymbol{\Sigma}_{t|t-1}\boldsymbol{C}^T + \sigma^2\boldsymbol{I}_M, \tag{13}$$

$$\boldsymbol{K}_t = \boldsymbol{\Sigma}_{t|t-1}\boldsymbol{C}^T\boldsymbol{E}_t^{-1}, \tag{14}$$

$$\hat{\boldsymbol{s}}_{t|t} = \hat{\boldsymbol{s}}_{t|t-1} + \boldsymbol{K}_t\boldsymbol{e}_t, \tag{15}$$

$$\boldsymbol{\Sigma}_{t|t} = \boldsymbol{\Sigma}_{t|t-1} - \boldsymbol{K}_t\boldsymbol{C}\boldsymbol{\Sigma}_{t|t-1}, \tag{16}$$

$$\hat{\boldsymbol{p}}_{t|t} = \boldsymbol{C}\hat{\boldsymbol{s}}_{t|t}, \tag{17}$$

$$\boldsymbol{\Sigma}^p_{t|t} = \boldsymbol{C}\boldsymbol{\Sigma}_{t|t}\boldsymbol{C}^T, \tag{18}$$

where $\boldsymbol{Q} = \mathbb{E}\left[\boldsymbol{\omega}\boldsymbol{\omega}^T\right]$ and σ^2 is the variance of Gaussian noise $\boldsymbol{\beta}$. $\hat{\boldsymbol{s}}_{t|t-1}$ is the prior estimate of the state vector with corresponding covariance matrix $\boldsymbol{\Sigma}_{t|t-1}$. The measurement residual is denoted by $\boldsymbol{e}_t$ with covariance matrix $\boldsymbol{E}_t$. $\boldsymbol{K}_t$ is the Kalman gain and $\hat{\boldsymbol{p}}_{t|t}$ is the posterior estimation of output with covariance $\boldsymbol{\Sigma}^p_{t|t}$. We assume the initial position and speed of a UAV is given as $\boldsymbol{p}_0 = \left[x_0, y_0, z_0\right]^T$ and $\boldsymbol{v}_0 = \left[v_{x,0}, v_{y,0}, v_{z,0}\right]^T$. Therefore, the initial state vector is $\boldsymbol{s}_0 = \left[\boldsymbol{p}_0^T, \boldsymbol{v}_0^T\right]^T$ with covariance $\boldsymbol{\Sigma}_0$.

The above KF procedure works iteratively and combines the data from the two sensors. At each iteration, it first uses the data from IMU to predict the position and the velocity of the object before VLIS is obtained. Once the position is calculated by the DTW algorithm, it will update the position using Kalman gain as a weighted average. Thereby, the updated position will be closer to the estimated position with higher certainty. Since the sampling frequency of IMU is much larger than DTW, the trajectory can be corrected by KF during the period lacking VLIS.

2.3.3 Real-world experiments

To rigorously assess the efficacy of our proposed IPIN system, we have undertaken a proof-of-concept experiment. This experiment involves a UAV outfitted with a photodiode (PD), IMU, and an Arduino microcontroller. The setup is illustrated in **Figure 6**, highlighting the integration of these components.

For the experiment, we selected the wireless-capable Arduino D1 for its ability to persistently receive signals. This microcontroller is paired with an OSD15-E PD,

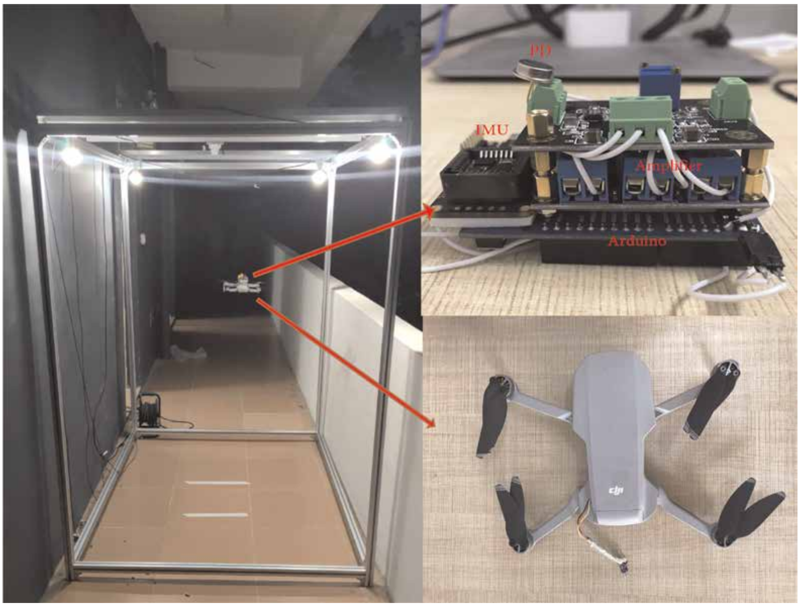

Figure 6.
UAV used in this experiment.

chosen for its sensitivity and reliability in capturing light intensity variations, crucial for the VLC component of our system. The IMU provides real-time acceleration and orientation data, essential for the dynamic positioning aspects of the UAV. The core components in the experimental setup are detailed in **Table 1**.

The Arduino D1 serves as the central processing unit, receiving and analyzing data from the PD and IMU to execute the fusion algorithm detailed earlier. The PD, specifically the OSD15-E model, is tasked with detecting the modulated light signals emitted by the VLC system, which are then converted into electrical signals indicative of the UAV's relative position. The IMU supplements this positioning data by providing continuous movement information, allowing for the correction of any drifts or inaccuracies between VLC measurements. This integrated approach combines the strengths of VLC for precise localization and IMU for movement tracking, offering a comprehensive solution for indoor navigation challenges. The experiment aims to validate the design principles of the proposed system, demonstrate its practical applicability, and identify areas for further refinement.

Components	Type	Function
Photodiode(PD)	OSD15-E	Measure the light intensity
Amplifier	IV Amplifier	Amplify the current of PD
Arduino	WeMos D1 R1	Wireless control
IMU	MPU 9250	Calculate the relative displacement of distance and direction
UAV	DJI Mavic Air	Realize 3D movement
LED	Panasonic 25 W	Transmit light

Table 1.
Component description.

The experiment is to investigate the system's performance under real-world conditions, informing future enhancements and paving the way for broader application scenarios. Through careful analysis of the experiment's results, we aim to underscore the IPIN system's potential for reliable and accurate indoor positioning, toward UAV navigation in practice.

3. Prototype 2: vision-based localization for UAVs

Vision-based localization is a powerful technique that utilizes cameras mounted on UAVs to determine their position in the environment. By analyzing visual cues and features captured by the cameras, UAVs can accurately estimate their location and navigate with precision.

In the last decade, UAVs have garnered significant interest from researchers, industry professionals, and enterprises, largely due to their advantages such as versatile 3D mobility, affordability, and portability [34]. Despite these benefits, several challenges remain to be addressed to fully leverage UAV potential. One notable issue is the limited flight duration of UAVs, which restricts their capability for prolonged tasks such as extensive routine inspections. To mitigate the constraints related to flight time, recent years have seen innovative research focused on automatic battery replacement mechanisms. Erdelj et al. [35] developed a strategy enabling an unmanned aerial system (UAS) to conduct continuous, uninterrupted structural inspections with the use of multiple diverse UAVs. Alternatively, a hardware platform was proposed in [36], where an unmanned ground vehicle (UGV) holds a buffer of eight batteries to enable the battery swapping. Similarly, a prototype of the UAV power-relay platform was designed to realize automatic battery replacement in [37]. Unfortunately, apart from the high expense and complicated structure, the aforementioned proposals require the precise autonomous landing, which is under-investigated in the literature.

The use of vision-based localization offers several advantages for UAVs. First and foremost, it provides high accuracy in determining the UAV's position. By leveraging computer vision algorithms, UAVs can extract features from the captured images and match them with preexisting maps or reference images. This allows for precise localization, even in complex and dynamic environments. Furthermore, vision-based localization can operate in both indoor and outdoor settings. Whether it is navigating through a cluttered indoor space or flying over vast outdoor areas, UAVs equipped with vision-based localization can effectively determine their position and adapt to different environments.

Another advantage of vision-based localization is its versatility. With cameras providing a continuous stream of visual data, UAVs can not only estimate their position but also perceive and understand their surroundings. This enables them to make intelligent decisions and autonomously navigate through complex scenarios. However, vision-based localization also poses certain challenges. The accuracy of the localization heavily relies on the quality of the captured images and the robustness of the computer vision algorithms. Factors, such as lighting conditions, occlusions, and the presence of similar visual features, can affect the performance of vision-based localization systems.

To overcome these challenges, ongoing research and development efforts focus on improving the reliability and accuracy of vision-based localization for UAVs. Advanced computer vision techniques, such as feature detection, tracking, and 3D reconstruction, are being explored to enhance the extraction and matching of visual features. Additionally, machine learning algorithms are being employed to improve the robustness and adaptability of vision-based localization systems.

In summary, vision-based localization stands as a crucial innovation for UAVs, providing them the ability to ascertain their locations with high accuracy through the integration of cameras and advanced computer vision algorithms. The field has seen significant progress with advancements in computer vision and sensor fusion techniques enhancing both the precision and reliability of these systems. This evolution broadens the scope of UAV applications across numerous sectors, including but not limited to surveillance, inspection, delivery, and transportation services. As the development and exploration of vision-based localization technologies advance, UAVs are expected to exhibit even greater proficiency in maneuvering through intricate settings, demonstrating enhanced precision and operational efficiency.

3.1 Estimating altitude and distance using multi-scale QR codes

The pinhole imaging model for vision-based distance estimation, as discussed in [32], exhibits limitations in accuracy when applied in real-world settings. To address this shortfall, our approach involves the development of an empirical formulation centered around the use of multi-scale QR codes, as depicted in **Figure 7**. Our methodology entailed conducting a series of experiments to ascertain the pixel dimensions of these QR codes at varying altitudes, with the comprehensive experimental outcomes documented in the study on QR-code recognition [33]. By utilizing these experimental results, we can formulate a fitting function to describe the relationship between the pixel p and the height h as follows:

$$h(p) = \frac{ap^2 + bp + c}{p + d}, \tag{19}$$

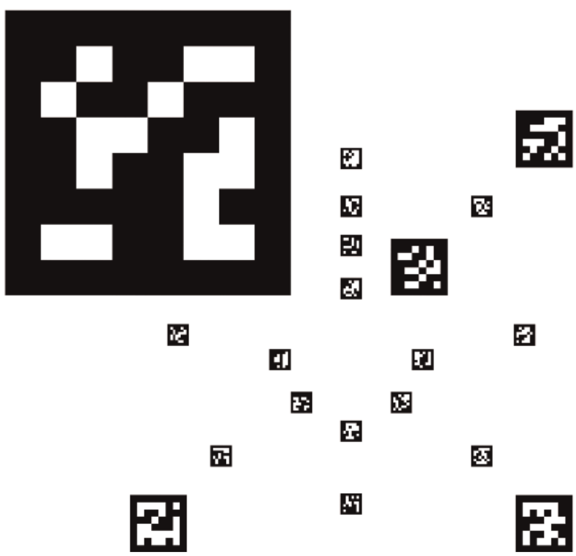

Figure 7.
Multi-scale QR codes utilized in this study.

where a, b, c, and d are constant parameters that are associated with the size of the QR codes. The empirical function was derived using the curve fitting toolbox in MATLAB, and we selected this particular function due to its high R-squared value, which is very close to one. It should be noted that the QR-code structure is not symmetric as space saving was taken into consideration during the platform design.

In this study, there are QR codes in three sizes: 0.042, 0.113, and 0.362 m, which represent the diagonal lengths of the multi-scale QR codes. The empirical minimum number of pixels required for recognition is 20. The values of the parameters, as well as the R-squared test for Eq. (19), are listed in **Table 2**. Therefore, the theoretical maximum heights for each size are 2.2529, 5.4677, and 16.6516 m, respectively. From our experiments, we observed successful detection at heights of 2.8, 5.3, and 17.2 m, as shown in **Figure 8**.

Size(m)	a	b	C	D	R-squared
0.042(Small)	0.00690	−0.9531	87.92	11.79	0.9914
0.113(Middle)	−0.0429	3.8030	15.32	−6.428	0.9863
0.362(Large)	0.0373	−4.771	578.3	9.896	0.9971

Table 2.
*Parameters for Equation (19) in **Figure 8**.*

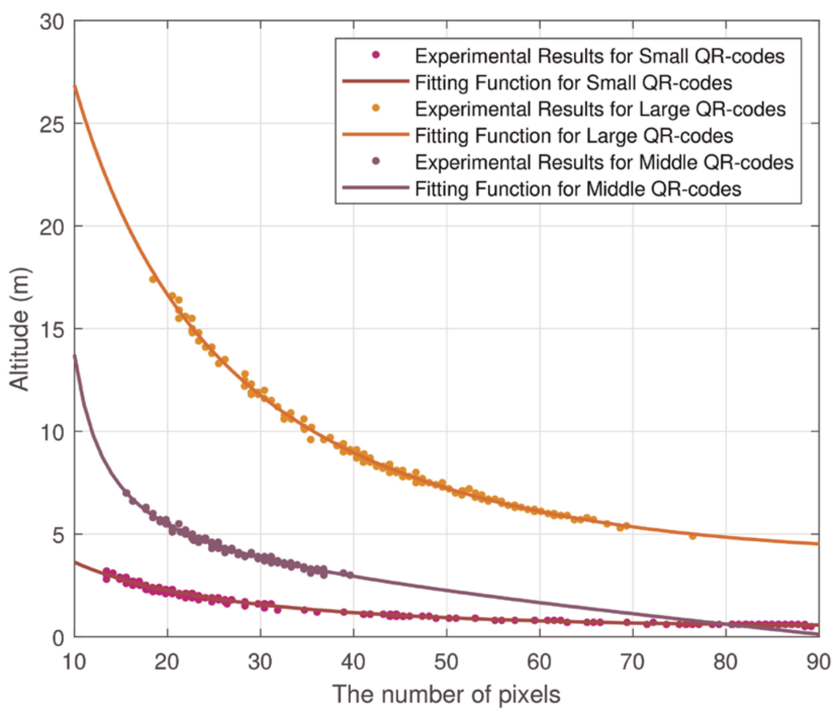

Figure 8.
Data fitting for the number of pixels as a function of height.

By leveraging the offset of the detected QR codes from the center of the image captured by the UAV, we can calculate the horizontal distance between the UAV and UGV using the following equation:

$$D = \frac{p_i^r R_i^{os}}{p_i}, \tag{20}$$

Here, p_i^r and R_i^{os} represent the real size and offset of the first QR-code, respectively.

It is important to note that visibility limitations can affect the recognition ability of the QR codes. In addition to dark environments, strong light can result in severe reflection, making the QR codes difficult to recognize. We have identified that the recognition capability of the vision-based system is limited during the time period of 12:00–14:00 in Shenzhen, China, due to the presence of strong sunlight. Furthermore, the maximum altitude for QR-code recognition is approximately 20 m, depending on the lighting conditions.

If the UAV's altitude is significantly lower than the theoretically recognizable height and no QR codes are detected, the UAV will resume communication with the UGV while checking the GPS or VIO data to adjust its position. Based on the multi-scale QR codes, we will introduce the vision-based autonomous landing in the following section.

3.2 Implementation

After the autonomous landing, the accuracy of the UAV positioning must be improved before battery replacement. Inspired by the mechanism in [38], the platform

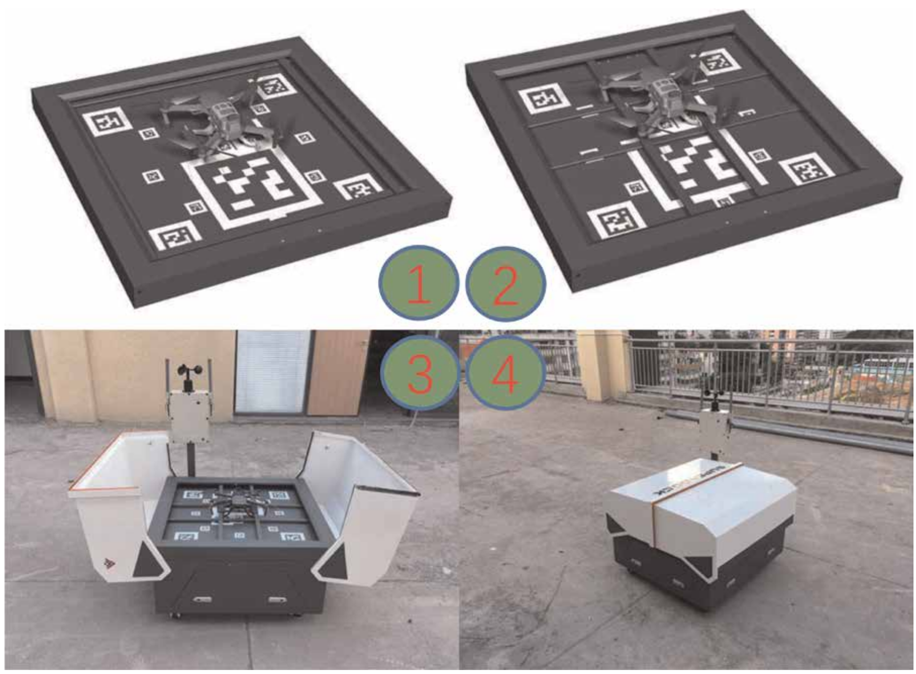

Figure 9.
The procedure for automated landing battery replacement: The UAV lands on the station. ① The UAV's position is adjusted by the servomotor arms. The equipment is designed for practical experiments. ② The platform is closed to protect the UAV from severe weather conditions [39].

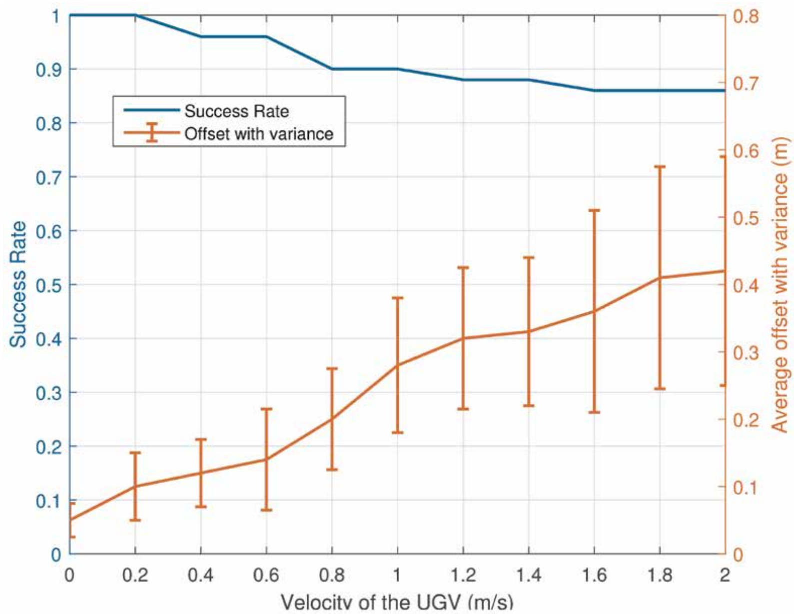

Figure 10.
Success rate and landing error [39].

is equipped with servomotor arms to adjust the UAV's position for battery replacement or charging as shown in **Figure 9**. The maximum tolerated error depends on the size of the platform. Although a platform of a larger size is able to tolerate more stochastic errors, the cost and mobility must be fully considered as an engineering problem.

The landing error in terms of velocity of the UGV is investigated in **Figure 10** by conducting 50 experiments for each case. The success rate slowly decreases as the velocity increment. Nevertheless, the success rate is higher than 85% with velocity lower than 2 m/s. In the meanwhile, the landing offset from the center of the platform increases due to the wind air resistance and error on velocity estimation.

4. Conclusion

This chapter has comprehensively explored advanced UAV localization techniques, including indoor and outdoor environments using GPS, VLC, IMU, and vision-based methods. The role of sensor fusion and artificial intelligence in refining the precision and efficiency of UAV navigation has been emphasized, marking a significant advancement in the indoor localization. Through proof-of-concept experiments and the introduction of two prototypes, including VLC system modularization and vision-based distance estimation with multi-scale QR codes, the practical applicability and effectiveness of these methodologies have been demonstrated. The integration of various sensors and the use of artificial intelligence have been shown to significantly enhance localization precision and efficiency. The investigations reveal the potential of these technologies to improve the UAV applications across diverse sectors, highlighting the progress made and pointing toward future advancements in indoor and outdoor UAV localization.

Conflict of interest

The authors declare no conflict of interest.

Abbreviations

UAV	unmanned aerial vehicle
UGV	unmanned ground vehicle
IPIN	indoor positioning and navigation
GPS	global positioning system
VLC	visible light communication
QR Code	quick-response code
IMU	inertial measurement unit
AI	artificial intelligence
GNSS	global navigation satellite system
DEM	digital elevation model
SLAM	simultaneous localization and mapping
ToF	time-of-flight
NLoS	non-line-of-sight
UWB	ultra-wideband
DTW	dynamic time warping
VILS	visible light indoor localization system

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Section 3

Technologies and Challenges in Indoor Positioning Systems

Chapter 4

Modern Challenges in Indoor Positioning Systems: AI to the Rescue

Saša Pešić

Abstract

In the realm of Indoor Positioning Systems (IPS), navigating the intricate challenges posed by dynamic interior environments demands a pivot towards more sophisticated solutions. This chapter underscores the crucial role of Artificial Intelligence (AI) in transcending the conventional limitations of IPS, thereby facilitating a paradigm shift towards self-calibrating, adaptive, high precision navigation systems within complex indoor spaces. Through an expansive discussion encompassing use cases across varied sectors such as retail, healthcare, and smart building management, this chapter delves into the technological underpinnings of IPS and their evolution aided by AI technologies. It highlights key challenges, including accuracy, adaptability, and predictive modelling, and presents AI-driven solutions and case studies that illustrate the transformative impact of AI on enhancing system capabilities. This narrative serves as a testament to the potential of AI in revolutionizing IPS by enabling systems to understand and predict human movement patterns, adapt to changes in real-time, and offer personalized user experiences. The discourse laid out in this chapter not only contributes to the scholarly understanding of IPS challenges and AI's role in addressing them but also charts a course for future innovations in the domain of intelligent indoor navigation and positioning solutions.

Keywords: autonomous indoor space modeling, indoor paths modeling, floor plan layout detection, obstacles detection, self-calibration, machine learning, occupancy patterns, occupancy prediction

1. Introduction

Indoor positioning (IP) is increasingly recognized as a cornerstone for advanced location-based services (LBS), pivotal in transforming the landscape of navigation and interaction within enclosed spaces. Unlike outdoor environments, where GPS has established dominance, indoor spaces present unique challenges that preclude the direct application of satellite-based solutions. The quest for precise, adaptable indoor positioning systems (IPS) is not merely an academic endeavor but a practical necessity across various sectors including retail, healthcare, and logistics. The significance of IPS is further highlighted by other researchers for its potential to enhance operational efficiencies, improve user experiences, and even save lives in emergency situations [1, 2].

Recent advances have underscored the limitations of traditional methodologies in addressing the complex dynamics of indoor environments. Kunhoth et al. [2] emphasize the role of IPS in facilitating seamless navigation and wayfinding, underscoring the technology's growing importance [2]. Similarly, the work of Brena et al. [3] chronicles the evolution of IPS, highlighting the shift toward AI-enhanced systems as a response to the need for greater accuracy and flexibility [3]. These explorations into the IPS domain underscore the critical role of innovation in overcoming inherent challenges such as signal interference, architectural complexities, and the dynamic nature of indoor spaces.

The integration of AI and machine learning (ML) technologies into IPS emerges as a promising solution to these challenges, offering the potential for systems that can learn from and adapt to their environment in real time. Nessa et al. [4] provide a comprehensive survey on the application of machine learning for indoor positioning, illustrating the wide-ranging implications of AI technologies in enhancing system performance and user experience [4]. This paradigm shift toward AI-driven solutions is not merely technological but conceptual, marking a departure from static, hardware-intensive models toward more agile, software-driven frameworks.

The introduction of AI into IPS also opens new avenues for research and development, as evidenced by the works of Pascacio et al. [5], who review collaborative indoor positioning systems, shedding light on the potential for AI to foster collaborative, cross-system enhancements [5]. These advancements signal a move toward more integrated, intelligent IPS capable of providing not just navigation assistance but comprehensive situational awareness and predictive analytics.

This chapter aims to distill these advancements and challenges into a coherent narrative, exploring the technological foundations, key challenges, and transformative potential of AI-enhanced IPS. By examining real-world applications and case studies, it seeks to illuminate the path forward for researchers, practitioners, and policymakers alike, highlighting the pivotal role of AI in ushering in the next generation of indoor positioning solutions. In doing so, it contributes to a deeper understanding of the current state of IPS technology and its future trajectory, underscoring the indelible impact of AI on the field. The chapter examines the role of AI in IPS by explaining various data science and AI principles and methodologies that can help with the following tasks:

- Automated adjustment of IPS to changing circumstances, such as variations in the movement of people and disruptions in signals.

- Involvement of AI in detecting the presence and creating predictive models for intelligent spaces, thus facilitating smarter and more responsive environments.

- Utilization of AI in the process of mapping movement trajectories and identifying patterns within these areas highlights its capacity to generate systems that are more streamlined and focused on user needs.

The rest of the chapter is structured as follows. Section 2 will shed light on the most common use cases for location-based services in indoor positioning systems, including asset tracking, inventory management, geofencing, and smart building management systems. Section 3 explains the technological foundations of indoor positioning systems, discussing deployment strategies (their advantages and disadvantages), scanning technologies, operational methodologies, and AI-assisted IPS. Next, Section 4 explains the core challenges of modern IPS, from civil engineering, that is, structural and architectural issues, to those presented by the choice of technology, deployment option or else. Finally, Section 5 discusses the importance of autonomous, context-aware IPS as a critical requirement for precise indoor positioning through various case studies highlighting data science principles that can aid them.

2. Location-based services: use cases

This section explores the transformative impact of location-based services (LBS) across industries, highlighting their use in retail, healthcare, and building management. LBS leverages real-time geospatial data to enhance customer experiences and operational processes. The widespread adoption of smartphones and Internet of Things (IoT) devices has driven the proliferation of LBS, with specific use cases in retail, healthcare, and urban planning [6]. The section provides readers with a comprehensive understanding of LBS's practical applications and impact on daily life in three use cases: asset tracking and inventory management, smart building management systems, and geofencing.

2.1 Asset tracking and inventory management

Asset tracking and management in hospitals have significantly evolved with advancements in technology, particularly through the integration of AI and real-time location systems (RTLS). Traditional RTLS solutions, such as Wi-Fi-based systems, have limitations in accuracy, especially in complex hospital settings [7]. AI-powered RTLS using Bluetooth technology has emerged as a game-changer, leveraging AI algorithms to enhance the accuracy and reliability of asset tracking. These systems utilize Bluetooth Low Energy (BLE) beacons for real-time accuracy and employ machine learning algorithms to interpret signal strength and asset movement, enabling precise location determination [8]. This reduces the time medical personnel spend searching for assets, leading to enhanced operational efficiency and staff productivity. Moreover, it aids in optimizing asset utilization and reducing capital expenses by providing insights into asset usage patterns [9].

In smart hospitals, RTLS technology extends beyond asset tracking to enhance patient experiences. It can be integrated into a patient-facing app, enabling smooth navigation of complex hospital facilities and providing real-time updates on treatment and wait times. This system not only improves patient flow and reduces waiting times but also optimizes space and processes based on trend data [10]. The integration of RTLS into an overarching IoT strategy is crucial for maximizing its benefits, including energy saving, better space utilization, and controlled inventory [11].

2.2 Geofencing

A geofence is a digital boundary that encompasses a specific designated area. Coordinates of either a user or an object are utilized to determine if they fall within or outside the designated target area, as well as whether they traverse into or out of the target area. The configuration of geofencing can result in various actions, such as initiating mobile push notifications, activating text messages or alerts, delivering targeted social media advertisements, enabling vehicle fleet tracking, or providing location-based marketing data. One strategy that a retailer can employ is to establish a virtual geofence around its stores. This geofence will trigger smartphone notifications for customers who have installed the retailer's smartphone app [12]. Geofencing is a technique that enables the management and monitoring of vehicles in the shipping industry [13] or livestock in the agriculture sector [14]. There are also numerous applications in the field of e-health [15]. Geofencing plays a crucial role in ensuring the safety and security of personnel in various industries [16].

2.3 Smart building management systems

Location data plays a crucial role in the development of smart buildings, enabling the use of location-based services (LBS) to improve efficiency, safety, and user experience. LBS can optimize energy consumption and environmental conditions, such as lighting, heating, and air conditioning, based on occupancy [17]. This not only enhances energy efficiency but also provides a comfortable environment tailored to occupants' needs. Inferring spatial and temporal occupation in all its forms (binary, numerical, or continuous) is one of the key contextual inputs required for smart building management systems (SBMS). Furthermore, data analysis, tenant pattern searching pipelines, and machine learning models trained to predict occupancy patterns in different areas of a smart building further enhance the efficacy and cost savings of SBMS [8].

LBS can also assist in asset tracking and management, ensuring the availability of critical equipment in large buildings like hospitals or corporate offices. This reduces the time spent searching for equipment and improves asset utilization. Furthermore, LBS can enhance security and safety measures, providing real-time data on occupants' whereabouts in emergencies and aiding in evacuation and rescue operations. LBS can also be used for access control, allowing entry to restricted areas based on an individual's location and authorization level [18].

From a business perspective, mobility patterns and occupancy data can be utilized to inform strategic decisions such as determining the optimal location for a vending machine. This can be achieved by identifying areas with the highest average occupancy or by identifying recurring points (in 2D or 3D) that are consistently observed in various device mobility patterns [19].

Overall, location-based services in smart buildings lead to more intelligent, efficient, and safe environments, enhancing both operational aspects and the overall experience of occupants.

3. Technological foundations

This section discusses key deployment strategies, including proximity-based services using technologies like Bluetooth beacons and asset-tracking systems. It also highlights the use of LiDAR for high-precision mapping, Wi-Fi for urban and indoor positioning, and energy-efficient Bluetooth, particularly BLE beacons. The section introduces AI-driven solutions, such as data analysis, pattern recognition, and predictive analytics, which enhance accuracy and enable adaptive responses to dynamic environments, showcasing the potential of AI in revolutionizing Location-Based Services.

3.1 Technologies

Indoor positioning technologies can be classified into distinct categories according to their technology and methodology (see **Figure 1**). These systems encompass radio frequency (RF)-based systems, which utilize the signal strength emitted by Wi-Fi access points to ascertain position. Proximity detection and location can be achieved through the use of Bluetooth and Bluetooth low energy (BLE) systems. For high accuracy, ultra-wideband (UWB) systems are utilized. Movement and orientation tracking can be accomplished using Inertial Measurement Units (IMUs) that incorporate accelerometers, gyroscopes, and magnetometers. Acoustic systems, which utilize sound waves for position determination, optical systems encompass advanced technologies such as LiDAR, visual simultaneous localization and mapping (SLAM), and computer vision. Magnetic positioning exploits anomalies in the earth's magnetic field within buildings. Hybrid systems integrate multiple technologies to enhance accuracy and dependability. The selection of technology is contingent upon the precise demands of the application, encompassing factors such as precision, scalability, infrastructure, and cost considerations [20].

Each category possesses distinct advantages and limitations, and the selection of technology typically hinges on the specific requirements of the application, such as the necessity for precision, scalability, infrastructure, and cost considerations.

3.2 Types

Indoor positioning systems (IPS) are divided into several types based on their operational methodologies and technologies (see **Figure 2**). The primary types include proximity-based systems, which determine location based on proximity to a fixed point, trilateration systems, which use known distance from at least three fixed points, triangulation systems, which use the angle of arrival (AoA) or time difference of arrival (TDoA) of a signal from at least three different points, dead reckoning systems, which calculate current position using a previously determined position and estimated speeds over time, and fingerprinting systems, which map signal characteristics at various points in an area and match the user's current signal characteristics to determine their location [21].

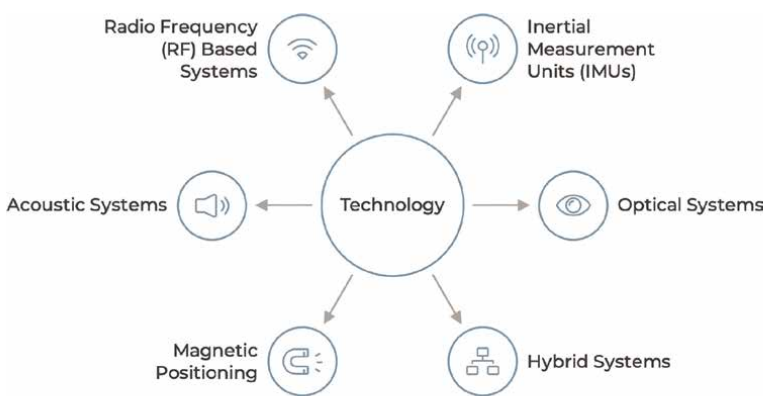


Figure 1.
Indoor positioning technologies categorization.

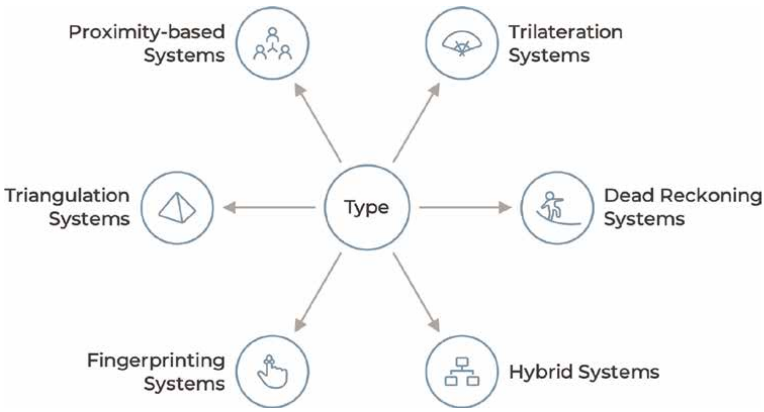


Figure 2.
Indoor positioning type categorization.

Detecting user/object proximity is dependent on either direct contact or proximity between a receiver and a computer. There are a range of possible solutions: QR codes, near field communication (NFC) or radio-frequency identification (RFID) tags, Bluetooth low energy (BLE) beacons, visible light communication (VLC), Wi-Fi access points (WAPs), and ultrasound devices. Trilateration (or multilateration) positioning uses signal strengths computed as distances between several emitters and a receiver to calculate the position of the receiver. Distances are typically computed on the client-side (e.g., smartphone) using relative signal strength indicator (RSSI) or time of flight (ToF) values. Ultra-wide band is another new technology that gives very precise positioning information, thanks to the use of ToF to measure distances between receiver and emitter. However, there are many disadvantages to this technology, such as lack of standardization, smartphones not equipped with UWB, and high costs.

Fingerprinting techniques can be used alone or combined with other positioning technologies to increase accuracy. BLE and Wi-Fi fingerprinting are most commonly used in industrial location tracking systems, requiring spectral image scanning of the indoor space and a database for their storage. Magnetic positioning-based fingerprinting relies on each building or structure having a specific magnetic fingerprint based on how building materials influence and distort the Earth's otherwise permanent magnetic field. Photo fingerprinting requires image processing of the interior of the building, working well when there are significant distinctions between floors and furnishings. Motion positioning inside closed spaces operates on the same concepts but with different technologies. Since conventional inertial measurement units (IMUs) cannot be used, smartphone sensors are used for the identification and quantification of movements. Algorithms such as Kalman filters process data that is used to measure relative movement from those sensors. However, these techniques have low accuracy due to the small size of sensors and accumulated errors.

Hybrid systems combine these methods to enhance accuracy and reliability, adapting to the strengths and weaknesses of each technology. Each type of IPS has its unique strengths and is suited for different scenarios. Proximity-based systems are simpler but less precise, trilateration and triangulation offer more accuracy but require a more complex setup, dead reckoning is useful for continuous tracking, and fingerprinting adapts well to indoor environments with signal variations.

3.3 Deployment options

Traditionally, the deployment of radio-based indoor positioning systems (IPSs) requires the installation of several stationary devices that emit signals, such as Bluetooth beacons. Beacons are physically spread out within the enclosed area being observed, and the device being monitored (such as a smartphone) serves as the central point of the system (scanner). This device is responsible for scanning for beacons, performing calculations, and ultimately determining its own position on the map of the area [22–26]. This is a common application for large shopping malls, stadiums, and similar venues. Deploying beacons on a large scale is cost-effective, and it is now reliable to assume that every user device, including smartphones and smartwatches, is capable of performing location determination calculations. Nevertheless, this approach encounters multiple drawbacks:

- Typically, it involves a prolonged process of collecting fingerprints to generate a comprehensive spectral map of the entire area. Managing large spaces requires a significant amount of manual labor.
- RF-based devices, such as beacons, that are installed in indoor spaces are stationary and not easily adjustable.
- System recalibration is a time-consuming process that necessitates a significant amount of downtime. This involves adjusting the advertising interval of each beacon and generating a new fingerprint map, among other tasks.
- The system lacks the ability to adjust to variations in the surrounding environment, such as changes in the patterns of people's movement over different time periods (e.g., day, week, and year) and the introduction of new physical obstacles.

In smart spaces, IoT devices are plentiful and can function as radio signal scanners while simultaneously performing other IoT tasks within their respective systems, such as single-board computers like Raspberry Pi. If the purpose is to scan for signals, then the emitter can be any device with the capability to transmit radio signals, such as Wi-Fi, Bluetooth, ZigBee, or any other similar technology. Edge devices, like the Raspberry Pi, possess sufficient resources to execute sophisticated filtering, computations, and even limited-scale (centralized or distributed) machine learning operations. Moreover, they possess the capability to be easily reconfigured and interconnected in a mesh-like structure to efficiently manage a substantial volume of requests and safeguard data while enhancing data confidentiality at the edge level. An IoT IPS could utilize edge devices as radio signal scanners, offering significant benefits compared to the previously mentioned deployment topology:

- Positioning calculations are performed on the scanner devices themselves rather than on user devices or other tracked objects, thereby relieving those devices from any computational burden. The calculations occur within a regulated and optimized environment, enhancing the capacity for data processing and privacy, as well as system responsiveness.
- Scanners have multiple applications beyond performing calculations related to IPS. They can also be utilized in other Internet of Things (IoT) functions such as

collecting and processing data, as well as functioning as actuators. They have the ability to effortlessly exchange information with other systems and hardware, such as sensors and actuators.

- Manual fingerprinting can be circumvented by detecting the proximity of assets to the scanners. By determining if an asset is in close proximity to a scanner, we can ascertain its precise location in the space without the need for further calculations. Furthermore, machine learning models can be trained to rapidly compare fingerprints of a specific asset at a specific time with a specific scanner. The process of fingerprinting, which involves calculating the signal spectral map of the indoor space between the scanners at regular intervals, enables the ability to make reactive updates to the context of the space. In addition, positioning techniques can be employed as a secondary measure to enhance the precision of the system. However, our primary reliance is on fingerprinting-based proximity detection.

- Each scanner has the ability to independently manage all aspects of the system at any given moment. This includes adjusting its scanning parameters and implementing system-wide updates to any parameter that is crucial for enhancing position calculations.

- The system undergoes recalibration as a seamless background process without any interruption. This entails conducting a new scan of the indoor area to identify any additional scanners and acquiring their unique fingerprints for the purpose of proximity detection based on fingerprinting. The system is capable of operating using pre-established parameters and can update itself once the recalibration process is completed.

3.4 AI-powered solutions

AI-driven solutions for indoor positioning systems (IPS) can be categorized based on their application and the type of AI technology used (see **Figure 3**). These include data analysis and signal processing, pattern recognition and environmental mapping,

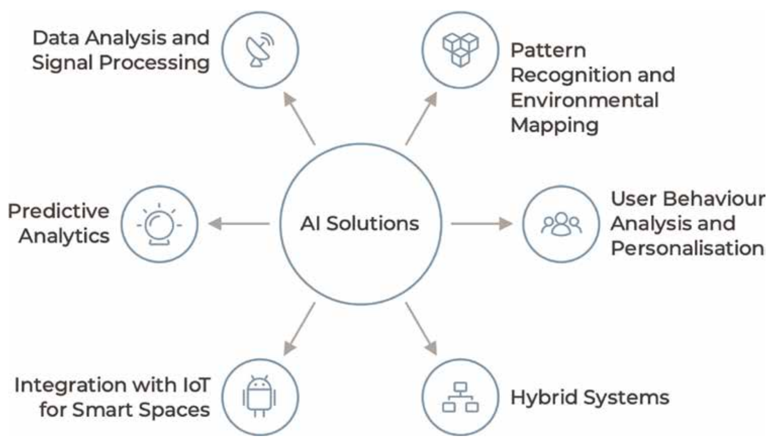


Figure 3.
AI-powered indoor positioning systems categorization.

predictive analytics, user behavior analysis and personalization, and integration with IoT for smart spaces.

AI algorithms analyze complex data patterns from sensors and signals, filtering noise and enhancing system accuracy. They create detailed environmental maps and understand user movement patterns, leading to more accurate and efficient positioning. AI also predicts future positioning needs, enabling resource allocation and management in various settings. AI algorithms can learn and adapt to individual user behaviors, offering personalized navigation assistance or recommendations in spaces like malls, museums, or airports. AI integration with IoT in smart buildings ensures more intelligent and responsive indoor environments [27, 28].

4. Key challenges in indoor positioning

Achieving high accuracy in the labyrinthine and dynamic landscapes of indoor environments remains a daunting challenge for IPS. From the architectural complexities of multi-storied buildings to the ever-changing nature of indoor spaces, this section delves into the core challenges faced by IPS. These challenges are broadly classified into issues concerning accuracy, adaptability, and predictive modeling.

Firstly, achieving high accuracy in varied and complex indoor environments is a significant challenge. This difficulty primarily arises due to signal propagation and perturbation issues, where radio signals, such as Wi-Fi or Bluetooth, reflect off surfaces, causing distortion. Moreover, the diverse architectural designs of buildings further complicate this issue. Different materials, like metal or concrete, can obstruct signals, and intricate layouts can create zones with weak or non-existent signal strength. Another factor impacting accuracy is the limitations and integration of various sensors. Ensuring precise calibration and effectively combining data from multiple sensors, a process known as sensor fusion, requires sophisticated algorithms and poses its own set of challenges.

The second major challenge is the adaptability of IPS to dynamic indoor spaces. Indoor environments are not static; they are characterized by moving people, shifting furniture and other obstacles, and changing room configurations. An efficient IPS must rapidly adapt to these changes to maintain its accuracy. Additionally, the strength and reliability of radio signals can fluctuate due to environmental factors or interference from other electronic devices. This requires real-time data processing and a high degree of responsiveness in the system, demanding significant computational resources and advanced algorithmic solutions.

The third challenge reflects on the goal of the IPS hence directly influencing the physical (network, devices, beacons) deployment of the system. Pre-deployment efforts for IPS involve multiple fixed beacons stationed in the observed indoor space, where the device being tracked is the midpoint of the system. If the goal of the IPS is proximity detection, this deployment type is acceptable. However, for location tracking, inventory management, and wayfinding, where system adaptability is critical, this approach brings several major issues: an excessive fingerprinting phase is required (prior to deployment and must be repeated over time); fixed beacons deployment that cannot be reconfigured or changed easily; long downtime is required for system recalibration.

Lastly, there is the challenge of predictive indoor space usage modeling. This involves understanding and predicting how people move and use indoor spaces, which can significantly enhance the functionality of IPS. Achieving this requires the analysis of large datasets (in real-time, near real-time, and offline) to discern movement patterns and behavioral trends. Furthermore, for comprehensive and effective modeling, IPS need to be integrated with IoT devices and SBMS, which brings additional complexities in terms of data compatibility, privacy, and security. Developing scalable and customizable predictive models is a complex task, demanding expertise in data analytics and machine learning techniques.

Indoor positioning is a crucial aspect of modern smart building management systems (SBMS), but it presents several challenges, including the choice of technology and signal characteristics, pre-deployment effort, selection of filtering algorithms, and selection of machine learning algorithms. Together, these challenges paint a picture of the current state of indoor positioning systems and the hurdles that need to be overcome. Addressing these issues requires a cross-disciplinary approach, drawing upon advancements in wireless communication, sensor technology, data science, and Artificial Intelligence.

5. Context awareness as a requirement for indoor positioning systems: case studies

AI techniques, data mining and data analysis together offer diverse methods for constructing exceptionally flexible IPS. For instance, self-calibrated IPS offer advantages like easy expansion, reliable positioning, and the ability to detect walls and obstacles. They maintain precision in intricate indoor layouts and use trilateration to achieve higher levels of robustness. Next, IPS can also analyze movement patterns for efficient resource utilization and decision-making. Graph-based approaches for modeling social behavior data can enhance building management systems (BMS) by enabling meaningful interaction between proximate users and network serendipitous social encounters. Integrating large language models can make IPS more user-friendly and adaptive in complex environments. This section is devoted to elucidating these use cases by providing practical examples.

5.1 Self-calibrating IPS

Self-calibrated internal positioning systems offer several advantages, including easy expansion, reliable positioning in fluctuating signal conditions, and the ability to detect walls and obstacles. These systems can adjust their calculations to maintain precision in intricate indoor layouts, ensuring continuous operation and context awareness. They also provide real-time recalibration without downtime, making them crucial for dynamic indoor environments. Furthermore, these systems can identify and alleviate the consequences of erroneous signals, enhancing the precision and dependability of location tracking. This section will cover several use cases behind self-calibrating IPS: continuous online fingerprinting and indoor space modeling techniques to support AI models to enhance contextual learning and autonomous detection of floor plan layouts [29]. *Fingerprint-based localization* IPS in general omit integrating system context updates, and the only method to create a new fingerprint spectral map is to repeat the entire procedure. In an indoor space that often transforms, fingerprinting can be applied only if the IPS is capable of continuously adapting to the indoor space. In a self-calibrating IPS, the process of generating a new fingerprint map does not require any interruption in system operation, and it can be carried out seamlessly. This model of operation improves the accuracy of position estimations by eliminating noisy and improbable values. This can be achieved through constant and systematic spectral snapshots or continuous online fingerprinting of the indoor area per several identified tracking candidates to fill the spectral map (see visualized in **Figure 4**).

Categorization of indoor floor space areas is a machine learning task that uses grid and graph space models to determine if a location is a transitional, urban area or a non-urban area. This model impacts the filtering of position estimations over time, suggesting whether the Beacon is currently in motion or most likely not moving. Filtering components are applied per that categorization, refining the Beacon trajectory in the observed space. This and similar AI models require specialized data modeling approaches.

In IPS using trilateration, other methods can be applied to achieve higher levels of robustness and resilience to contextual changes. Using new data models to increase the amount of contextual information about the observed indoor space is crucial. Firstly, IPS should constantly maintain indoor space grids [30]. An indoor space grid is a 3D matrix, a mathematical representation of the indoor space (that can be consumed and updated by the IPS over time). A grid representation of an indoor space can be determined as a 3D matrix of $1m^2$ fields of the indoor areas (see **Figure 5**).

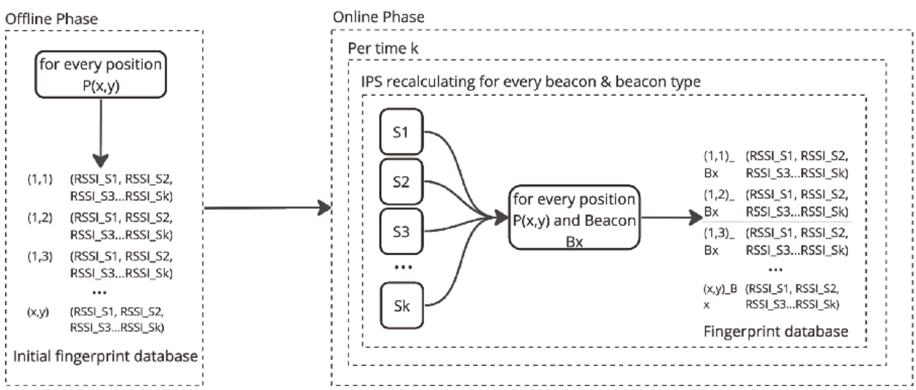


Figure 4.
Autonomous self-calibrating online fingerprinting system design.

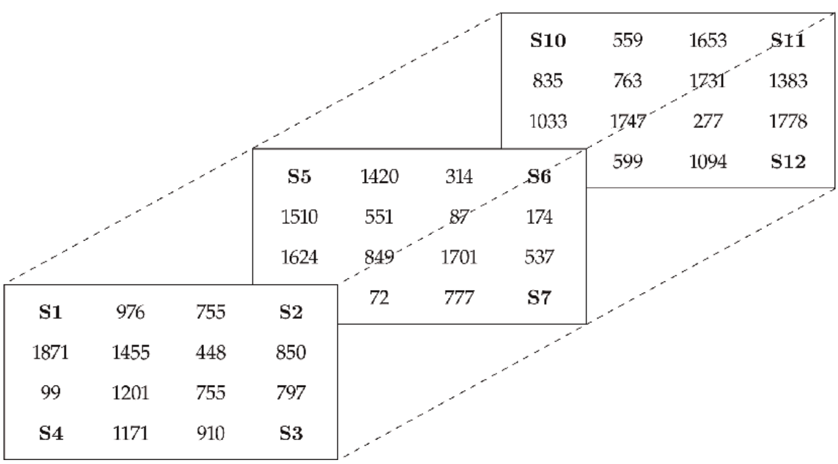


Figure 5.
3D indoor space model (grid) of a multistory building.

$S_1 \ldots n$ represents scanner devices in charge of operating the IPS (typically wireless access point (APs)). Matrix field represents the frequency of the visit of a certain indoor space area.

Furthermore, by forming tenant path (movement) graphs, the system can be uniquely adapted to each tenant while also maintaining a general understanding of how the indoor space is being used by people. Thus, the space grid 3D matrix can be further refined by associating a tenant path graph node with (x,y) position (see **Figure 6**).

Looking at **Figure 6**, C_k represents IPS scanners; green lines represent low standard deviation of RSSI, while blue lines represent high standard deviation of RSSI, indicating unstable signal readings. Branches/edges between the nodes remember transitions and their frequency, which represents the weight of a branch. The duration of stay at each node is saved in a node weight. By finding subgraphs with the largest node weight, we can conclude that they represent a *frequently visited and stayed at space (a room)*, and on the other hand lightweight branches between heavyweight subgraphs represent direct or indirect transitions, indicating that there might be an *obstacle* between the two—a wall. RSSI values between all points from a Scanner to a Beacon are collected, and the standard deviation is used to determine whether the RSSI fluctuates much between the two points of a grid. $w_1..n$ refer to branch weights, and $d_1..n$ refer to duration of stay at node. If there are two heavyweight subgraphs $(weight + duration)$, such as that there is a lightweight subgraph between them, then the space the light subgraph represents is position of a possible obstacle in the closed space. This approach is relevant for the following reasons: (1) the system decides whether a node is a location the device stays at longer or just passes through it, thus categorizing nodes and analyses subgraphs; (2) their weights, and transitions between them; suggesting where obstacles may be; and (3) collecting device paths along the space for deeper data analysis is important to detect what is the usual path, and thus detect deviations upon that path [8].

Detection of floor plan layout involves inferring information about physical obstacles in the observed indoor space. Most IPS have information about the exact layout of the indoor space, which is considered ground truth. This is sufficient for office buildings, residential buildings, and public buildings, as the physical layout of these spaces will not change over time. However, for simpler indoor spaces like large warehouses with no dedicated physical layout, which has large equipment, movable separating

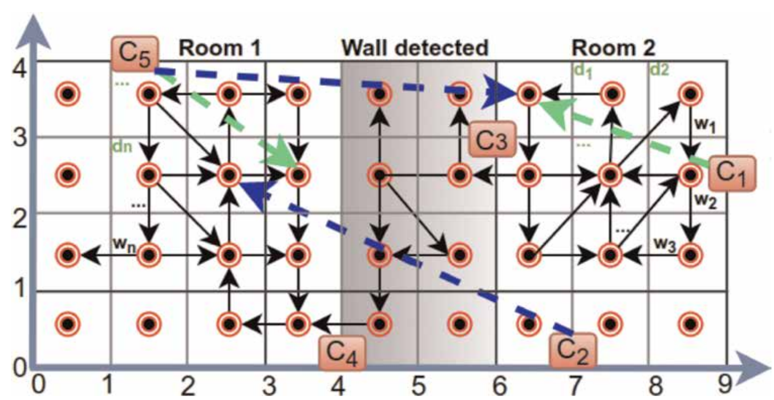


Figure 6.
Tenant path (movement) graph in a 2D indoor space (model) grid.

walls, machines, and large racks/shelves that count as obstacles for signal propagation, having a static floorplan layout is insufficient. An autonomous solution to approximate a floor plan layout based on gathering positioning data of observed Beacons must be employed.

To build a representable space model, combining weighted graph-based and grid-based space modeling is necessary. Detecting and predicting indoor obstacles is hence based on consuming the enhanced grid coupled with tenant graph paths (also based on high standard deviation of RSSI between two fields of a grid). By maintaining space grid and tenant graphs models, an IPS is enhanced by various functions from creating heatmaps, calculating the popularity of certain areas and probabilistic obstacles detection (analytical) to forecasting space usage and movement paths, categorizing space areas, and approximating the floor plan layout (predictive).

5.2 Movement patterns detection and prediction

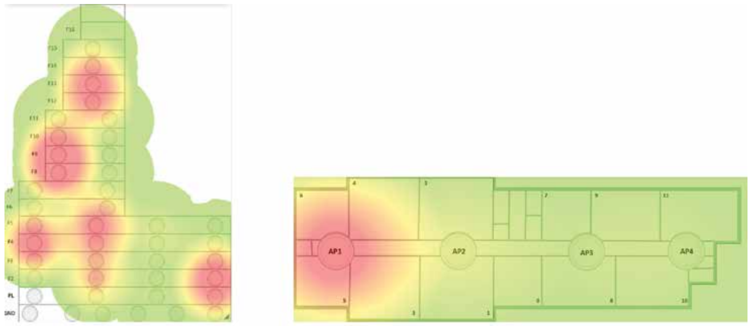
Movement patterns are crucial for efficient resource utilization in indoor spaces, as they represent interaction patterns between users and the indoor space. Detecting movement patterns is essential *for real-time detection of deviations* and proactively utilizing resources, such as turning on lights or calling an elevator. In emergency scenarios, information about a tenant's movement pattern can be used to build individual, guided escape routes that are more efficient. Collective observation of movement patterns can also be used to plan emergency escape routes more efficiently.

Movement patterns can be modeled as path graphs, providing a visual overview of the tenant's movement in 2D and 3D. Overlapping multiple tenant path graphs can pinpoint intersection points and areas, leading to the discovery of potential frequently used indoor areas. For IPS deployed on resource constraint devices, by transforming path graphs into sentences, similarity algorithms can be run faster than for two consecutive graphs. These algorithms give a probabilistic approximation of the possibility of pattern existence, inferring behavioral patterns for the entire building [8].

Correlating movement with occupancy patterns gives a better outlook on tenants' interaction with the observed indoor space, which can be used for decision-making related to efficient resource utilization. Movement patterns can be used to infer activity or inactivity of tenants, indicating potential human-emergency situations. By knowing a tenant's movement pattern, custom emergency escape routes can be built, overlapping areas of space best known to the tenant with the shortest escape route, taking into account real-time congestion and flocking of people [31].

5.3 Occupancy detection, patterns, and prediction

Occupancy detection and prediction in buildings are crucial for efficient operation and resource utilization. IoT-enabled Building Management Systems automate processes and resources, improving overall efficiency. However, modeling buildings' occupancy remains a challenging, expensive, and error-prone task. Approaches to solving this problem include choosing ML models, selecting data sources for occupancy extraction, determining temporal characteristics, and defining occupancy monitoring methods like detection, counting, tracking, or behavior recognition [32]. Building management systems prioritize energy efficiency by accurately predicting occupancy patterns for hours, days, and weeks. This allows them to plan, prepare, and utilize energy resources for heating, ventilation, and air conditioning (HVAC) and lighting systems. By using intrusive or high-cost-inducing approaches like video



(a) Entire building occupancy heatmap

(b) Floor occupancy heatmap

Figure 7.
Sample occupancy heatmaps of residential building (see details in Pesic et al. [8]).

surveillance, smart building management systems (SBMS) can negotiate and purchase electricity at lower rates, ensuring sufficient storage to satisfy predicted demand.

Occupancy detection can be achieved by using various technologies: relying on current network infrastructure (Wi-Fi), Bluetooth device scanning, light, audio, or motion-based sensors, or by employing a hybrid approach. Once occupancy data is established on a unit level (apartment, office), advanced AI techniques need to be employed to ensure that data can be predicted reliably. Categorizing mobile and static user devices and using a binary classification approach can help in inferring occupancy. From a business perspective, mobility patterns and occupancy data can be used to model decisions such as where to place a vending machine. As a result, occupancy detection algorithms can help visualize overall building occupancy or occupancy per floor (see **Figure** 7).

The problem of accurately *detecting and forecasting occupancy* in indoor areas presents a significant opportunity for models, techniques, and algorithms. Forecasting binary occupancy in residential buildings is more challenging than in commercial buildings due to stochastic tenant behavior [33]. Long-term forecasting requires a good dataset and finer Artificial Neural Network model calibration per observed unit, as well as continuous retraining of the AI models to ensure reliability [8].

Furthermore, pattern searching is a crucial tool in understanding and analyzing tenant behavior [34]. Typically, a week is a representative time delimiter for pattern occurrences, as it is the most common time-wise delimiter for organizing habits and commitments. Useful end results of identifying occupancy patterns for SBMS include successfully detecting the longest sequences of apartment occupancy/unoccupancy and finding regularities when those sequences are combined for multiple apartments for a given time range. This helps the SBM optimize vertical/horizontal (multiple apartments on the same floor or vertical) resource utilization, as well as optimization per multiple apartments at once. By running these steps on all unit levels (apartments, offices), specific information per unit can be extracted, such as if a tenant goes to work or attends school. This information can be used for deeper inspection and other data analytics pipelines, varying what patterns are found relevant.

5.4 Social communities

Indoor positioning systems (IPS) play a crucial role in providing specialized location-based services and understanding the context of their operation. However, *observing social behavior* in residential buildings is often overlooked due to the highly stochastic movement patterns of tenants [35]. This section discusses graph-based approaches for modeling social behavior data, including modeling of tenants' movement paths, detecting the existence of patterns, modeling of tenants' social relationships (frequency, quality), and *detecting social communities* and tracking their evolution.

Characterizing social behavior inside a network of people is a challenging task, as it requires assumptions and patterns of typical behavior. Still, by constantly observing and persisting occupancy data and movement graphs (see Section 5.1), social relationship graphs at unit level (which can be projected to tenant level) can be maintained (see **Figure 8**). The nodes of this graph represent apartments/common rooms/tenants while the branch weights between them represent the strength of the (social) relationship by evaluating the frequency and duration of (social) interactions.

Additionally, observing the formation and evolution of social groups is significantly harder to maintain for such ad-hoc, stochastic networks modeling human social behavior [19].

IPS can enhance the underlying building management system (BMS) with the information enabling them to animate and support meaningful interaction between proximate users, network serendipitous social encounters, and seamlessly integrate events with the way interaction takes place in the observed social network [36]. BMSs can use this information to drive business decisions such as building a common entertainment room, organizing indoor social events, and targeted community marketing. Social network models are statistical procedures for describing relationships between entities, and social behavior information can be used to extrapolate social dynamics and contribute to a deeper understanding of the observed space context. For example, the social behavior of networked tenants has effects on peer network energy consumption. Social interaction networks of residential neighborhoods can be used to animate and support meaningful interaction between proximate users [37].

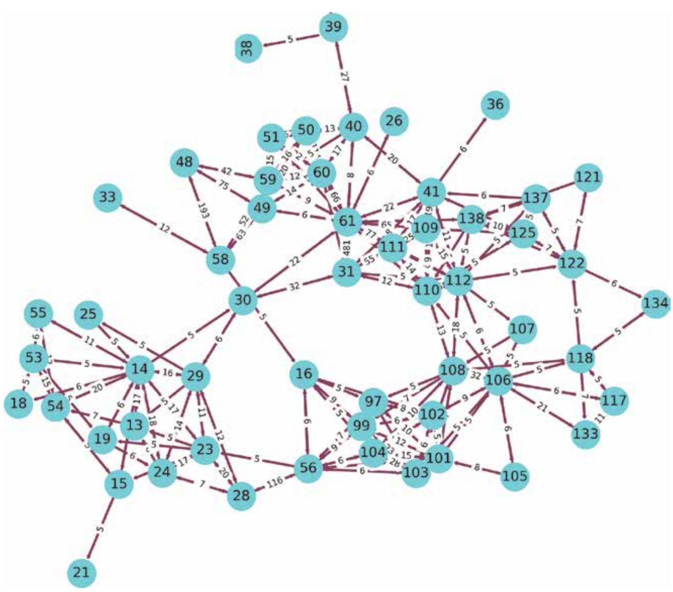


Figure 8.
Example social relationship graphs for a residential building.

Communities are often present in social networks, representing a collection of entities forming a specifically connected sub-network in the larger observed social network. Observing social communities from an evolutionary standpoint can infer information about how the community changes over time. For IPS in residential buildings, the detection of communities can be used to extrapolate social relationship information (number, frequency, and period) and evolution of those communities over time. These inputs can be used by a BMS to positively impact the social well-being of tenants through animation and support for forming social relationships and communities and drive business decisions such as building a common entertainment room, organizing indoor social events, or targeted community marketing [19].

5.5 Large language models

Large language models can significantly improve indoor positioning systems by analyzing vast amounts of data, enhancing accuracy, and enabling natural language processing for user interaction. They can offer personalized recommendations based on user location and behavior patterns, such as less crowded routes or nearby points of interest. They can also develop accessibility features for individuals with disabilities, providing audio-based directions or detailed descriptions of indoor environments. The models can process user feedback to continuously improve the indoor positioning system, adapting to changes in the environment or user behavior. In emergencies, they can guide people to the nearest exits, considering real-time conditions and crowd movements. Overall, integrating large language models can make indoor positioning systems more user-friendly, adaptive, and efficient in complex environments like malls, airports, and large office buildings.

6. Conclusions

In conclusion, this chapter presents a comprehensive exploration of modern challenges and technological advancements in indoor positioning systems (IPS), emphasizing the crucial role of Artificial Intelligence (AI) in overcoming these obstacles and enhancing system capabilities. Through detailed discussions, it highlights the dynamic nature of indoor environments and the complexities involved in achieving high-accuracy positioning, pointing out the limitations of traditional methods and the potential of AI and data science principles to address these issues effectively.

The chapter outlines various use cases of IPS across industries, such as retail, healthcare, and smart building management, showcasing the transformative impact of location-based services (LBS) in improving operational efficiency and user experience. It delves into the technological foundations of IPS, presenting a taxonomy of indoor positioning technologies and methodologies, and underscores the importance of deployment strategies that leverage edge computing and IoT devices for enhanced data privacy and system responsiveness.

Furthermore, it identifies key challenges in IPS, including the need for high accuracy, system adaptability to dynamic conditions, and the ability to model predictive indoor space usage. It discusses the application of machine learning and AI techniques in addressing these challenges, such as through self-calibrating systems, movement pattern analysis, and occupancy detection and prediction, thereby illustrating the significant benefits of integrating AI into IPS solutions.

The chapter also presents case studies to demonstrate the practical application and effectiveness of AI-enhanced IPS in various contexts, from self-calibrating IPS for reliable positioning to graph-based approaches for modeling social behavior within indoor spaces. These examples highlight the capacity of AI to enable more intelligent, efficient, and user-centric indoor positioning systems.

By offering a detailed examination of the current state of IPS and the innovative use of AI and data science, this chapter contributes valuable insights into the ongoing evolution of indoor positioning technologies. It underscores the potential of AI to transform IPS into more adaptive, accurate, and context-aware solutions, paving the way for future advancements in the field. The discussion sets a foundation for further research and development, encouraging the exploration of AI's full potential in enhancing indoor positioning and navigation systems.

Abbreviations

IPS	indoor positioning system(s)
BMS	building management system(s)
SBMS	smart building management system(s)
IoT	ultra-wide band
UWB	Internet of Things
RSSI	relative signal strength indicator
BLE	Bluetooth low energy
VLC	visible light communication
AoA	angle of arrival
TDoA	time difference of arrival
IMUs	inertial measurement units

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Chapter 5

RF Modules and Antennas Design for Indoor Positioning Systems

Albert Sabban

Abstract

The main goal of indoor positioning system (IPS) is to locate people or objects, especially inside the building. Satellite technologies and GPS lack precision and cannot function inside buildings, airports, parking garages, and underground locations. Several techniques and devices are used to provide indoor positioning, such as smartphones, Bluetooth, radio waves, Wi-Fi, light, magnetic fields, acoustic signals, and behavioral analytics, which are all used in IPS systems. IPS can achieve position accuracy up to 2 cm. Radio frequency (RF) IPS components and antennas are described in this chapter. MIC, MMIC, and LTCC technologies may be used to develop IPS RF modules and systems, which are presented in this chapter. Moreover, in the design of RF devices for IPS systems, we can use the features and benefits of these technologies in the design of transmitters and receivers for communication systems. Efficient metamaterials antennas are employed to develop radiating elements for radio frequency IPS systems. Monopulse antennas are used to find position and direction in IPS and radar systems. The monopulse antenna S11 parameter is −9.5 dB with 11% bandwidth. The antenna beam width is around 36°. The computed and measured antenna directivity and gain is 10 dBi. A circular patch antenna with SRRs is developed in this chapter. The antenna bandwidth is around 8% for VSWR, better than 3:1. The antenna beam width is around 82°. The antenna directivity and gain are around 7.6 dBi.

Keywords: indoor positioning, radio frequency, RF, antenna, monopulse, metamaterials

1. Introduction

RF technologies, such as MIC and MMIC, are employed to develop indoor positioning systems (IPS). In the design and development of RF devices for IPS systems, we can use the features and benefits of these technologies, such as MIC and MMIC, in the design of transmitters and receivers for IoT, IPS, and communication systems, see [1–12]. Compact, low-weight, and low-cost active devices such as mixers and amplifiers are manufactured by employing MMIC technology.

Indoor positioning system (IPS) is a network of modules used to locate people or objects, especially inside the building. GPS and other satellite technologies lack precision and cannot function inside parking centers, industrial buildings, airport terminals, and underground train stations. Several techniques, networks, and devices are employed to achieve indoor positioning, such as smartphones, Wi-Fi, Bluetooth, RF systems, acoustic devices, magnetic fields, and behavioral analytics. The accuracy of IPS devices is that their positioning is up to 0.02 m. IPS uses different technologies, including distance measurement, Wi-Fi, Bluetooth, mobile devices, and tags; IPS has broad applications in commercial applications, military networks and applications, and retail and inventory tracking industries. There are several commercial systems on the market. Due to the signal attenuation caused by construction materials, satellite-based systems are not as effective as indoor positioning systems. Reflections and diffraction from buildings and reflecting surfaces cause multi-path propagation effects that cause uncontrollable and unexpected errors. These effects are affecting and degrading other known solutions for indoor positioning, which employ microwave technologies.

Many researches and papers present IPS systems and analysis in [13] a Multi-Channel Radio-Over-Fiber Communication Systems Through Modulation Instability Phenomenon is discussed. In [14], a Low-Cost Multiband Four-Port Phased Array Antenna for Sub-6 GHz 5G Applications With Enhanced Gain Methodology in Radio-Over-Fiber Systems Using Modulation Instability is discussed. In [15], A Novel MIMO Antenna Integrated with a Solar Panel and Employing AI-Equalization for 5G Wireless Communication Networks is discussed. In [16], Meta surface-Inspired Flexible Wearable MIMO Antenna Array for Wireless Body Area Network Applications and Biomedical Telemetry Devices is discussed. Efficient metamaterial antennas were used in indoor posting and direction-finding systems. A circular patch antenna with SRRs is developed in this chapter. Metamaterials antennas concept and theory are discussed in detail in [4, 5]. In Ref. [17], A Comprehensive Survey on Antennas On-Chip Based on Metamaterial, Meta surface, for Millimeter-Waves and Terahertz Integrated Circuits and Systems is discussed. Design considerations of passive devices and antennas for IPS systems are discussed and presented in this chapter.

1.1 RF components

1.1.1 Low-cost compact RF resistors

Capacitors, Resistors, and inductors are basic components that are employed in the development of IPS devices. The compact RF resistor is presented in **Figure 1**. The resistance can be calculated by employing Eq. (1). The resistor equivalent circuit is shown in **Figure 2**.

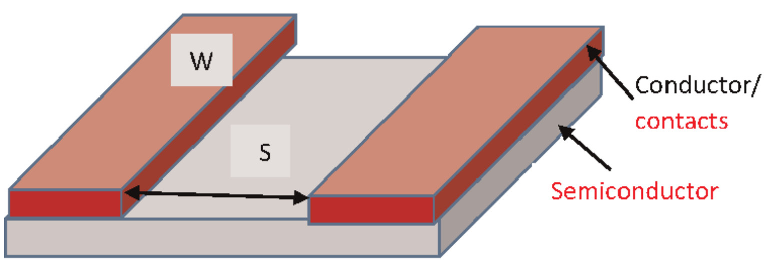

Figure 1.
Layout of a compact resistor [5].

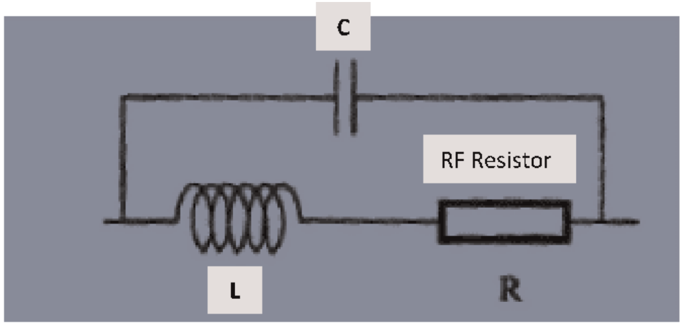

Figure 2.
Resistor RF model [5].

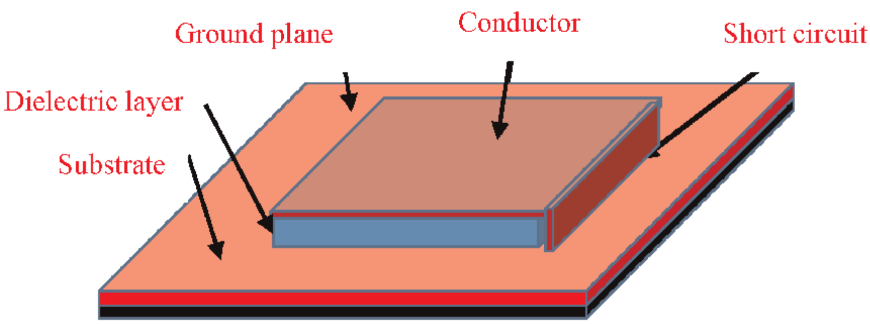

Figure 3.
Compact MIC capacitor [5].

$$R = R_{sh}\frac{S}{W} + 2R_c \tag{1}$$

Rsh – The resistance of the metal film.
S – Distance between Ohmic contacts.
W – Conductor width.
Rc – The contact resistance.

1.1.2 Low-cost compact capacitor

The capacitor has two metal parallel plates, with area A, separated by a dielectric substrate with thickness d and dielectric constant ϵ_r. The capacitor schematic is illustrated in **Figure 3**. Eq. (2) is used to calculate the capacitance.

$$C = A\frac{\epsilon_0\epsilon_r}{d} \tag{2}$$

where $\epsilon_0 = 8.8510^{-12}\ F/m$.

1.1.3 RF inductor

The short printed line presented in **Figure 4** operates as a printed inductor. The inductor circuit model is given in **Figure 5**. Eqs. (3) and (4) are used to compute the inductance L and the capacitance C.

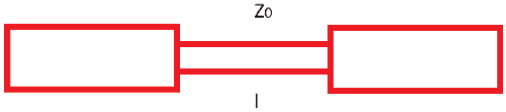

Figure 4.
Short-printed transmission line.

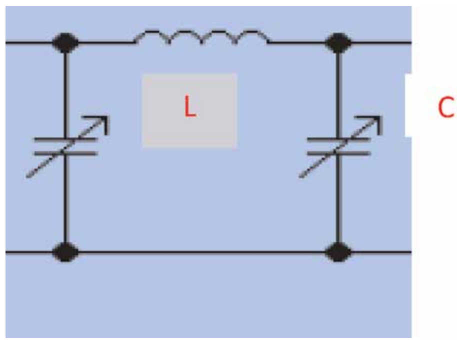

Figure 5.
Compact inductor model [5].

Passive and active elements in MMIC design are shown in **Figure 6**.

$$L = \frac{Z_0}{2\pi f} \sin\left(\frac{2\pi l}{\lambda}\right) \tag{3}$$

$$C = \frac{1}{2\pi f Z_0} \tan\left(\frac{\pi l}{\lambda}\right) \tag{4}$$

1.1.4 Couplers

Couplers are employed to couple RF energy from the input port to a coupled port. Usually, two coupled quarter wavelength transmission lines are designed as a coupler. The coupler has four ports: P1 is the input port, and P2 is the transmitted port, as presented in **Figure 7**. The coupled port is P3 and P4 is the isolated port. The couplers are employed as built-in test units to obtain information about the transmitted or received power (such as power level and frequency) without disturbing the main signal flow in the system. The coupling level is the ratio between the coupled energy and the input energy in dB when the other ports are terminated. It may be computed by using Eq. (5). Eq. (6) is used to compute coupler insertion losses. In a 3 dB coupler, the power coupled to the coupled port is half of the input power. The power on the main transmission line is also 3 dB below the input power. This coupler is called a 90° hybrid coupler. The coupler losses are due to transmission line losses, coupling losses, radiation losses, and matching losses.

$$Coupling\ Factor = CF = -10\, log\, \frac{\text{P3}}{\text{P1}} \tag{5}$$

$$Insertion\ Loss = IL = 10 \log\left(1 - \frac{\text{P3}}{\text{P1}}\right) \tag{6}$$

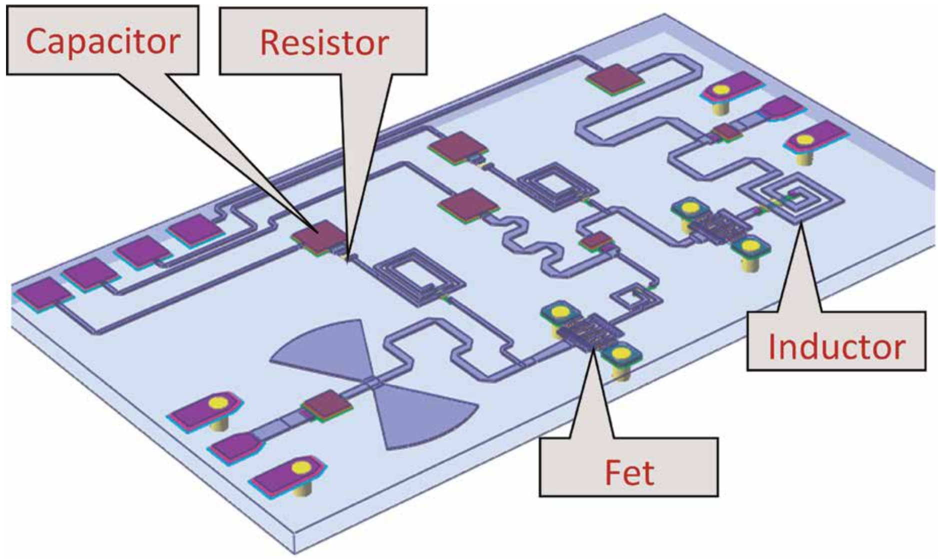

Figure 6.
Passive and active elements in MMIC design [5].

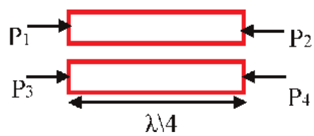

Figure 7.
Coupled λ\4 transmission lines.

The coupler isolation ratio may be calculated by using Eq. (7) which is the ratio between the power in port P4 to the input power in dB. The other ports are terminated:

$$Isolation = -10\,log\,\frac{\mathrm{P4}}{\mathrm{P1}} \tag{7}$$

The coupler directivity ratio may be calculated by using Eq. (8) which is the ratio between the power in port P4 to the power in port P3 in dB. The other ports are terminated:

$$Directivity = D = -10\,log\,\frac{\mathrm{P4}}{\mathrm{P3}} \tag{8}$$

In RF and communication systems, the amplitude and phase balance between the system ports should be considered in the signal processing process. Amplitude balance defines the power difference in dB between two output ports. Theoretically, the amplitude difference should be 0 dB. However, in commercial couplers, the amplitude balance is frequency-dependent. The phase difference between two output ports is the function of the coupler structure and can be 0, 90, or 180 degrees.

1.1.5 A wide band RF coupled lines

A wide band, 18 to 40 GHz, RF coupler is presented in **Figure 8** and is fabricated on Alumina with 9.8 dielectric constant. The substrate thickness is 0.13 mm. The coupler was designed by using RF software [18]. **Figure 9** presents the coupling level at around 13 dB. **Figure 10** presents the coupler insertion loss that is less than 0.5 dB. The coupler VSWR is better than 1.1:1, see **Figure 11**. The couplers and power dividers presented in this chapter were designed and optimized by using full-wave electromagnetic software [18].

1.2 RF power splitters and combiners

RF Power splitters and combiners are employed to split or combine microwave energy. Several structures and types of RF power splitters are presented in this chapter.

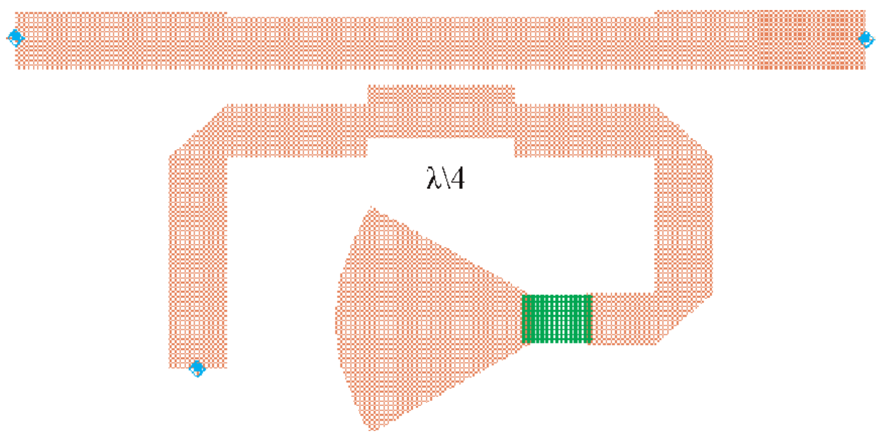

Figure 8.
A wide band MM wave coupler.

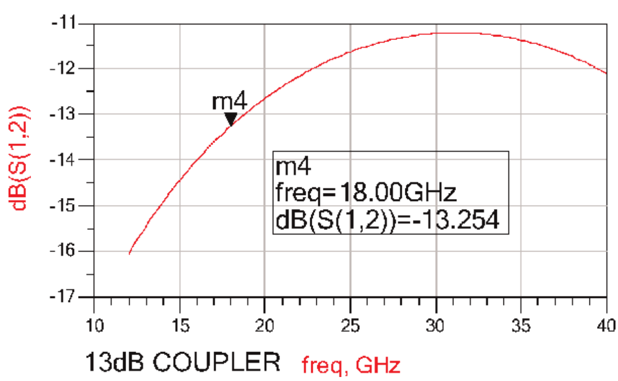

Figure 9.
The MM wave coupler coupling measured results.

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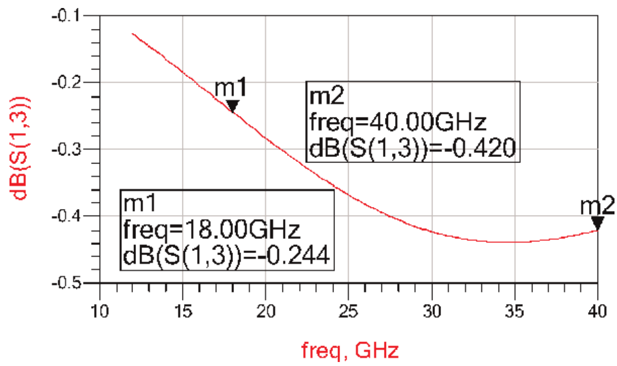

Figure 10.
The insertion loss of the wideband microstrip coupler.

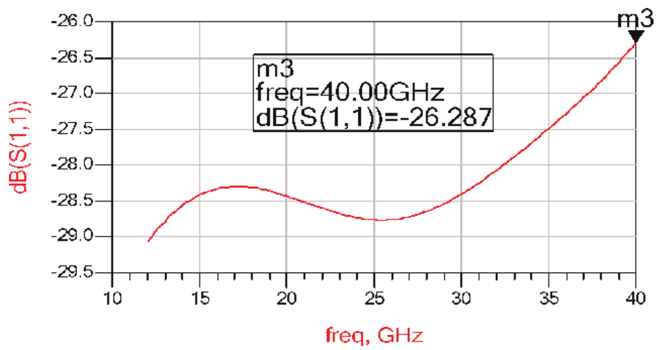

Figure 11.
The coupler S11 parameter.

1.2.1 Wilkinson power splitter and combiners

The Wilkinson power splitter is presented in **Figure 12**. At the splitter junction, O, the power is half of the input power. The impedance at the junction point, O, will be twice than Z0, where Z0 is the input impedance. The impedance 2Z0 is matched to Z0 by a quarter wavelength transformer. The bandwidth of the RF splitter is around 25% for S11, which is lower than −9 dB. However, multiple-section quarter wave transformers can have around 50% bandwidth for S11 lower than −9 dB. To get 15 dB isolation between the output ports a 2Z0 resistor should be connected between the output ports. Without a resistor between the output ports, the isolation will be lower than 6 dB.

1.2.2 Rat-race 3 dB/1800 coupler

Figure 13 presents a rat-race coupler. The length of the line from A to Δ port is 3λ\4. The length of the line from A to ∑ port is λ\4. The coupler circumference is 1.5 λ.

The input port impedance is 50 Ω, and the impedance of the entire ring lines is 70.7 Ω for an equal power coupler. The output signals at ports 2 and 4 are around 3 dB with a 180-degree phase difference.

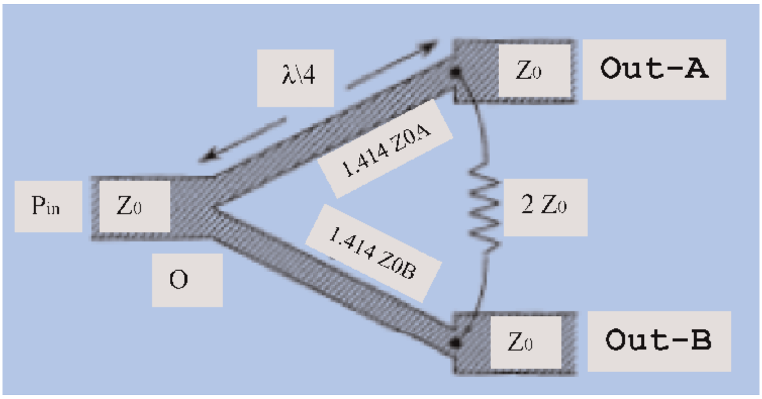

Figure 12.
Wilkinson power splitter, [5].

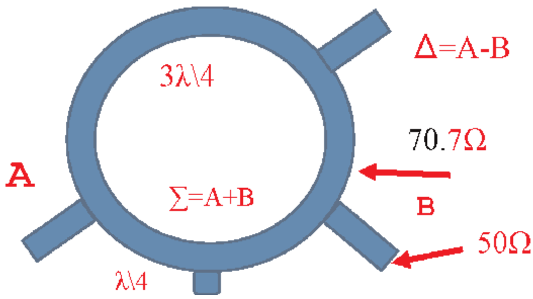

Figure 13.
Rat-race coupler.

1.2.3 Gysel power splitter

Figure 14 presents a wideband Gysel power splitter with around 60% bandwidth for S11 lower than −9 dB. This splitter may be used in high-power transmitters.

1.2.4 Unequal power RF couplers

We can design unequal power couplers by using rat-race RF couplers, as presented in **Figure 15**. The unequal power division may be designed by calculating the impedances. Z_{0A} and Z_{0B}, as presented in Eqs. (9) and (10):

$$Z_{0A} = Z_0 \left[\frac{1 + \frac{P_A}{P_B}}{\frac{P_A}{P_B}} \right]^{0.5} \tag{9}$$

$$Z_{0B} = Z_0 \left[1 + \frac{P_A}{P_B} \right]^{0.5} \tag{10}$$

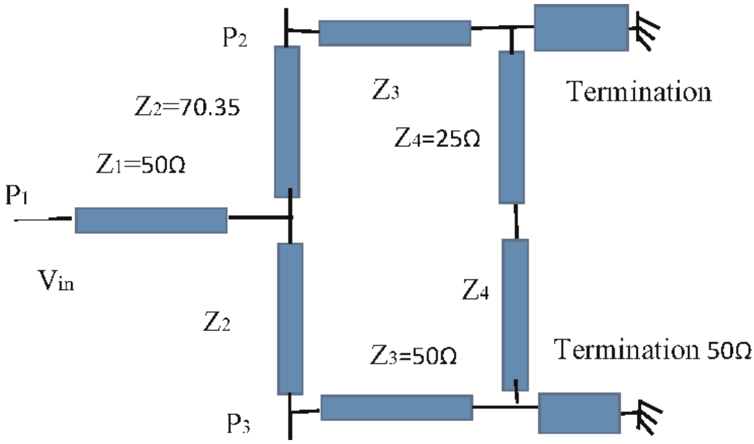

Figure 14.
Gysel power splitter.

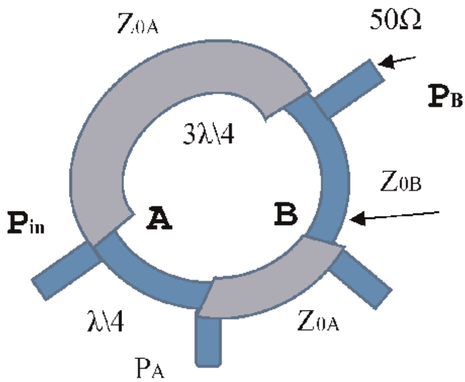

Figure 15.
Unequal rat-race power splitter.

1.2.5 Wide band three-way unequal power splitter

A 6 to 18 GHz three-way power splitter is presented in **Figure 16**. The unequal power splitter is printed on a substrate with 0.25 mm thickness and 2.2 dielectric constant. The power splitter was evaluated and optimized using ADS RF software [18]. The unequal splitter size is around 40 × 24 × 0.25 mm. The unequal power splitter is realized by printing three-quarter wavelength transformers. The incident power is divided into three and two-thirds of the incident power. The two-thirds of the incident power is divided by an equal power splitter to a third of the incident port power. The unequal power splitter insertion loss is around 1 dB. The power splitter VSWR is better than 2:1 for frequencies from 6 to 18 GHz.

1.2.6 Wide band six-way unequal power splitter

Figure 17 illustrates a wideband 6 to 18 GHz unequal six-way power divider is presented. The power splitter is printed on a substrate with 0.25 mm thickness and 2.2

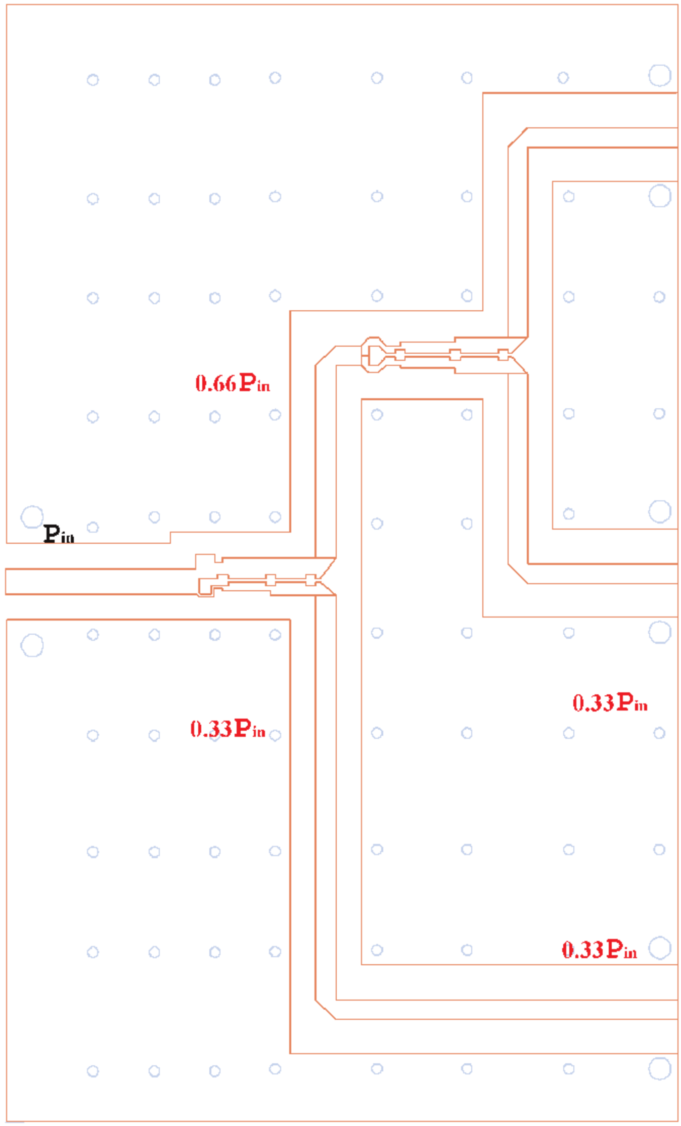

Figure 16.
Wide band three-way printed unequal power splitter.

dielectric constant. The size of the unequal splitter is 68.8 × 23.5 × 0.25 mm. The power splitter was evaluated and optimized using ADS RF software [18]. The unequal six-power splitter is realized by printing three-quarter wavelength transformers. The incident power is divided into third and two third of the incident power. The two-thirds of the incident power is divided by an equal power splitter to a third of the incident port power. The six-way splitter insertion loss is around 1.5 dB. The power splitter VSWR is better than 2:1 for frequencies from 6 to 18 GHz. The power dividers presented in this chapter were designed and optimized by using full-wave electromagnetic software [18].

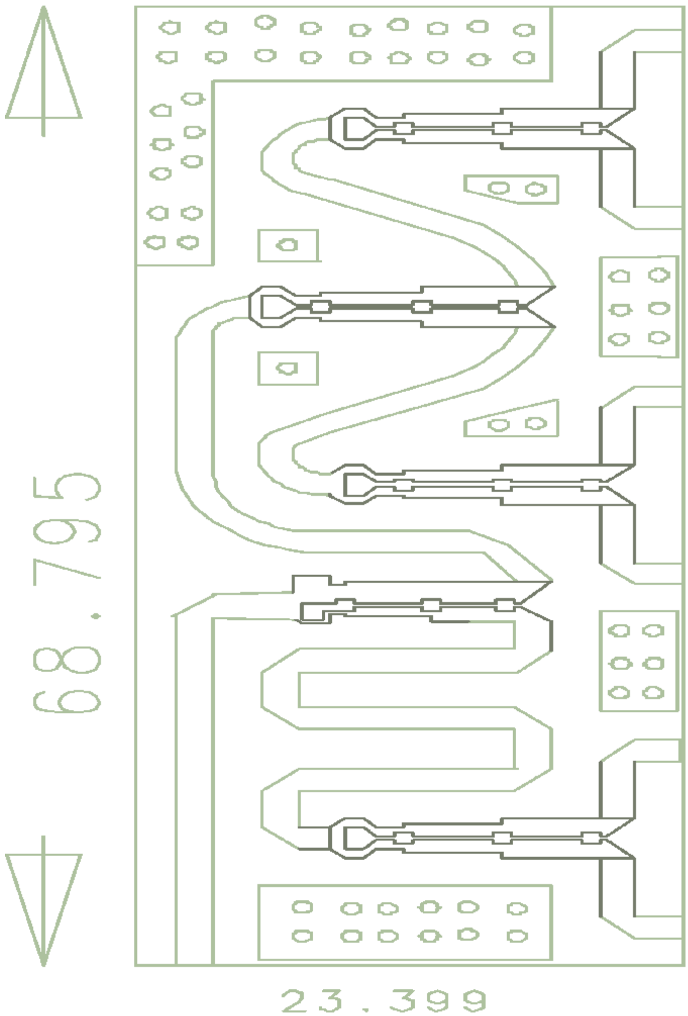

Figure 17.
Printed wide band six-way unequal power splitter.

2. Circular compact microstrip metamaterials antennas for IPS systems

Microstrip antennas can be used in IPS systems [19]. Monopulse microstrip antennas are used in indoor positioning and direction-finding systems. Efficient metamaterial antennas were used in indoor positioning and direction-finding systems. A circular patch antenna with SRRs is developed in this section. Metamaterials antennas concept and theory are discussed in detail in [4, 5, 16]. The antenna is printed on a dielectric substrate 0.16 cm thick with a dielectric constant of 2.2 and a loss tangent of 0.0018. The radiator consists of a circular antenna with 18 SRRs. The radius of the circular patch with SRR, shown in **Figure 18a**, is 1.8 cm. The antenna radiates efficiently at 2.5 to 2.7 GHz. The resonant frequency of the dominant mode TM11 of the circular patch is given by Eq. (11); see [10, 11]. Where c is the light velocity in a vacuum. Where a_e is the radius of the circular microstrip antenna and it may be

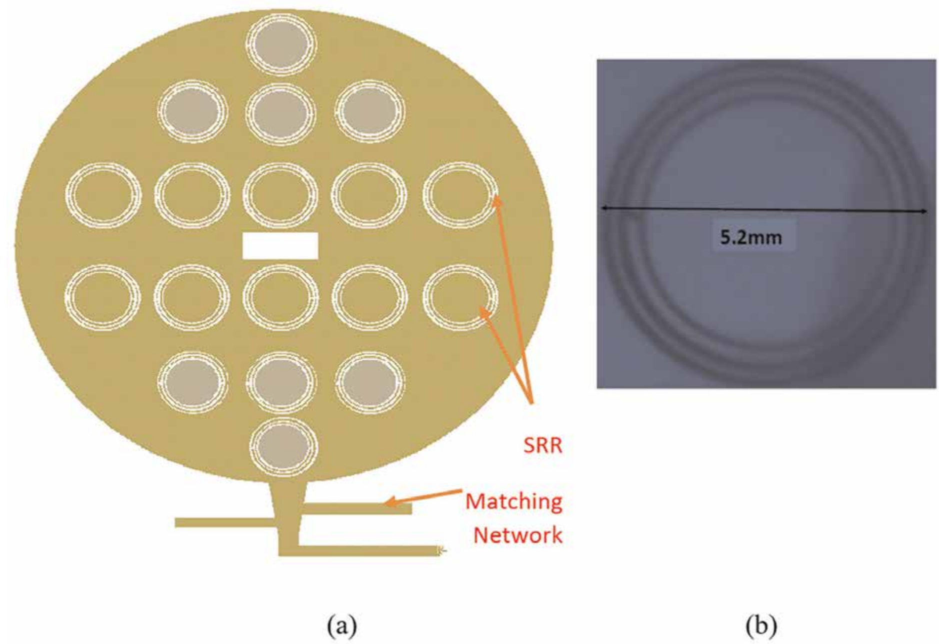

Figure 18.
a. Circular microstrip antenna with SRR b. Photo of a single SRR.

computed by employing Eq. (12) [10]. ε_e is the effective dielectric constant. The radius of the circular microstrip antenna should be 2.33 cm at 2.6 GHz. The SRR outer diameter ring is 5.2 mm, as shown in **Figure 18b**. The width of the SRR strip is 0.15 mm. All the antennas discussed in this chapter were designed by using 3D full-wave software, see [18]:

$$f = \frac{1.8412c}{2\pi a_e \sqrt{\varepsilon_e}} \tag{11}$$

$$a_e = \frac{1.8412c}{2\pi f \sqrt{\varepsilon_e}} \tag{12}$$

The radius of the circular patch without SRR is higher by 23% than the diameter of the circular patch with SRR. The SRR design details were described in previous publications; see Refs. [10, 11]. The circular antenna bandwidth is around 5% for VSWR, better than 2:1. The antenna bandwidth is around 8% for VSWR, better than 3:1, as shown in **Figure 19**. The antenna bandwidth can be improved by adding a second radiating layer. The antenna beam width is around 82°. The antenna directivity and gain is around 7.6 dBi, as shown in **Figure 20**. The antenna efficiency is around 83%. The gain and directivity of the circular patch antenna without SRR is lower by 2.5 to 3 dB than the circular patch antenna with SRR.

Metamaterials antennas may be used in WLAN, wireless local area networks, and in LAN (local area network) indoor positing and direction-finding systems.

Microstrip circular antennas can be employed to develop monopulse antennas.

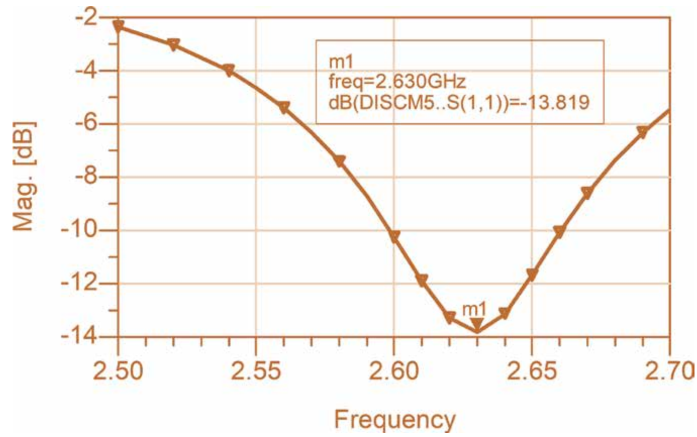

Figure 19.
S11 of the wearable circular microstrip antenna with SRR.

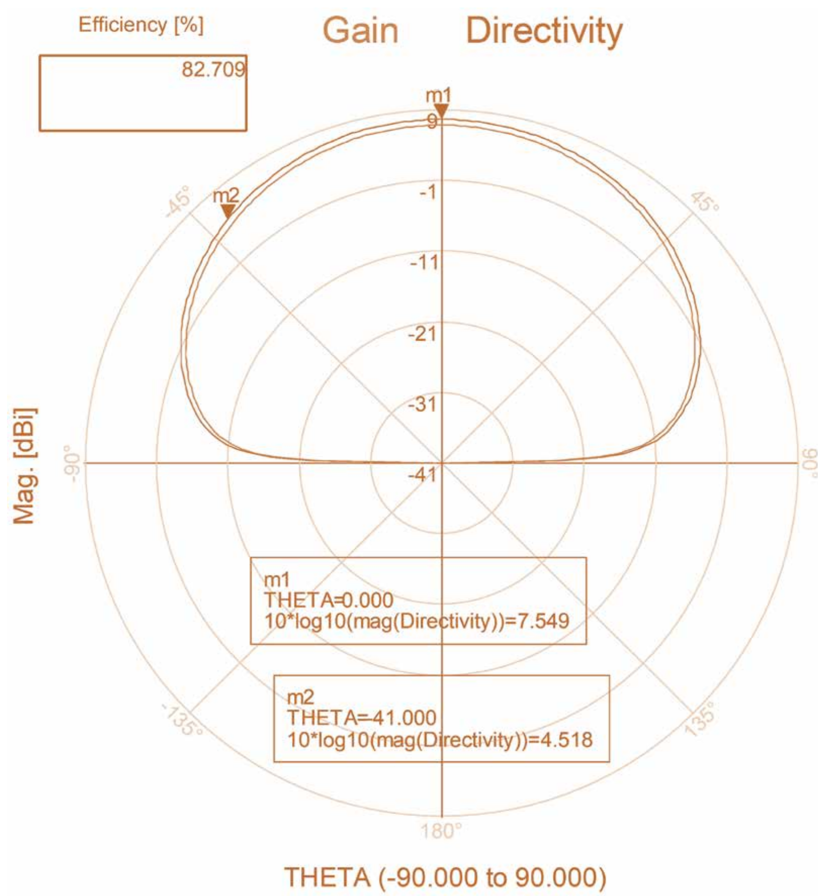

Figure 20.
Radiation pattern of the 2.6 GHz circular microstrip antenna with SRR.

3. Monopulse double layer circular microstrip antenna

Monopulse antennas are used to find positioning and direction [4, 5]. **Figure 21** presents the orientation between two antenna arrays. The distance between the radiating elements is d. A wavefront is incident at an angle θ. The phase difference between the two antennas is ΔΦ. The angle θ may be computed by using Eq. (13):

$$\theta = \sin^{-1}\left(\frac{\lambda \Delta \Phi}{2\pi d}\right) \tag{13}$$

A monopulse stacked patch antenna was developed at 2.6 GHz. The monopulse double-layer antenna consists of four circular patches, as shown in **Figure 21**. The resonator and the feed network were etched on a substrate with relative dielectric constant of 2.45 with thickness of 0.8 mm. The resonator is a circular patch with 2.1 cm radius. The circular microstrip metamaterial resonator diameter should be 3.6 cm. The circular patch was printed on a substrate with relative dielectric constant of 2.25 with thickness of 0.8 mm. The radiating element is a circular patch with 2.25 cm radius. The circular microstrip metamaterial radiator diameter should be 4 cm. The four circular microstrip antennas are connected to three 3 dB 180° rat-race couplers by the antenna feedlines, as presented in **Figure 22**. The feed network consists of three strip-line 3 dB 180° rat-race couplers etched on a substrate with relative dielectric constant of 2.45 with thickness of 0.8 mm. The comparator has four output ports: a sum port $\sum$, difference port Δ, elevation difference port ΔEl, and azimuth difference port ΔAz, as presented in **Figure 22**. The antenna bandwidth is around 12% for S11 lower than −9 dB. The measured monopulse antenna gain is around 10 dBi. The monopulse antenna beam width is around 36°.

Monopulse comparator specifications

Frequency: 2.5–2.7 GHz

Insertion loss: 0.6 db

VSWR: 1.3:1

The feed network insertion losses are around 0.8 dB. The resulting local minimum in the Δ port at the center of the bore sight is very deep, more than −20 dB, as

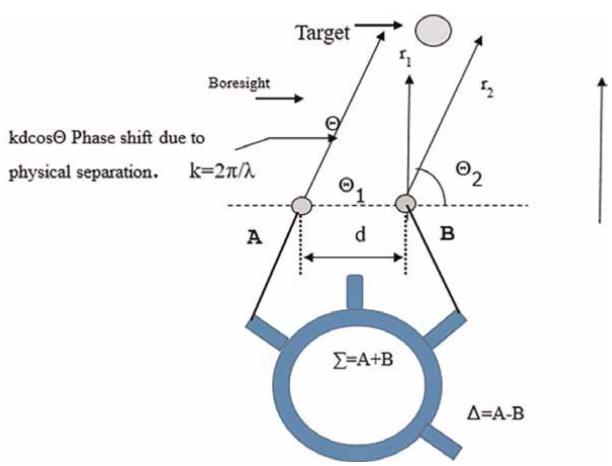

Figure 21.
Orientation between the monopulse antenna and the target.

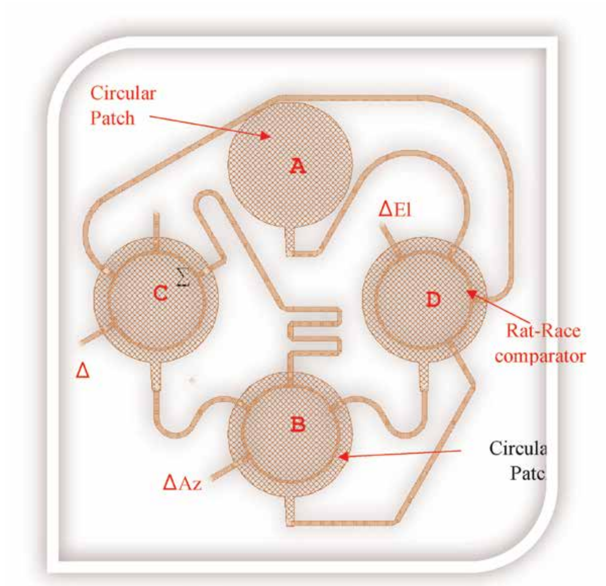

Figure 22.
A microstrip stacked monopulse antenna and monopulse comparator [5].

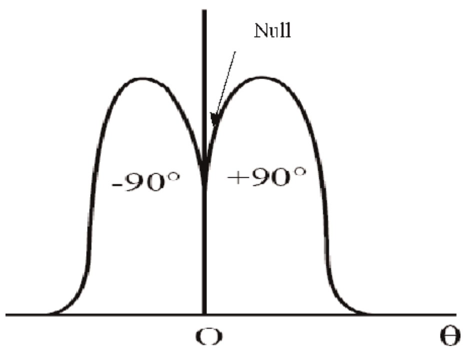

Figure 23.
Monopulse antenna radiation pattern at the Δ port.

presented in **Figure 23**. A high angular accuracy in the tracking process is achieved by comparing the sum and difference signals. A unique tracking algorithm is implemented inside the monopulse processor. The monopulse antenna presented in **Figure 23** uses four stacked circular patch antennas that are connected to a monopulse comparator to get the sum radiation pattern and the difference radiation pattern of the antenna in the azimuth and elevation plane. The concept and theory of momopulse antennas and comparators are presented in several publications [4, 5].

4. Conclusions

RF technologies, such as MIC and MMIC, are employed in this chapter to develop indoor positioning system (IPS). In design and development of RF devices for IPS systems, we can use the features and benefits of these technologies, such as MIC and

MMIC, to design transmitters and receivers for IoT, IPS, and communication systems. The cost of MMIC amplifiers, mixers, and other MMIC modules in huge production numbers is significantly cheaper than MIC modules. Design considerations of components and antennas for IPS systems were presented in this chapter.

Efficient metamaterial antennas for indoor posting and direction-finding systems were presented in this chapter. A circular microstrip antenna with SRRs was developed. The circular antenna bandwidth is around 6% for VSWR, better than 2:1. The antenna bandwidth is around 8% for VSWR, better than 3:1. The antenna beam width is around 82°. The measured antenna directivity and gain is around 7.6 dBi.

The monopulse antenna bandwidth is 10% for VSWR, better than 2:1. The antenna beam width is around 36°. The measured antenna gain is around 10dBi. The depth of the null in the difference radiation pattern is lower than −20 dB.

RF technologies such as MIC, MMIC, and metamaterials are used to develop IPS devices, smart devices, medical health monitoring systems and devices, and IoT devices.

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This book explores innovations in indoor positioning systems (IPS). An IPS is a network that continuously and in real-time detects the position of a person or an object within indoor environments such as warehouses, buildings, rooms, and so on. IPS has many applications in inventory-tracking industries, medical applications, retail, military operations, and other commercial sectors. The book provides readers with essential information on the basic theory of IPS systems, their architecture and modules, algorithms for optimizing the positioning of people and objects, as well as the innovations, limitations, and future trends within the IPS field. It highlights key features of IPS, such as accuracy, coverage and scalability, adaptation to environmental conditions, and cost. The book also discusses the integration of Artificial Intelligence (AI) into IPS. By leveraging AI technology, IPS devices can achieve remarkable accuracy and adapt effectively to dynamic environmental conditions and human behaviour. AI enables IPS systems to not only locate individuals but also to understand and predict their movements and behaviours in indoor spaces. The book also explores novel localization techniques for unmanned aerial vehicles (UAVs) and discusses the development of radio frequency (RF) IPS modules and printed antennas. Additionally, the book discusses how MIC (Microwave Integrated Circuits) and MMIC (Monolithic Microwave Integrated Circuits) technologies can be employed in developing RF devices, including transmitters and receivers for IPS systems. Microstrip mono-pulse antennas are presented as effective tools for determining position and direction in both IPS and radar systems.

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