Precision Positioning for Smart Logistics Using Ultra-Wideband Technology-Based Indoor Navigation: A Review

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ABSTRACT Logistics is an important driver for the competitiveness of industries and material supply. The development of smart logistics, powered by precise positioning and communication technologies can significantly improve the efficiency of logistics. The emerging technology of ultra-wideband (UWB) precision positioning has attracted significant attention throughout the previous decade owing to its promising capabilities over other radio frequency-based indoor localisation systems. In addition, UWB is characterised by large bandwidth and data rate, short message length, low transmission power and high penetration capability, which are all favourable for indoor positioning applications. However, UWB localisation technology faces several challenges that are somewhat similar to other technologies, such as mitigating errors that originate from non-line-of-sight (NLOS) situations and tackling signal interference in dense environments, and when required to operate in extreme conditions. This paper reviews the most recent advances made in UWB positioning systems over the last five years, with a focus on high-ranking articles. In addition to going through more conventional solutions to UWB challenges, modern solutions, which involve the use of machine learning and sensor data fusion, are discussed. We highlight the most promising findings of the recently implemented and foreseen UWB positioning systems by providing a summary of each reviewed article. Additionally, we address a major challenge that faces the UWB positioning technology: NLOS situations, focusing on some proposed remedies such as multi-sensor fusion and machine learning. As an application, this study introduces how UWB technology promotes smart logistics by offering indoor positioning to improve efficiencies in the delivery of goods from the source to the customer. Furthermore, it demonstrates the benefits of UWB technology for accurate positioning and tracking of both stationary and moving items, and machinery in an indoor logistics environment.

INDEX TERMS Ultra-wideband (UWB), indoor positioning systems (IPS), smart logistics, navigation and localisation, machine learning, sensor fusion.

I. INTRODUCTION

In recent years, the importance of indoor positioning systems (IPS) has been significantly increasing due to the rapid development and popularization of smart devices and technologies. The extensively used technology for positioning is the global navigation satellite systems (GNSSs) that provide reliable outdoor positioning information. However, due to the

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rather weak signals, their performance in the indoor environment is not sufficient. In addition, indoor surroundings are usually complex and varying in nature due to transferable obstacles that cause variation of signal and noise levels [1]. In such situations, substantial research and development of indoor positioning systems are required with alternative wireless technologies such as Wi-Fi [2], geomagnetic field [3], Bluetooth low energy (BLE) [4], dead-reckoning technique [5], ultra-wideband (UWB), and radio signal tags [6].

Precise location information of people and assets is a crucial element for Internet of Things (IoT) and smart logistics applications [7]. The various IPS technologies have been widely adopted by researchers and industrial companies during the past decade due to their broad spectrum of applications, including smart logistics [8], tracking medical equipment in healthcare centres [9], tracking individuals in crowded venues [10], ship-building and offshore industry [11], and construction industry [12].

There are numerous indoor localisation technologies with diverse properties. They are often distinguished by positioning accuracy, system robustness, computational power and cost. When compared to indoor positioning technologies using narrowband signals, such as Bluetooth and Wi-Fi, UWB has many advantages [10], [13].

An UWB signal contains different frequency components due to its wide bandwidth, which increases its probability of penetrating obstacles. In addition, because of its low power spectral density, UWB does not interfere with most other radio systems. Because of its short pulse duration, UWB yields high ranging accuracy and good performance under multipath conditions.

Several technologies have been proposed for obtaining a tracking solution in indoor logistics. The selection of an appropriate technology mainly depends on the required precision, number of assets that need to be tracked and speed of the moving assets. Compared to other available technologies, UWB can provide low-cost accurate positioning within few centimetres accuracy; hence, it is frequently used in industrial environments such as smart factory [14], smart logistics [15], [16], warehouse management [17], vehicle localisation [18], robot positioning [19], and smart city [20]. UWB enables simultaneous real-time tracking of objects and provides their localisation despite indoor obstructions due to the advantage of working under non-line-of-sight (NLOS) conditions [21], [22]. UWB technology enables an efficient combination of accuracy, scalability and reliability, which are very crucial in the applications of indoor logistics, such as tracking people and assets, and controlling the automated guided vehicles (AGVs) [23], [24].

Numerous survey articles were presented throughout the past decade with a focus on addressing UWB as an IPS. For example, in 2016, Alarifi *et al.* [10] published their comprehensive survey paper that presented UWB-IPS technology with new taxonomies as well as analysing the strengths, weaknesses, opportunities, and threats (SWOT) to form a widely acknowledged state-of-the-art review. Similar approach to Alarifi, was presented by Mazhar *et al.* [25] in 2017. Another survey article that was focused on IPSs in general and UWB in particular was Yassin *et al.* [26], in which the authors presented a detailed review about the structure and challenges of UWB-IPS compared to other IPS technologies. More surveys are tacitly cited throughout the article and discussed in the relevant sections.

This paper highlights the advances achieved in the realm of UWB localisation during the past half-decade, with a focus on the most recently published literature found from IEEE Xplore, Google Scholar and Crossref platforms. The search terms were limited to "Ultra Wideband" AND "Positioning" OR "Localisation" within the last five years. In addition to the newness of the articles, their selection criteria were based on impact, relevance, higher ranking in the Finnish national system [27], novelty and citation score. However, some older articles were also included due to their importance and the unchanged scientific principles that they describe.

Note that the addressing of UWB throughout this article is intended to review UWB as an IPS rather than a communication system. Hence, we focus on presenting the recent momentum of UWB technology from an IPS design perspective.

Throughout the article, a particular focus was given on applying the UWB technology to deploy indoor positioning in smart logistics systems. For smart logistics, indoor positioning plays an essential role by tracking resources, materials and employees in real-time. This location-based indoor navigation enables logistics providers with asset tracking with reduced search times, process automation and optimisation, increased efficiency and safety for employees [17], [28]. In the case of assets tracking, indoor positioning offers real-time seamless tracking of goods, pallets, vehicles and monitoring of goods' conditions, such as temperature, humidity and dew points. For process automation and optimisation, IPS supports automation through precise geo-based task assignments. By providing precise positioning, IPS provides added safety and security in logistics sites with access authorisations and ensures faster evacuation of employees in case of emergencies [23], [24].

The main contribution of this article is to present the most recent advances in the fast-developing UWB precise positioning technology with a focus on smart logistics applications that can embrace the technology to achieve better system enhancements and optimisations. The availability of new UWB chips at affordable prices has catalyzed the development of new algorithms for new application areas, including machine learning, sensor fusion and collaborative positioning. This article dissects the topic thoroughly down to the basic concepts of localisation and algorithms besides keeping a compact style of summarizing the literature to help researchers and industrial firms cope with the recent advances in UWB technology and its foreseen future.

In addition, a major objective of this review is to provide the researchers, practitioners of smart logistics and related fields with a starting point to understand the potential and limitations of UWB indoor navigation. To the best of our knowledge, other existing reviews have not adopted a similar approach. This article explains the fundamentals of positioning techniques and algorithms not only at the detailed mathematical and algorithmic level but also at the conceptual level. Commercially available equipment is presented, as well. Moreover, numerous articles are summarized in several application-specific tables to easily compare the methods and algorithms in the selected application areas.

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Consequently, also readers who do not have previous knowledge of positioning techniques can utilize this article to obtain the basic knowledge of UWB positioning and its use in smart logistics.

The rest of the article is organized as follows: Section II contains a brief review of existing IPSs and presents the role of IPSs in smart logistics. Section III discusses the advantages and challenges of UWB, licensing and regulations, signal attributes, system architecture, and commercial applications.

Section IV explains the observables and positioning technologies used with UWB. Section V discusses positioning algorithms, such as least-squares methods, closed-form solutions and various kinds of Bayesian filters. In addition, NLOS identification and mitigation methods are explained. Recent advances in UWB positioning literature is stated in Section VI, whereas advances in sensor fusion techniques are elaborated in Section VII. As the last few years have witnessed a surge on the literature on the adoption of artificial intelligence (AI) solutions, various machine learning (ML) approaches for UWB are discussed in Section VIII. A final discussion on indoor positioning is stated in Section IX, while, the paper is concluded in Section X.

II. INDOOR POSITIONING SYSTEMS

An IPS is a real-time system that uniformly calculates the location of an agent or object, moving or stationary, inside buildings [10], [29]–[31]. An IPS has facilitated numerous navigation applications that require continuous knowledge of the indoor locations of people and objects. It provides assisted navigation for limited-sight and vision-impaired people, tracking of visitors in heavily crowded venues, such as airports and malls, and automated guidance in tourist attractions. Industrial applications use IPSs to ensure precise navigation of industrial robots and accurate positioning of personnel, tools and equipment. Medical applications include monitoring of patients in hospitals and healthcare centres, localisation of crucial medical equipment and enabling navigation for medical robotic assistants [10].

Outdoor positioning has been made feasible owing to GNSSs, such as Global Positioning System (GPS), Galileo, GLONASS and stand-alone cellular positioning systems [31], [32]. However, these systems perform poorly in indoor venues due to the satellite signal deterioration caused by signal attenuation, shadowing and multipath fading imposed by indoor concrete and metallic structures [26], [32]–[34]. Thus, accurate indoor positioning techniques have been proposed to address the deep fading of conventional positioning methods. In addition, hybrid approaches have been proposed to combine multiple indoor and outdoor positioning techniques to mitigate errors and provide more accurate and robust navigation. Numerous indoor positioning techniques can provide positioning accuracy of only a few centimetres as stated in [10], [26], [30]. However, combining multiple indoor positioning techniques requires scrutinised studies to allocate suitable resources for each method and identify the optimal combination as the resource

requirements vary from method to method. The optimisation objectives and constraints may concern the energy budget, RF bandwidth budget, infrastructure costs, number of beneficiaries (users) and active time budget.

A. SMART LOGISTICS AND MANUFACTURING

Nowadays, smart logistics is considered a fundamental pillar of Industry 4.0. It enables companies to orchestrate several critical activities, such as demand forecasting, sales planning and inventory management [35], [36]. Smart logistics or 'Logistics 4.0' promotes the acceleration of all logistics processes through planning and controlling with smart tools, technologies and methods. The use of smart technologies helps to gather the necessary information to monitor and control the material flow and for many other purposes. Through intelligent positioning technologies, tools and equipment, global supply and logistics chains are becoming increasingly efficient and effective [37]. Such positioning technologies significantly contribute to end-to-end visibility, improvement in product routing as well as control and replenishment of inventories and mobile assets [38]. A generic supply and logistics chain is displayed in Figure 1, which is divided into inbound and outbound supply and logistics chains.

Smart logistics is considered a fairly complex phenomenon that can be easily applied in geographically dispersed areas for tracking raw materials of the highest quality but lowest cost. Such a phenomenon is generally characterised by the use of new technologies, such as IoT, 5G, sensors, radio frequency identification (RFID) tags, smart products, actuators and intelligent machines [38], [39]. It has the ability, reliability, traceability and authenticity of the information, which are useful to establish intelligent contractual relationships among the stakeholders of the supply chains. Moreover, smart logistics includes considerable potential for improving the logistics process through the application of communication and information technologies at all levels of the value chain. Figure 2 displays the fundamental elements and functionalities of the smart supply and logistics chain, showing that it starts from the supplier and eventually moves forward till the end customer through smart transportation, manufacturing, smart warehousing and smart delivery stages.

Figure 2 also shows that, at each stage in the smart supply and logistics chain, several activities are orchestrated. For instance, at the transportation stage, activities such as traceability of items, location tracking and real-time routing are orchestrated and monitored for smoother operations. Tracking logistics items is an essential issue in today's supply chain and inventory management. In addition, finding items both in indoor and outdoor environments is most critical in any supply chain and logistics management [40]. Due to the trend towards autonomous systems, most logistic systems today are operated without the direct involvement of the workforce to control them. In such a changing environment, smart logistics can be helpful to deliver items through various available precise positioning technologies [41], [42].
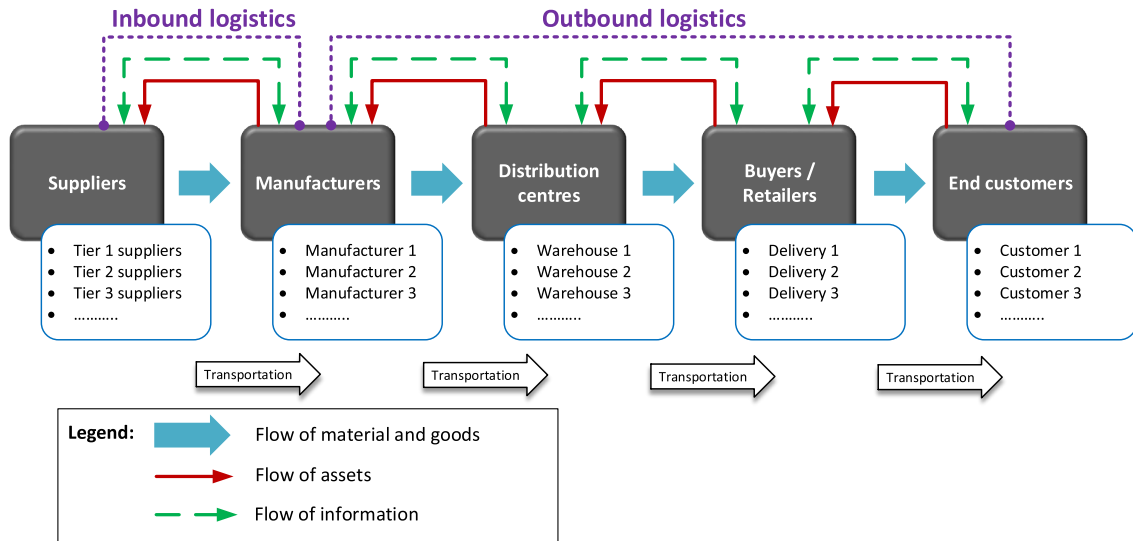
FIGURE 1. Various stakeholders and the flow of material, assets and information in a generic supply and logistics chain.
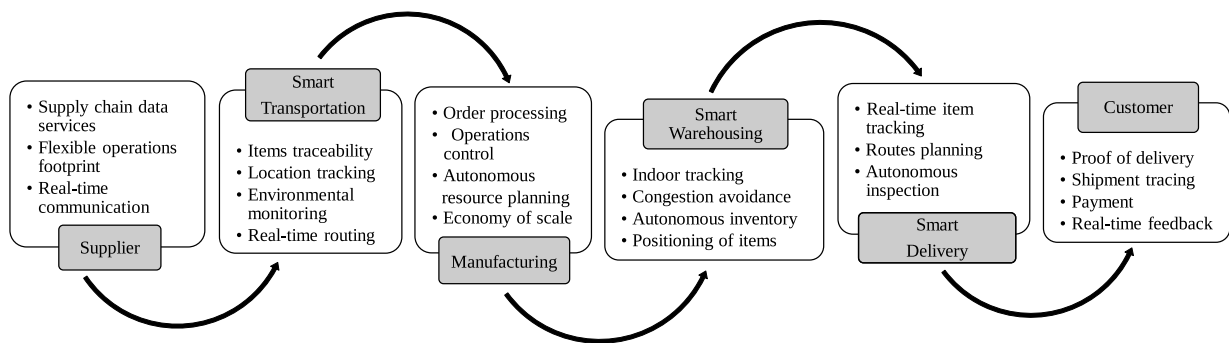

FIGURE 2. Fundamental elements and functionalities of smart supply and logistics chain.

Although several technologies are available to provide outdoor positioning towards logistics items, most of them are not suitable for indoor positioning. In indoor environments, such as warehouses and factory floors, precision positioning of components, parts and products can be achieved through available technologies, such as UWB, Wi-Fi, 5G, 3D imaging, sensors and imaging radio signals [25], [43], [44]. The application of such technologies helps to track indoor logistics items, which can help in minimising the time required to locate items and avoid delays due to the wrong location. A precision positioning technique enables the automatic delivery of goods by using uncrewed intelligent vehicles and aerial vehicles (UAVs) to designated locations while reducing environmental influences.

B. INDOOR POSITIONING SYSTEMS IN SMART LOGISTICS AND MANUFACTURING

Due to the recent advancements in indoor positioning technologies, a growing interest has emerged to utilize location data in logistics and manufacturing. Location data of assets and materials can be used to improve the efficiency, safety and security of manufacturing operations. Real-time tracking of machines and materials yields new possibilities to improve the production processes and follow the material flows. The authors of [45] divided logistics units into six identification layers: (0) raw material (items), (1) package, (2) transport unit, (3) unit load (pallet), (4) container and (5) transportation unit (e.g. truck, ship and train). GNSSs are typically used for tracking containers and transport equipment (two highest layers). However, the smaller cargo units (layers 1-3) are typically handled indoors, which can be tracked using indoor positioning technologies, such as UWB. However, UWB is still a relatively expensive and power-consuming technology, and RFID is a better technology to track the materials and lowest level packages and items.

Real-time location tracking is increasingly attracting global logistics companies due to the need for visibility. Especially, the application of IPSs in logistics and manufacturing

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has increased recently [46]. In the case of an indoor environment, such as a warehouse, an IPS contributes to tasks such as minimising the time spent to look for the right pallet, optimising routes and preventing accidents. In the case of smart logistics, companies generally use RFID technology, which can track the inventory and identify goods [42], [47], [48]. However, the limited power source of RFID tags minimises their operational range to a couple of metres. Therefore, they are mainly used for identification rather than positioning purposes. Similarly, Bluetooth and Wi-Fi are also used for indoor positioning, but their operating ranges are no more than 3-5 m [49]. To obtain accurate positioning of logistics items, companies are nowadays exploring UWB-based positioning systems, which enable real-time positioning of goods, assets and people with an accuracy level of 5 to 30 cm. It can provide out-of-the-box localisation with higher ranging accuracy than Wi-Fi or Bluetooth or other active radio solutions [50], [51].

In the case of autonomous robots operating in indoor environments (e.g. warehouses), accurate positioning is essential for navigation. While GNSS-based localisation is unreliable in indoor environments, localisation by UWB technology can accelerate the adoption and ubiquity of distributed robotics systems. Nowadays, UWB-based technology is commonly used in indoor robotic applications from home cleaning to warehouse transportation, including the rapidly emerging autonomous last-mile delivery solutions [46]. In the case of intelligent manufacturing, it is essential to track the parts along the production chain to take the right decisions. Real-time tracking of both stationary and moving parts in the production floor ensures safer operation with a reduced lead time [52], [53]. In addition to parts, it is also essential to track workers' movement on the production floor to enhance operational flexibility. For smart manufacturing, UWB-based location technology is suitable because of its inherent accuracy and reliability [15], [54]. It is considered as the most optimal and accurate approach to ensure indoor localisation [55]. By providing indoor localisation and tracking solutions for vehicles, people and goods, UWB technology promotes increased transparency, safety and productivity in internal logistics on the factory floors [55].

C. PERFORMANCE METRICS OF INDOOR POSITIONING SYSTEMS

The performance of localisation technologies can be assessed using a pyramid-like scheme with system accuracy as the baseline, integrity as the second metric, continuity as the third, and availability as the peak paramount [56]. System accuracy is the degree of conformance of the estimated positioning values to the ground truth. The integrity of localisation systems, as defined by [56], is the trustworthiness of the information provided by the navigation engine. Continuity is the probability of the system to maintain the desired service level within the operation period, while availability is the percentage of time in which the navigation engine is up-running for positioning and can be used by its intended users.

Accuracy of the estimated position is one of the most important performance metrics for indoor positioning systems. Accuracy is often reported as the error distance between the estimated and actual locations, while a location precision is reported in percentages of position information, which is within the distance of accuracy. The most commonly used metrics of accuracy and location precision are the root mean square error (RMSE), the mean absolute error (MAE), the distance root mean square error and circular error probability.

The accuracy of the location estimate depends on the accuracy of individual measurements and the mutual geometry of the tag and anchors. In the time of arrival (TOA) and time difference of arrival (TDOA) methods, the accuracy of the position is expressed as the product of a geometric factor and a range measurement error factor.

In addition to the above mentioned metrics, there are other performance metrics presented in the literature, such as scalability, cost and privacy [10]. The scalability of IPS describes how many tags the system can support per time unit per geographic area. The cost measures the physical limitations and requirements associated with the implementation of a particular technology in terms of technical and financial resources. Money, power consumption and hardware dimensions are examples of cost metrics. Privacy is a concern in network-centric systems, where the location estimation takes place in the server. In the self-positioning model the device estimates its own position, and no one else may know where the device is. Coverage was mentioned as an important parameter [10]; however it can also be considered a property of IPS rather than a performance metric.

D. INDOOR POSITIONING TECHNOLOGIES

IPSs can use various signal technologies, such as radio frequency, infrared, ultrasonic, inertial, optical and electromagnetic [10], [57]. In addition, the positioning system commonly estimates the location of the target device by fusing measurements of two or more signal technologies. The indoor positioning applications have various requirements in terms of the performance metrics. Thus, the technology should be carefully chosen to satisfy these requirements [10]. For example, the navigation systems of AGVs might require highly accurate and reliable position estimates, but the power consumption or price of the sensor mounted in an AGV is not critical. In contrast, low price and power consumption are required from the tags used to locate people and assets in a warehouse, but the accuracy of the position estimate is less critical than that in AGV applications.

Laser triangulation is commonly used in the indoor navigation of AGVs [58]. The laser positioning system uses a laser scanner mounted on top of the vehicle. The laser scans the mirrors mounted at the known locations in the area and measures the angles between the vehicle and device. The vehicle's position is estimated using triangulation with centimetre-level accuracy. Another commonly used approach for AGV navigation is to use light detection and ranging (LiDAR) and inertial motion unit (IMU) measurements [59] or

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TABLE 1. Summary of RF-based signal technologies for local positioning systems.

Technology	Typical Accuracy	Range	Method
UWB	2-50 cm	15-50 m	TOA/TDOA trilateration
Wi-Fi RSSI	< 10 m	35 m	Location fingerprinting
Wi-Fi CSI	< 5 m	35 m	Location fingerprinting, AoA
Wi-Fi RTT	> 1 m	35 m	TW-TOA
Bluetooth RSSI	< 5 m	< 50 m	Location fingerprinting
Bluetooth DF	< 1m	< 50 m	AOA, AOD
5G sub-6 GHz	3-10 m	0.5-2 km*	TDOA, TW-TOA, AOA, AOD
5G mmWave	0.2-0.5 m	200 m	TDOA, TW-TOA, AOA, AOD

* Depends on the frequency and the transmit power

TABLE 2. Different communication band usage scenarios and their terminology.

Band Type	Fractional Bandwidth B_F	Band Ratio $b_r = \frac{f_h}{f_l}$
Narrowband (NB)	$0.00 < B_F \leq 0.01$	$0.00 < b_r \leq 1.01$
Wideband (WB)	$0.01 < B_F \leq 0.25$	$1.01 < b_r \leq 1.29$
Ultra-Wideband (UWB)	$0.25 < B_F < 2.00$	$b_r \geq 1.29$

image-based (visual) localisation [60] together with simultaneous localisation and mapping (SLAM) algorithms.

However, the laser and vision-based technologies are relatively expensive, and their energy consumption is too high for the tags required in the applications to locate people, materials and assets. In such applications, radio frequency-based signal technologies are commonly used for positioning. An RF signal is used for positioning for the same reasons as it is used for communication. The most important advantages of RF signals are that they can penetrate obstacles and have a wide communication bandwidth. RF-based IPSs use RFID, UWB, wireless local area network (WLAN), Bluetooth or cellular network signals for location estimation [10]. The position can be estimated from the signals of these systems by using proximity information, trilateration, triangulation or location fingerprinting methods. The properties of these systems are summarised in Table 1.

In the case of RFID, the proximity method is generally used. Location fingerprinting, which provides a room-level or couple of metres accuracy, is commonly used with WLAN [61] and Bluetooth [62] received signal strength indicator (RSSI) measurements. RSSI describes only the average attenuation of the signal in the communication channel. More accurate and stable results may be achieved using channel state information (CSI), such as channel impulse response (CIR), which contains more information than a single RSSI value [63]. Some researchers used an antenna array in a Wi-Fi network to estimate CSI, thus, enhancing the accuracy and stability of the fingerprinting positioning system to a few metres [64], [65]. A WLAN signal can also be used for trilateration using the Wi-Fi round trip time (RTT) measurements, referred to as 802.11mc [66]. In Bluetooth direction finding (DF), the target's position is estimated using the triangulation method with the angle of arrival or departure measurements of Bluetooth signals. According to the authors

of [67], Bluetooth DF can achieve accurate measurements if not severely affected by multipath interference. Future 5G NR mmWave technology is expected to provide centimetre-level positioning accuracy and one degree orientation accuracy for the device when the TOA, TDOA and angle of arrival (AOA) are used [68].

UWB is well suited for many positioning applications. In the case of UWB, the position can be estimated with centimetre-level accuracy using triangulation or trilateration positioning methods or both, as discussed in subsequent chapters.

III. UWB POSITIONING

UWB is a wireless short-range radio technology whose communication channel propagates information over a wide spectrum by modulating either a carrier-based waveform or a carrier-less baseband signal in the form of short-width pulses [69]. According to the Federal Communication Commission (FCC) and the International Telecommunication Union (ITU)-R, UWB possesses a spectrum that occupies a bandwidth greater than 20% of the central frequency or has a bandwidth of at least 500 MHz. A UWB RF signal occupies the ultra 500 MHz bandwidth, which facilitates the transmission of large data sizes upon the consumption of lesser energy than other technologies [10], [31], [70]. To differentiate among narrowband (NB), wideband (WB) and UWB, the FCC classification scheme adopts fractional bandwidth calculation, B_F which is a dimensionless frequency-independent indicator, calculated using Equation (1) as follows: [70], [71]

$$B_F = 2 \left(\frac{f_h - f_l}{f_h + f_l} \right) \tag{1}$$

where f_h, f_l are the higher and lower frequency bands of the signal, respectively. Hence, the band type is determined using the data shown in Table 2 [70].

In 2002, the FCC described UWB technology as an emerging promising technology that holds great advances for various applications [72], such as imaging systems, ground-penetrating radars (GPRs), wall-imaging systems, medical systems, surveillance systems, vehicular radar systems, communications and measurements systems [73]. UWB can transmit high data rates using tiny pulses of the spectrum spread over wider frequency bands with low PSD, which provides the signal higher penetration capability than most RF waves. Moreover, some types of UWB signals (e.g. impulse radio UWB) do not require sinusoidal carrier waves, which

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in turn reduces the power required for transmission. The combined advantages of a UWB signal makes it a prominent candidate for real-time applications, such as 1) tracking and navigation, 2) sensor network communications, 3) ranging and imaging, and 4) extremely high-data-rate short-range communication (e.g. wireless UWB).

Recently, UWB has been widely adopted in personal area networks (PANs), precise indoor positioning, indoor tracking and navigation systems. UWB positioning relies on the unique radio frequency characteristics associated with UWB technology to provide accurate estimates for indoor locations based on the TOA, AOA and TDOA of the signal. The UWB positioning signal takes the form of a low-power short-pulse transmission with large bandwidth [10], [31], [70], making it robust, precise and secure.

A. ADVANTAGES AND CHALLENGES OF UWB COMPARED TO OTHER INDOOR POSITIONING TECHNOLOGIES

1) ADVANTAGES

UWB was first commissioned by the FCC for public use in 2002. Earlier, it was utilized solely by the US military for classified applications [13]. The structure of a UWB signal comprises the transmission of short pulses within large bandwidth ranges between 3.1 and 10.6 GHz, which yields UWB superiority over NB signals. Owing to the large bandwidth and short duty cycle, UWB possesses a larger capacity and higher data rate, which make it a suitable candidate for RF-based IPS implementation. Moreover, UWB lies in the unlicensed spectrum, which can be used by anyone without prior notification. Additionally, the pulse nature of the UWB signal increases its penetration capability. Therefore, UWB tags on mobile targets do not require a direct line of sight (LOS) with its anchors.

However, some scenarios found in dense environments might have negative effects on the UWB signal, causing multipath deterioration and interference with neighbouring frequencies in the spectrum [10]. In addition, the low transmission power can be ineffective in large-sized indoor spaces, as it disallows the signal from travelling to longer distances due to path loss attenuation. Hence, additional UWB anchors are required, which increases costs and complexity [13].

UWB offers numerous benefits over narrowband signals, which widens the range of affected applications. First, UWB is an unlicensed free spectrum that can be used without prior licensing. The UWB spectrum was made free for commercial use in 2002, but before that, it was restricted to military operators, mainly the Department of Defense, for classified applications [13]. UWB has a larger bandwidth than other positioning techniques, ranging from 3.1 to 10.6 GHz [73], [74], which provides it with the superiority in many aspects. For example, based on Shannon's law, the large UWB bandwidth provides large capacity for an RF signal, which implies a high data rate transmission that can support real-time applications, such as instant video streaming [13], [73]. Owing to their large bandwidth, UWB communication
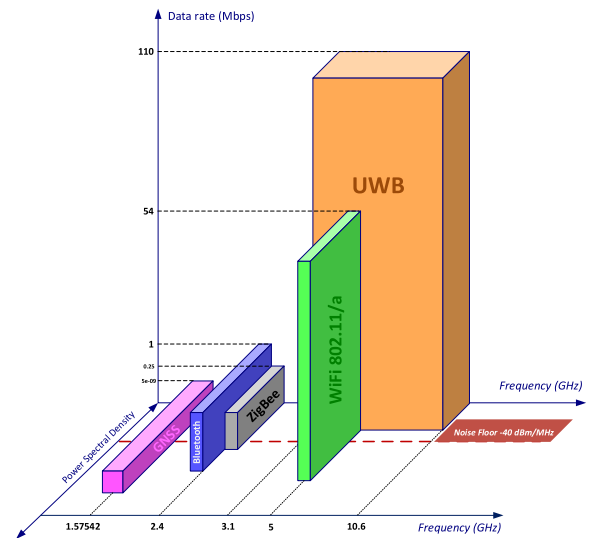

FIGURE 3. Comparison between the attributes of UWB and other various positioning technologies (the dimensions of the shapes are only indicative).

systems are highly robust, operating at higher data rates (110 Mbps) than other RF technologies, making it the highest data rate achieved so far in the precise positioning realm. Another benefit of the large bandwidth is the UWB system's capability of performing in low signal-to-noise-ratio (SNR) communication channels [13], which provides immunity against multipath degradation. The high level of multipath resolution is mainly attributed to the nature of pulse-based RF communication, which occupies the entire bandwidth for each pulse, unlike other carrier-based communications [75], UWB systems do not require a clear LOS, but the UWB communication is perfectly possible under NLOS conditions. However, in positioning applications, NLOS situations might produce erroneous sensor readings, which can disturb the position estimation. Additionally, the short-pulse low-power nature of UWB signals is a major advantage of UWB, making it a suitable candidate for indoor positioning applications, as demonstrated in Figure 3 [26], [76].

Additionally, the UWB signal transmits at low average power due to the short-pulse nature of transmission, submerging it within the noise floor(-40 dBm/MHz), which helps in saving transmitter energy, enhancing the battery life and bestowing resistance against jamming and interception.

2) CHALLENGES

Although UWB technology offers numerous benefits for indoor positioning applications, the technology faces several challenges and drawbacks that affect its performance.

UWB technology is known for its coexistence with other RF systems, but this is not always true. The technical report published by the US National Institute of Standards and Technologies [77] stated that UWB can cause interference to existing nearby RF systems and vice versa. Examples

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of the potentially affected RF technologies are the GPS, 3G and WiMAX communication systems [10], [77] due to the misconfiguration of wireless transceiver devices. Many countries have imposed regulations to mitigate the possible interference, which are covered in the following sections.

The low power transmission of UWB is considered an advantage, yet it limits the overall power consumption for the transmitter and receiver. For example, the low-power UWB signal can either travel short distances at a high data rate or long distances at a low data rate [78]; hence, the range of the UWB anchor will be limited. This can only be compensated by using more UWB anchors, which limits the scalability [51], [79] and increases the system complexity and computational load, thus compromising the system accuracy and robustness. Additionally, the processing of wide-band signal usually leads to high power consumption [80]. The high power consumption can be mitigated using a multiband approach in which the signal is split into sub-bands. The sub-band processing method will be briefly discussed in subsection III-C3.

Another advantage that creates a challenging situation is the short pulse nature of UWB signals. The coding of short width pulses requires longer synchronisation times, limiting the data capacity. Moreover, the short-width pulses increase the number of multipath components [77], which also compromises the overall system performance. Researchers have proposed a solution for this issue by devising special schemes and protocols to avoid repeated synchronisation [77]. In addition, the authors of [81] proposed the use of multiple-input multiple-output systems to mitigate the effect of short communications. One last disadvantage of UWB is its limited usage outdoors. According to various countries' regulations, fixed UWB transmitters operating outdoors are not allowed [82], [83], refer to subsection III-B for more details.

B. UWB LICENSING AND REGULATIONS
The UWB bandwidth license is free for indoor applications, yet the regulations for UWB devices are country- or region-specific to define the technical requirements and certification procedures for legal and safe operation [84], and more importantly, to minimise the potential interference to licensed services [69]. These regulations comprise the boundaries and safety limits of the operating frequency, power levels, emissions, energy disruptions, service times and antenna locations. For example, the regulations for UWB devices in the United States are published by FCC in 2002 under the "Code of Federal Regulations Part 15, subpart F" [82], while those in the EU region are issued by the Harmonised European Standard in 2016 (the process started in 2006) under the radio equipment directive "ETSI EN 302 065 – 1 to 5" [83].

Additionally, these official UWB regulations distinguish between the different types and usages of UWB devices, and each type and usage has its own regulation. For example, the FCC has set specific rules for each category of UWB devices and their respective application, such as indoor UWB systems, handheld UWB devices, GPRs and wall imaging

systems, surveillance and transportation systems (e.g. UWB on-board aircrafts and UWB installed on rail vehicles) [69].

According to the FCC, the bandwidth of the UWB systems belonging to the indoor and the handheld categories must be kept between 3100 MHz and 10,600 MHz [82]. The indoor UWB systems may not be used outdoors, and they must be designed so that they are capable of operating only indoors. The emissions from UWB devices may not be intentionally directed outside of a building to perform an outside function. Also, the use of outdoor mounted antennas is prohibited. The device may only transmit when sending information to an associated receiver.

An UWB device belonging to the handheld category must be relatively small. These devices are primarily kept in hand while being operated, and they do not employ a fixed infrastructure [82]. Antennas may be mounted only on the handheld UWB device. The use of antennas mounted on outdoor infrastructure is prohibited.

Part 1 of the EU regulation "ETSI EN 302 065" contains requirements for generic UWB applications, and it applies to fixed (indoor only), mobile or portable applications [83]. The UWB transmitter conforming to that document may not be installed at a fixed outdoor location, for use in flying models, aircraft and other forms of aviation. Allowed operation frequency band is from 3.1 to 4.8 GHz and from 6.0 to 9.0 GHz.

Requirements for UWB location tracking are defined in Part 2 of the EU regulation "ETSI EN 302 065". This document covers three types of UWB location tracking system, of which two are applicable for smart logistics applications [85]:

- LT1 systems: These systems, operating in the 6 GHz to 9 GHz region, are intended for general location tracking of people and objects. They operate on an unlicensed basis. The transmitting terminals in these systems are mobile (indoors or outdoors), or fixed (indoors only). Fixed outdoor LT1 transmitters are not permitted.
- LT2 systems: These systems, operating in the 3.1 GHz to 4.8 GHz region, are intended for person and object tracking and industrial applications at well-defined locations. The transmitting terminals in these systems may be located indoors or outdoors, and may be fixed or mobile. They operate at fixed sites and may be subject to registration and authorization.

The regulation documents contain additional points describing the operation peak powers and tabulated emission limits for UWB devices, which vary regionally (e.g. US and EU). Both the ETSI and the FCC regulations allow the use of UWB indoor location tracking, which is very important for many industrial and smart logistics applications. However, the unlicensed outdoor use of UWB is limited to handheld or mobile devices. Because the FCC or LT1 of ETSI do not allow fixed outdoor transmitters, development of UWB outdoor positioning systems becomes difficult. Without transmitting anchors, it is not possible to use TW-TOA and multilateration for position determination. In addition, TDOA scheme with wireless clock synchronization is inapplicable, since

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the anchors must transmit synchronization messages to each other. Thus, the only possible way to implement outdoor UWB location system, operating under the provision of FCC or ETSI LT1, is to use TDOA approach with a wired clock synchronization. However, implementing the wired clock synchronization is complex and expensive.

LT2 of ETSI allows the fixed outdoor transmitters in the EU, but the LT2 systems are subject to registration and authorization. In addition, local coordination with possible interference victims has to be performed, and the possible permission would be granted only to a specific site [85]. Currently, developing an UWB-based positioning system for outdoor environment is very difficult.

In June 2020, the fine-ranging alliance (FiRa), the largest UWB consortium, was founded to pave the way for the widespread adoption of UWB-driven applications. Some well-known company members of the FiRa alliance are NXP, Samsung, Qorvo, Qualcomm, Cisco, Apple and BOSCH. The FiRa consortium is committed to providing seamless user experience through secured fine ranging and positioning capabilities of interoperable UWB technologies [86].

C. UWB SIGNAL ATTRIBUTES

The earliest attempt of UWB standardisation within IEEE standards was made by the WiMedia alliance workgroup in IEEE 802.15.3a-2003. This workgroup was responsible for standardising the physical and medium access control (MAC) layers of UWB indoor signals for wireless PANs. The detailed technical aspects of a UWB signal are described in the currently, active UWB standard (802.15.4z-2020), which was developed by the ''LAN/MAN Standards Committee'' of the IEEE Computer Society [87]. UWB signals can be generated using different techniques, the most popular of which is the impulse radio (IR) method. However, there are several other methods that can be adopted in UWB systems. The authors of [69] classified the types of UWB signals into the following six categories:

1) IMPULSE RADIO ULTRA WIDEBAND (IR-UWB)

The IR-UWB modulates the baseband signal through short pulses (order of nanosecond duration each), which have a low duty cycle to transfer information. The frequency spectrum characteristics of IR-UWB can be controlled by varying the pulse shape, phase, amplitude and duration to formulate the spectrum envelope of the signal. IR-UWB can be carrier-based, which requires an external high-frequency sinusoidal carrier signal and a mixer, or carrier-less, which can operate without a local oscillator (LO) in the transceivers, only using the baseband signal. The IR-UWB is typically the most adopted system and is standardised in the IEEE 802.15.4z UWB standard.

2) DIRECT SEQUENCE ULTRA WIDEBAND (DS-UWB)

Direct sequence spread spectrum (DSS) version of the IR-UWB forms the DS-UWB, which treats the signal by a pseudorandom number (PN) code before the amplitude modulation of a train of short pulses. The new bandwidth of the transmitted signal is affected by a spread code, which is typically much higher than the symbol rate at which the chip interval is longer than the pulse width.

3) MULTIBAND ULTRA WIDEBAND (MB-UWB)

The orthogonal frequency division multiplexing (OFDM) version of the IR-UWB can be considered to form the MB-UWB, in which the total bandwidth is divided into multiple frequency sub-bands (minimum 500 MHz each) to occupy the spectrum efficiently. The MB-OFDM approach utilizes the quadrature phase-shift keying (QPSK) modulation with 128 subcarriers and five-band groups containing two or three bands each (14 sub-bands in total). The MB-OFDM recently received approval from ISO/IEC and ETSI.

4) FREQUENCY HOPPING ULTRA WIDEBAND (FH-UWB)

It is a non-conventional carrier-based method in which the transmission occurs through fixed frequency hops over a broad bandwidth and using variant frequency carriers. The hopping sequence is determined by a spreading code or a PN sequence set by the user in which a narrow-band transmission occurs periodically, which can be smaller than (fast hopping), greater than (slow hopping) or equal to the symbol rate. The total spectrum bandwidth is determined by the range of hopping frequencies and not the symbol rate.

5) STEPPED FREQUENCY HOPPING ULTRA WIDEBAND (SFH-UWB)

SFH-UWB is a particular case of FH-UWB, in which the hopping frequencies are selected by the spreading code to form linearly increasing discrete steps until the desired bandwidth is achieved. Then, the hopping frequency is reset to the starting sequence, and the process is repeated.

6) SWEPT FREQUENCY ULTRA WIDEBAND (SF-UWB)

SF-UWB is also known as 'Chirp signalling'. It is the frequency variation of the FH-UWB, in which the carrier frequencies of the UWB waveform are generated by a voltage-controlled oscillator using a continuous variable speed. The symbols are modulated on the slope (chirp) using M-ary modulation and then sent sequentially or superimposed.

D. ARCHITECTURE OF UWB POSITIONING SYSTEM

A typical UWB indoor positioning system includes fixed UWB sensors (anchors), mobile UWB targets (tags), location server and system interface. The location server stores and processes the sensors data, and the system interface (e.g. smartphone, computer or tablet) is for viewing the positioning results, as illustrated in Figure 4. Planar, two-dimensional positioning requires at least three anchors to solve the coordinate equations of the tag, while three-dimensional positioning requires at least four anchors.

Additional optional units can be added to the previous structure to obtain a real-time location system (RTLS). For example, the location server is optional in small-scale
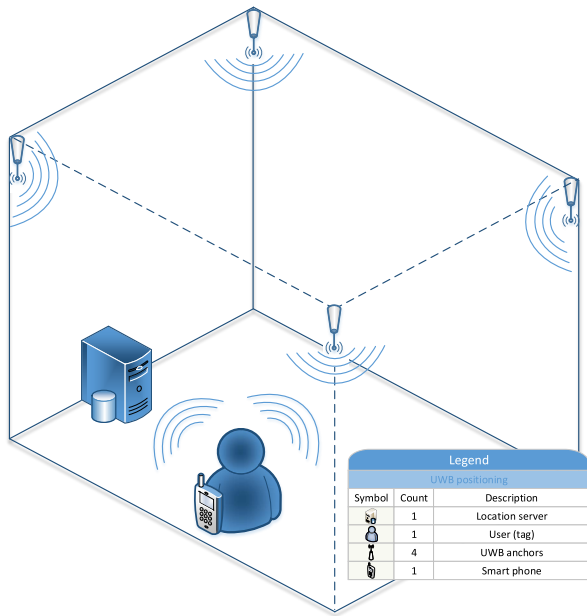
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FIGURE 4. Elements of UWB positioning system. User with a tag or mobile phone is located through UWB anchors. The location server can determine the position and provide an API for accessing the location information.

systems but crucial in large-scale systems. There are additional front-end and back-end units for complex indoor environments, such as navigation framework, network gateways, user interface and facilities for IoT integration or other accompanying multi-sensor technologies.

The process of UWB precise positioning commences with relative positioning between the anchors. A single initiator anchor is specified as a reference point or origin (0,0). An auto-positioning feature, such as Decawave's (Qorvo) RTLS application, measures the relative distance between all anchors and thus positions them in the coordinate system. A block diagram depicting an example of a complete process of UWB precise positioning is illustrated in Figure 5.

After fixing the coordinate system, the UWB system starts ranging the mobile UWB tag(s) within the indoor environment before sending the measured raw data to the positioning framework for additional processing. The positioning algorithm, which is pre-specified by the user, uses the raw measurements and a kinematic model to carry out position estimation. Precise position can be achieved by using the UWB system when the ranging method and the positioning algorithm are appropriate to the application and the properties of the environment.

Many applications in various environments require specific NLOS mitigation methods to improve the performance. This article focuses on two NLOS mitigation approaches, multi-sensor fusion and ML algorithms. Both approaches are discussed in detail in section VIII.

In the multi-sensor fusion approach, additional accompanying IPS technology is used to aid the UWB system with

a fusion algorithm that fuses data obtained from all sensors based on their weights and shares.

In contrast, the ML approach is designed using large offline data to train a learning algorithm to identify the outlier measurements caused by the NLOS conditions. This approach has its performance metrics as ML algorithms are assessed from the training and testing accuracies. Nevertheless, the overall efficiency of the system is determined by the combined metrics of each phase, in addition to the degree of relevance of the final positioning results to the ground truth.

E. COMMERCIAL PRODUCTS

The growing demand for location-based services in an indoor environment has increased the size of the UWB market during recent years. In addition, the recent advances in UWB technology have provided opportunities for new commercial applications.

The major manufacturers providing UWB chips for open markets are Qorvo and NXP. Qorvo entered the UWB market by acquiring the Irish semiconductor company Decawave in January 2020 [88]. Decawave has been one of the major providers of UWB technology during the past 15 years, along with some other companies, such as Ubisense and BeSpoon [89]. Decawave's UWB technology has been very popular and its chips have been used extensively in research [16], [90]–[93] and commercial IPS [94]–[97].

NXP launched its UWB precision chips in February 2020. Currently, NXP provides Trimension UWB modules for IoT, industrial, mobile and automotive market segments [98]. Trimension UWB modules can be used, for example, like tags or anchors in IPS systems, in mobile devices and in secure car access applications.

One of the most important markets for UWB is mobile phones. In 2019, Apple launched iPhones having an UWB chip called U1 [99]. Samsung released its first high-end mobile phones with UWB technology in 2020. Samsung was one of the founders of the FiRa consortium together with NXP and some other companies [100]. UWB technology provides new opportunities for mobile phone use cases, such as secure access control, location-based services and device-to-device communications. To support third-party application development, Apple has released its ''nearby interaction'' framework for developers and chipset manufacturers building UWB-based applications [101].

The automotive industry is developing UWB applications for secure access control and localisation. For example, Bosch's Perfectly Keyless key management system utilizes UWB in mobile phones for secure access control [102]. The vehicle access and start are controlled via a digital key on a mobile phone and the precise localisation of the phone.

IV. UWB POSITIONING TECHNIQUES

The positioning can be based on either multilateration or multiangulation techniques. When using multiangulation, the position of the unknown tag can be determined from known anchors geometrically by observing the angles of the received
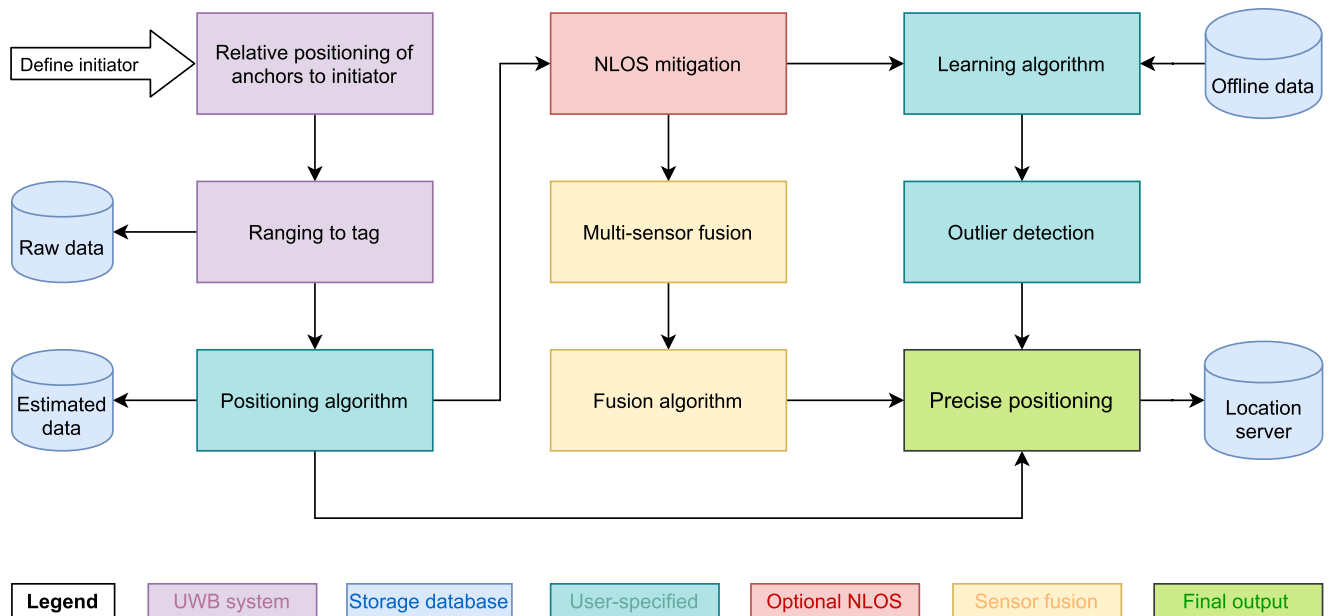
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FIGURE 5. Suggested building blocks of the UWB precise positioning process, based on the surveyed UWB literature.

signal either in anchors or in tags. When using multilateration, the ranges between the anchors and tags are obtained by measuring the time of flight (TOF) and multiplying it by the speed of light or by applying a channel attenuation model to the received signal strength (RSS) observations.

In general, the following four active strategies are used for estimating the TOF needed for multilateration:

- TOA: TOA of the signal is measured and subtracted from the known transmission time. The arrival timestamps are obtained by either using a precise clock (synchronous TOA) or by solving them together with the tag position by using at least N+1 anchors, where N is the number of spatial dimensions. The latter method is used in GNSS systems and is known as the pseudorange method. The clock synchronisation accuracy of the sub-nanosecond range is not feasible for moving targets [103], [104], and therefore, the pseudorange method is typically used.
- RTT: The RTT of signal propagation between two objects is measured, and the processing time is reduced to obtain double ToF. This method is also called two-way ranging (TWR) or two-way TOA (TW-TOA). The measurement is repeated between a tag and at least N anchors. This method is sometimes called asynchronous TOA. [105]
- Time of transmission (TOT): The arrival time of the signal sent by a tag is observed by at a minimum of N+1 anchors, and the TOT is solved together with the position of the tag.
- TDOA: The signal sent by the tag is received by at least N+1 anchors, which calculate the time differences of arrival times, avoiding the need for absolute time synchronisation in a tag.

The positioning techniques used with UWB are (1) TOA or TW-TOA; (2) AOA; (3) received signal strength (RSS); (4) TDOA and (5) a hybrid algorithm [10], [104]. The typical UWB system estimates position using a two-step procedure. In the first step, observables related to an unknown position of the tag and known positions of the anchors are determined. Among these, TOA, TDOA, AOA and RSS are given as examples [25], [26]. From these measurements, the RSS is considered the least suitable for use with UWB because its accuracy in an NLOS and a multipath environment is lower than that of time-based methods [104]. In the second step, the position of the tag can be computed using estimation methods such as least-squares (LS) method, Kalman filters (e.g. EKF and UKF) and particle filter (PF). In addition to the previous methods, some recent literature has adopted the AI approach through supervised learning to account for the position estimation in which the raw UWB data are compared with a trained ML model (e.g. support vector machine (SVM)) for predicting the unknown position of the target node [106]. Selecting a suitable positioning technique is vital to the whole precise positioning process as it affects the overall accuracy and defines the system complexity, and hence, the resources' total costs [76]. In this section, we summarise the most widely adopted techniques in the literature, highlighting their methodology, pros and cons.

A. ANGLE OF ARRIVAL

The position of an object can be estimated from the AOA or the angle of departure (AOD) of the signal. Each angle measurement defines a line between the base station and a mobile device. The object's location is determined from the intersection of these lines, as illustrated in Figure 6 a.
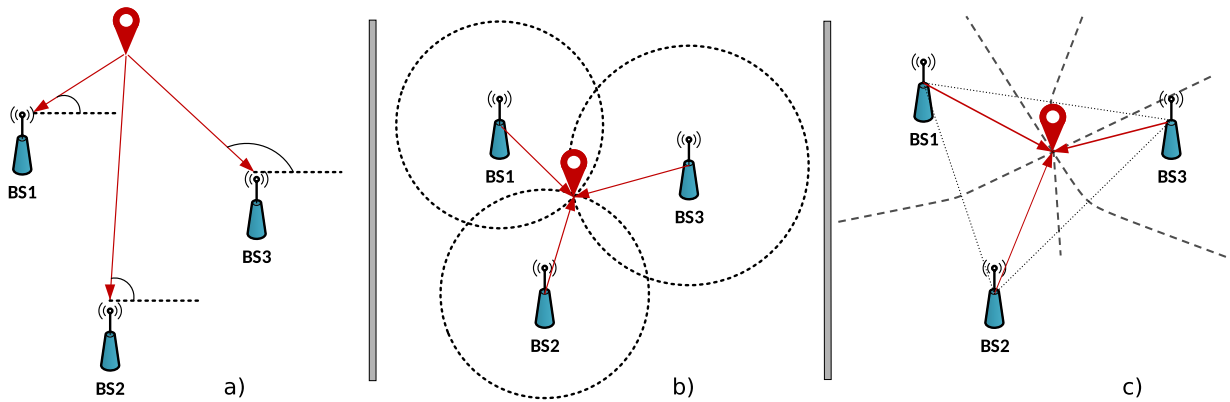
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FIGURE 6. Ranging and angulation techniques. a) AOA, b) TOA, TWR and RSS and c) TDOA. In AoA, TOA and TDOA techniques, the tag position is determined from the intersection of the lines, circles and hyperbolas, respectively.

In the AOA method, the tag transmits a signal using a single antenna, and the anchor (base station) receives the signal with multiple antennas arranged in an array. The signal direction is determined from different propagation delays of the signal between multiple antennas of the receiver antenna array and the single transmitter antenna.

In the AOD method, there is a single antenna at the receiver and multiple antennas arranged in an array at the transmitter. Usually, the anchor (beacon) transmits the signal, and the tag receives it. The signal direction is determined from different propagation delays of the signal between multiple antennas of the transmitter antenna array and the single receiving antenna.

The advantage of the AOA (or AOD) observable is that there is no need to time-synchronise the anchor clocks. However, the antennas have to be precisely calibrated to the correct orientation. The AOA can be measured with various techniques, but currently, antenna arrays are mostly used in positioning systems.

There is a significant advantage of using a UWB signal over a narrow band signal in phase difference-based AOA estimation. Due to the short duration of the pulse, the UWB receiver can separate the direct signal from the reflected signal better than the receiver of the NB signal [92].

In UWB-based systems, the AOA measurements are often used together with TOA or TDOA measurements [92]. For instance, the authors of [107] proposed an AOA estimation method for a UWB positioning system using a lower-cost single-anchor system. A centimetre-level UWB positioning system was proposed by [108] using a mono-station TOA/AOA positioning method. In addition, the cell phone applications of Samsung and NXP use both the TOA and AOA observables [109]. The Ubisense positioning system uses both AOA and TDOA measurements, but according to [89], this system is less accurate than the Decawave system, which uses the TOA observable only.

Authors of [110] have developed a TDoA-Based positioning system using a single hotspot. This hotspot consists of anchors placed very close to each other. The tag to be localised is around the hotspot. The system estimates the

range and AOA between the hotspot and the tag. According to the authors, the error in AOA estimate is less than 3 degrees when the target is in 15 m distance. The error in the estimated range may be 4 m.

B. TIME OF ARRIVAL
Most of the UWB-based positioning systems use the concept of TOA ranging to determine the user position. This concept is based on measuring the time taken for an RF signal transmitted by an emitter to reach a receiver. The time interval, due to signal propagation delay is multiplied by the speed of light to obtain the distance between the emitter and the receiver.

The TOA technique exploits trilateration to determine the position of the mobile users based on the range from the mobile unit to at least three (3D) anchors at known locations.

In the TOA method, the position is estimated by intersecting circles (2D) or spheres (3D) with radius r_i and centre (x_i, y_i, z_i), as illustrated in Figure 6 b. The radius of the circle r_i is obtained from the propagation delay of the signal. Point (x_i, y_i, z_i) is the known location of the anchor.

The 3D location of the object (x_u, y_u, z_u) can be derived from the set of nonlinear equations as in Equation (2):

$$\rho_i = \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2 + (z_i - z_u)^2} \qquad (2)$$

where i ranges from 1 to 3 and references the base stations at known locations, (x_i, y_i, z_i) denote the i-th base station coordinates in three dimensions and r_i is the range measured from the i-th base station.

The TOA method illustrated above requires the anchors and tags to be accurately synchronised. To avoid the synchronisation requirement, the TWR method can be employed to measure the signal propagation delay. The range between two devices is determined through the two-way exchange of a message and by measuring its arrival time. This method is also known as two-way time-of-arrival (TWR-TOA) or RTT.

The simplest version of the two-way ranging cancels the effect of the clock offset between the terminals, but the clock drifts of the terminals can still cause significant error
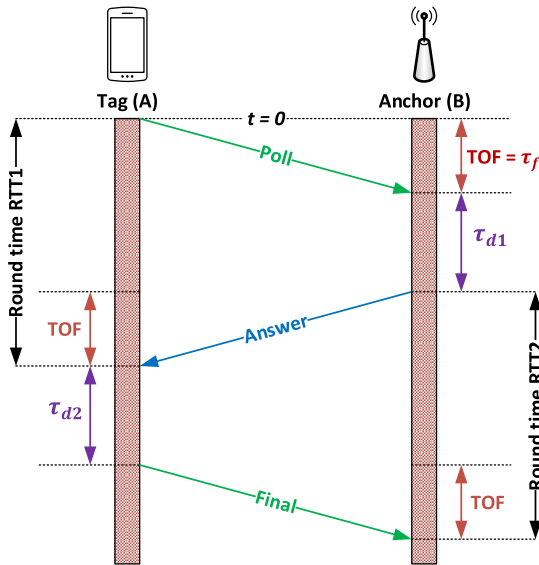
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FIGURE 7. Double-sided two-way ranging method to estimate signal flight time cancelling the effects of clock offset and drift.

in the signal flight time estimate. The error caused by the clock drift can be eliminated by making the two-way ranging measurement transaction two times [111]. This method called as double-sided two-way ranging is illustrated in Figure 7, and the TOF of the ranging message is expressed as in Equation (3):

$$\tau_f = \frac{1}{4}\left(\tau_{RTT1} - \tau_{d1} + \tau_{RTT2} - \tau_{d2}\right) \quad (3)$$

where τ_{RTT1} is the RTT measured by the tag, and τ_{RTT2} is that measured by the anchor. The terms τ_{d1} and τ_{d2} are the reply times of the anchor and the tag, respectively. τ_{RTT1} and τ_{d2} are measured using the tag oscillator, and both measurements are biased by the oscillator offset of the tag. Similarly, τ_{RTT2} and τ_{d1} are biased by the oscillator offset of the anchor. Double-sided TWR cancels these oscillator offsets.

C. TIME DIFFERENCE OF ARRIVAL

One method to obtain the signal propagation delay is the TDOA method, which measures the difference in the arrival times of two signals. The anchor clocks must be precisely synchronised, but the tags do not need to be synchronised. The tag position is obtained from the intersection of multiple hyperbolas (Figure 6 c).

The distance difference between the tag and the anchor where the signal arrives first, is expressed as in Equation (4): [112]

$$r_{i,1} = cd_{i,1} = r_i - r_1$$
$$= \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2 + (z_i - z_u)^2}$$
$$- \sqrt{(x_1 - x_u)^2 + (y_1 - y_u)^2 + (z_1 - z_u)^2} \quad (4)$$

where c is the speed of light, $r_{i,1}$ is the distance difference between the first and the ith anchor, r_1 is the distance between the first anchor and the tag and $d_{i,1}$ is the measured TDOA between the first and the ith anchor. Equation (4) defines a set of nonlinear hyperbolic equations whose solution provides the 3D coordinates of the tag.

In principle, the TDoA approach can be implemented in two ways, called as unilateral and multilateral techniques [113], [114]. In the unilateral system, the anchors transmit a signal and the tags measure the TDOA from the received signals. Also, the anchors transmit a signal with different time delays to avoid a signal collision. The unilateral technique has some advantages, such as infinite scalability in the number of tags [115]. As in GNSS, in the unilateral TDOA system the location privacy is preserved, since the position is estimated in the tag. However, in the unilateral architecture the design of the tag is complex and it has high energy consumption [114].

Because of the drawbacks of unilateral approach, most of the UWB-based systems using the TDOA scheme are based on multilateral technique. In multilateral approach the tag sends one message, often called a blink, and the arrival time is then measured by multiple anchors with respect to a common time reference. These arrival times are then sent to a master node or server, which computes the TDOA estimates by subtracting the arrival time of the pivot anchor from those of the other anchors. Thus, the number of TDOA estimates is one less than the number of arrival time measurements.

Even though the multilateral approach is less scalable than unilateral approach, it can still support many more tags than the TW-TOA system. In the multilateral TDOA architecture a tag needs to send only one message per range measurement, while in the TW-TOA scheme, several messages are required [51]. Scheduling techniques are needed to avoid packet collisions in the TW-TOA approach, limiting the number of supported tags. In the TDOA approach, the tags need not to be aware of the anchors, which makes message scheduling easier than in TW-TOA. The authors of [51] investigated the scalability of UWB-based indoor positioning for TDOA and TW-TOA approaches with different MAC protocol combinations. In the mathematical model proposed by the authors, when using a TDOA approach and time division multiple access (TDMA), more than 6000 tags per second can be supported in a single domain shell. The drawback of the TDOA method is that the anchors have to be accurately synchronised. Because the radio signal propagates at the speed of light, 1 ns time offset in the anchor clock would introduce a 30 cm error in the estimated range. Decawave DWM1001 achieves measurement accuracy within 10 cm in the TOA mode, which is equal to 333 ps accuracy in the propagation delay measurement. The synchronisation accuracy must be even better to achieve similar accuracy in the TDOA mode.

The anchors of the UWB-based positioning system can be synchronised either through wires or wirelessly. In wired time synchronisation, the clocks of all anchors are synchronised by means of wires or fibres. In wireless time synchronisation, each anchor has its own clock running independently of

the clocks of the other anchors. The time estimates of the different anchors are synchronised to the common time by sending synchronisation messages.

A time synchronisation mechanism for the TDOA-based UWB positioning system was investigated in [116]. The authors developed a test setup to measure the time synchronisation errors of wired and wireless approaches. The standard deviation of the wireless synchronisation was 400 ps, whereas that of the wired synchronisation was 133 ps. However, the time synchronisation of the anchors might be challenging. Wired clock synchronisation or more stable clocks makes the positioning system complex and expensive. Wireless clock synchronisation techniques lower the range estimation accuracy when unstable clocks are used. Many commercial UWB applications, such as Eliko [97] and Exafore [95], use the TW-TOA approach. Some UWB systems, such as Sewio [96] and Pozyx [94], support both the TDOA and TW-TOA schemes. According to Pozyx, the TW-TOA method provides more accurate position estimates, while TDOA is better suited for large-scale applications, which need multiple tags to be supported.

D. RECEIVED SIGNAL STRENGTH

The measurement of RSS is straightforward and is performed in most radio receivers. RSS decreases as the receiver–transmitter distance increases. This phenomenon can be used to estimate the location of a mobile device from the RSS measurements either by trilateration or location fingerprinting.

Radio signal attenuation is not only affected by the distance between the transmitter and receiver but also by multipath interference and any obstruction on the signal path. Thus, indoor positioning systems seldom compute the object position by using geometric range estimates derived from RSS. Instead, RSS-based indoor positioning systems use location fingerprinting more often. RSS is seldom used with UWB, because using the RSS observable does not completely exploit the benefit of UWB signals [117].

E. PASSIVE POSITIONING

In addition to previous active positioning techniques, location can also be determined by passively monitoring the communication of the UWB network [118] or by special arrangement; where a tag listens passively to the positioning messages sent by the anchors simultaneously [115]. Passive monitoring is not as accurate as active positioning, and the simultaneous positioning message method requires special hardware. Another passive UWB positioning strategy is to use UWB anchors as radars. In this case, the round trip time of the signal sent from the anchor and reflected from the target is measured [93], [119], [120]. Both magnitude and phase of the channel state can be used, in addition to signal reflections from walls. This method is called device-free positioning since it does not require any UWB specific hardware in the target. Passive and device-free methods are still under research. They are not as precise as the active

methods and are more sensitive to environmental changes and variation. Thus, they are not discussed further in this review.

V. UWB POSITIONING ALGORITHMS

The position can be estimated from TOA and TDOA observables by using various methods. When the position is estimated using measurements of a single time epoch, it is called static positioning, where the previous or future measurements are not accounted. The most common approach to solve the nonlinear system of equations of TOA and TDOA is to use the iterative LS method. Alternatively, the position can be estimated using closed-form solutions or methods based on likelihoods or probability.

Static positioning is not an optimal solution in most situations, as it does not account for the dynamic state model of the target. In many cases, a Kalman filter and PF provide a better position estimate, as they use the time series of the measurements for computing the current state estimate.

A. ITERATIVE LEAST SQUARES AND CLOSED-FORM SOLUTIONS

The overdetermined and nonlinear system of equations can be solved using the Gauss-Newton algorithm. As the linearisation of this algorithm is based on Taylor-series expansion, it is also called the Taylor algorithm. In this algorithm, the user's position is determined using an iterative process starting from an approximate position.

The true distance between the anchor i and the tag is as described in Equation (5):

$$r_i = \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2 + (z_i - z_u)^2} \tag{5}$$

where (x_i, y_i, z_i) is the position of the i-th anchor and (x_u, y_u, z_u) is the position of the tag. If (x_v, y_v, z_v) is the initial approximate position, let $x_u = x_v + \delta_x$, $y_u = y_v + \delta_y$ and $z_u = z_v + \delta_z$. By linearising Equation (5) using Taylor-series expansion and omitting the second-order and higher terms as in Equations (6)–(10) we have: [121]

$$H\delta = b \tag{6}$$

where

$$\mathbf{b} = \begin{bmatrix} r_1 - r_{v1} \\ r_2 - r_{v2} \\ r_3 - r_{v3} \end{bmatrix}, \quad \mathbf{H} = \begin{bmatrix} a_{x1} & a_{y1} & a_{z1} \\ a_{x2} & a_{y2} & a_{z2} \\ a_{x3} & a_{y3} & a_{z3} \end{bmatrix}, \tag{7}$$

$$\delta = [\delta x_u, \delta y_u, \delta z_u]^T \tag{8}$$

$$a_{xi} = \frac{x_i - x_v}{r_{vi}}, \quad a_{yi} = \frac{y_i - y_v}{r_{vi}}, \quad a_{zi} = \frac{z_i - z_v}{r_{vi}} \tag{9}$$

and

$$r_{vi} = \sqrt{(x_i - x_v)^2 + (y_i - y_v)^2 + (z_i - z_v)^2} \tag{10}$$

The LS solution to the position estimation problem is obtained from Equation (11): [121]

$$\delta = (\mathbf{H^T H})^{-1} \mathbf{H^T b} \tag{11}$$

The position of the object (x_u, y_u, z_u) is calculated using an iterative process. In the beginning, the approximated position,

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(x_v, y_v, z_v) is set to an initial value. Next, the direction cosine matrix **H** and the predicted-minus-observed range vector **b** are computed. Then, the unknown displacement vector δ is calculated using Equation 8. The iteration process is repeated until the length of the displacement vector does not decrease any further.

The ordinary LS method described above assumes that the error variance in each measurement is the same. The method of weighted LS (WLS) can be used when the error variances of the measurements are not constant. WLS method weights observations by the reciprocal of the error variance $w_i = 1/\sigma_i^2$ for that observation.

The weight matrix is calculated using Equation (12):

$$\mathbf{W} = \begin{bmatrix} \omega_1 & 0 & 0 & 0 \\ 0 & \omega_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \omega_L \end{bmatrix} \tag{12}$$

The WLS solution is obtained from Equation (13):

$$\Delta\mathbf{x} = (\mathbf{H}^{\mathbf{T}}\mathbf{W}\mathbf{H})^{-1}\mathbf{H}^{\mathbf{T}}\mathbf{W}\Delta\mathbf{p} \tag{13}$$

In addition to the Taylor-series method, several closed-form solution methods have been proposed to solve the set of TOA or TDOA equations. Caffery [122] presented a geometrical interpretation in which straight, rather than circular, lines of positions were used to determine the target device's position. This method is called the linear lines of position (LLOP) method [121], [123] or simply LS method [112]; it does not use linearisation. Another well-known closed-form solution is the Chan algorithm, which estimates the target position from TDOA equations [124].

Many authors have preferred closed-form solutions over the Taylor method [122], [124]. The Taylor-series method has been criticised as it converges towards a local minimum if the initial guess is not close enough to the true position. However, in a GNSS, for example, the Taylor-series method seldom converges towards the minima. The authors of [112] compared the LLOP, Chan algorithm and Taylor-series method and found that the Taylor algorithm provides the best positioning accuracy. A fusion algorithm combining both the Chan and Taylor algorithms can improve the positioning accuracy in the presence of NLOS errors [125].

B. BAYESIAN FILTERS
Recursive Bayesian state estimation, or Bayes filter is an abstract concept for tracking object's position in kinematic case, by combining a dynamic state model with observations. Bayesian filters recursively update the posterior belief to the current state as in Equation (14):

$$\text{Bel}(x_k) = p(x_k \mid y_{0..k-1}), \tag{14}$$

where x_k is the current state and y_k are the observations.

Practical implementations require the definition of dynamic and perceptual models and representation of beliefs. Depending on the implementation, the properties of Bayes

filters are different [126]. Some most common implementations are different variations of Kalman Filters, Particle Filter and factor graph optimisation, which are described in the following subsections.

C. KALMAN FILTERS
The Kalman filter algorithm is a recursive estimation method used for predicting the new optimal states in linear state-space systems considering additive white Gaussian noise [127]. The algorithm is based on using a priori knowledge to estimate the posterior states, calculate the Kalman gain and measurement residual caused by the mismatch error and then calculate the new state and covariance vectors and use them as input to the next iteration [127]–[131].

1) EXTENDED KALMAN FILTER
The extended Kalman filter (EKF) is an adapted version of the ordinary linear Kalman filter to estimate states in non-linear dynamic systems [132]. A discrete-time Kalman filter follows two steps: 1) prediction step, where the next state of the system is predicted given the previous measurements fed to the system, and 2) update step, where the current state of the system is estimated given the measurement performed at the active time step [131], [133]. Then, the Kalman filter algorithm is used to satisfy the equations of state-space estimation in Equations (15) as follows:

$$x_k = f(x_{k-1}, \ k-1) + q_{k-1}$$
$$y_k = h(x_k, \ k) + r_k \tag{15}$$

whereas x_k and y_k are the state and measurement vectors of the system at time step k and q_{k-1} and r_k are the process and measurement noises at time step *k-1*, where $q_{k-1} \sim N(0, Q_{k-1})$ and $r_k \sim N(0, R_k), f(.)$ and $h(.)$ are the nonlinear functions of model dynamics and measurement, respectively.

In EKF, the state transition matrix **F** and measurement matrix **H** in the linear Kalman filter are replaced by the nonlinear state transition function $f(.)$ and nonlinear measurement function $h(.)$, respectively, to map the algorithm through Gaussian distribution to work under nonlinear conditions. The complete Kalman algorithm for nonlinear systems is demonstrated in Table 3, which is adapted from [131].

Whereas $m_{\bar{k}}$ and $P_{\bar{k}}$ are the predicted mean and covariance of the state, respectively, at time step k before checking the measurement, and m_k and P_k are the estimated mean and covariance of the state at the time step k after checking the measurement. y_k is the measurements vector of the system at the time step k. S_k is the measurement prediction covariance at the time step k. K_k is the filter gain (i.e. the prediction correction coefficient at the time step k). $f(.)$ and $h(.)$ are the nonlinear functions of model dynamics and measurements.

2) UNSCENTED KALMAN FILTER
Unlike EKF, the unscented Kalman filter (UKF) employs the sigma-point Gaussian transformation to map the non-linear state transition function of the system and tends to

TABLE 3. EKF algorithm for nonlinear systems, adapted from [131].

0 Initialization	for $k = 0$ set $\hat{X}_0, P_0^-, Q_0, R_0$	
1 Prediction step	Prior estimate of the state:	$m_k^- = f(m_{k-1}, k-1)$
	Prior estimate of the covariance:	$P_k^- = F_x(m_{k-1}, k-1)P_{k-1}F_x{}^T(m_{k-1}, k-1) + Q_{k-1}$
2 Update step	Measurement residual update:	$V_k = y_k - h(m_k^-, k)$
	Measurement covariance update:	$S_k = H_x(m_k^-, k)\ P_k^-\ H_x{}^T(m_k^-, k) + R_k$
	Kalman gain calculation:	$K_k = P_k^-\ H_x{}^T(m_k^-, k)\ S_k^{-1}$
	Updating the posterior state:	$m_k = m_k^- + K_k V_k$
	Updating the posterior covariance:	$P_k = P_k^- - K_k S_k K_k^T$
	Return to step 1, repeat until k iterations are consumed.	
Output	Estimated state vector: $\hat{X}$	

linearise it through the so-called unscented transform [131], [134], [135]. In other words, while the EKF approximation relies only on one point (the mean), UKF uses more than one point, including the distribution mean. UKF selects additional weighted points (called sigma points) plus the mean for more accurate transformation. This procedure is called the unscented transform. Thus, UKF sometimes outperforms EKF in severely nonlinear systems, whereas EKF performs well in systems with modest nonlinearity [136]. In an ideal case, both EKF and UKF can be used to solve the spatial positioning equation when Newtonian equations of motion are used to form the state transition function and the measurements from motion sensor (e.g. inertial unit, gyroscope or accelerometer) are being filtered. However, various recently proposed approaches use measurements obtained from various sensors to input as the state-transition matrix. The authors in [137]–[139] implemented a fusion positioning method, whereas the state-transition function originates from inertial navigation sensors, such as the inertial measurement unit (IMU) or inertial navigation system (INS), while the measurement function is obtained from UWB sensors. The two streams are fed to EKF/UKF for optimal positioning. The procedures vary from method to method. In some cases EKF is used with multiple anchor readings and a single-observation anchor, whereas another method involves the use of EKF and UKF as a cascaded system to obtain the input parameters of the second filter from the outputs of the first filter. The results showed that the fused UWB, along with the inertial sensor data exhibited improved overall positioning accuracy and system robustness.

Kalman filters also perform well when they coexist with PFs, as in [136], where the authors developed a framework comprising three filters (EKF, UKF and PF) with detailed evaluative metrics. The results showed that the developed structure could be used for numerous purposes besides positioning improvements, such as target tracking and robot localisation. Numerous realisations that involve the use of Kalman algorithms and their variations have been proposed in [22], [34], [51], [136], [140]–[151].

D. PARTICLE FILTERS

Particle Filter (PF) is another realization of Bayes filters for position estimation. PF is a popular choice for positioning because it can be used for solving the DSS shown in Equation (15) without assuming that the dynamic or perceptual models are linear and that the noise is Gaussian. However, it is also possible to implement a PF which assumes Gaussian posterior distribution if a lighter but more restricted version is needed [152]. The reasons for using PF are that the conditions of linearity and Gaussian noise do not hold very often, and linearisation is only possible if the model is well known [152], [153].

PF estimates the posterior belief $\text{Bel}(x_k)$ of DSM through a sequential Monte Carlo (SMC) algorithm. The SMC is similar algorithm shown in Table (3), without resorting to linearisation nor Gaussian noise assumption. The posterior distribution can be anything representable by discrete samples (particles). Increasing the number of particles makes it possible to describe more complex distributions, but it also increases the computational cost of the method.

The algorithm is simple to implement, consisting of the following steps:

1) **Initialisation**: N particles are initialised according to the *a priori* knowledge described as probability distribution $p(x_{k-1})$. This distribution can be any suitable empirical distribution which can be presented with particles, or uniform distribution, if more informative distribution is not available.

2) **Estimation loop**

   a) **Predict**: All particles are moved based on the current DSM by sampling new particles, $x_k^i, i \in [1, N]$, from the distribution obtained by convolving the *a priori* distribution with the process model: $\int p(x_k | x_{k-1}, u_k)p(x_{k-1})\mathrm{d}x_{k-1}$. The process model includes also possible inputs, u_k, and process noise.

   b) **Update**: The weights of particles are updated according to the belief of the observations, $w_k^i = p(y_k | x_k^i)$ assuming that the particle, x_k^i, represents

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the correct location. Finally the weights are normalized so that their sum is 1.

  c) **Resample**: New set of particles is generated by sampling the existing set of particles using their weights so that particles with higher weights are selected more probably than the others.
  d) **Estimate**:The position estimate is obtained as a weighted average of the posterior distribution represented by particle locations and weights.

In NLOS conditions, the probability distribution of the position can be multimodal [154], and De Angelis *et al.* showed that ranging, which is based on RTT measurements can be affected by non-Gaussian noise even in LOS situations [143]. Therefore, PF can be more competitive in some realistic indoor environment than LS or EKF.

Many researchers have compared the performance of PFs with classical solutions for UWB-based indoor positioning. Usually, the performance is evaluated by examining the RMS error [155] or more often with the cumulative density function (CDF) of the positioning error in one to three dimensions [143], [148], [156]. These benchmarks show that, in many cases, a PF provides more accurate positioning results than classical methods, but in some cases, spurious errors are also detected when applying a PF (e.g. in the case of a kidnapped robot) [157]

It is also claimed that, instead of using the RMS error, comparing the whole posterior distributions of algorithms is more affective [152]. For example, the posterior distribution provided by a standard PF was assumed to be the most accurate and was compared with the Gaussian posterior distributions provided by EKF, UKF and GPF through Kullback-Leibler divergence and χ^2 information metrics. In this benchmark, the GPF was found to be more accurate in location tracking than EKF or UKF but incurred higher computational cost [152].

In addition to the increased computational cost, the problems identified in applying PF are sample degeneracy and impoverishment caused by the reduction in particle diversity [158]. A PF might also perform poorly in the kidnapped robot case when the robot is suddenly transferred to another location without allowing it to make measurements during the transfer. In this case, there might not be any particle near the actual position of the robot, and the robot might take a long time to find its new location. Counterintuitively, a PF does not also perform well when the measurement noise is too little [159], which is precisely the case in the controlled UWB positioning system. However, many methods have been proposed to overcome these problems. For example, dual MC localisation is a solution for too accurate sensor readings, and the kidnapped robot case can be solved by uniform particle augmentation [159]. Some other improvements are evolved distribution sampling methods [160], particle resetting approach [155], [161] or replacing PF with adapted FIR filter [157]. Zhu *et al.* improved the accuracy of a PF in UWB positioning by using a pre-build error distribution map [162].

At the cost of pre-computation, they gained increased 2D positioning accuracy.

It is relatively easy to fuse information from many sources into the PF estimations to compensate for NLOS issues, for example. Many researchers have fused INS sensors [91], [148], [156], mixing an EKF as a pre-processor of PF information [148]. The PF positioning algorithm can also include other models, such as UWB uncertainty model [91] or a model to predict the UWB signal obstruction caused by a pedestrian's own body [163]. The authors in [164] showed that the inclusion of digital maps into the PF model improved the positioning accuracy. The positioning of the anchor itself can be included in the PF-based positioning system [156].

E. FACTOR GRAPH OPTIMISATION
Factor Graph Optimisation (FGO) is a relatively new positioning algorithm among Bayesian filters. Some earlier publications from 2012 propose using FGO for multipath mitigation of GNSS positioning [165] and for multi-sensor fusion of GPS, IMU and stereo vision [166]. FGO models previous states as nodes and measurements as factors. Like KF and PF, FGO assumes Gaussian noise and utilizes the Bayesian filtering principle for solving the position estimation. The differences are that the FGO does not assume the Markov condition, but it uses information from previous states in addition to utilizing the latest state only. FGO solves the position by optimising the factor graph model with an iterative solver, therefore requiring more resources than KF or PF. However, it is still solvable in real-time, for example, by combining expectation-maximization and nonlinear optimisation methods [167], [168].

Even though FGO shares the unimodal Gaussian model with EKF, it can be more reliable in urban canyon environments for GNSS positioning cases [169]. Recently FGO has raised plenty of interest in positioning research, and it has been also applied to indoor navigation, including UWB positioning [167] and tight coupling of UWB and INS [170]. Besides, FGO can be useful in indoor positioning where multipath propagation causes channel impairments or in complex multi-sensor fusion situations.

F. PARTICLE SWARM OPTIMISATION
Particle Swarm Optimisation (PSO) algorithm belongs to the family of swarm intelligence, which also includes, for example, artificial Bee colony (ABC), Ant colony (AC) and Firefly algorithms. PSO was originally presented by Eberhart and Kennedy [171], [172]. PSO is an iterative global search technique that imitates the social behaviour of the swarm of birds. The algorithm is initialized with a random population of candidate solutions from a *D*-dimensional search space. Each candidate solution has a position and a velocity, and it is thus described as in Equation (16):

$$(x_i, v_i) = ([x_{i,1}, x_{i,2}, \ldots, x_{i,D}]^T, [v_{i,1}, v_{i,2}, \ldots v_{i,D}]^T) \quad (16)$$

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The quality of a solution represented by each particle is estimated by evaluating the loss function $L(x_i)$. The position of the best solution found by a particular particle is stored as the best local solution, $P_{i,\text{best}}$, and the position of the best solution among all particles is stored as global best G_{best}.

In each simulation step, the velocity and the position of each particle are updated according to the formula (17): [126]

$$\begin{cases} v_i^{k+1} = w v_i^k + c_1 \xi (P_{i,\text{best}} - x_i^k) + c_2 \eta (G_{\text{best}} - x_i^k) \\ x_i^{k+1} = x_i^k + r v_i^k \, , \end{cases} \quad (17)$$

where w is the weight coefficient corresponding to the inertia of the particle, c_1 and c_2 are respectively the self cognition and social knowledge coefficients determining how much the model utilizes local knowledge vs. swarm knowledge. Stochasticity to the model is provided by selecting random variables ξ and η from range [0..1]. Position updating ratio is constrained by a constant factor r.

Some examples of using variations of PSO in positioning are: the use of ensembles of particle swarms to enhance the robustness and accuracy of UWB positioning [173], [174], and [175]. Being a global search strategy, PSO can be useful in finding the global minimum from the search space, but since the UWB positioning problem is often unimodal, simpler optimisation methods are usually more effective. However, in NLOS conditions, for example, the probability of the position can be multimodal [154], then, the global optimisation strategies can be superior in a similar way to PF.

G. NLOS IDENTIFICATION AND MITIGATION
In addition to using PF and PSO algorithms, the robustness of positioning in NLOS conditions can also be increased by specific NLOS identification and mitigation strategies.

Although UWB has several advantages in indoor positioning, it can still suffer from errors caused by NLOS conditions. In an NLOS condition, only the reflected signal is received, while the direct path signal is missing, as shown in Figure 8. The use of reflected signals can cause a significant bias to the position estimate. Various methods have been developed to reduce the inaccuracies imposed by an NLOS condition in UWB-based positioning. The authors in [176] categorised these methods as NLOS identification and NLOS error mitigation techniques. The signal can be identified as an NLOS signal, for example, by analysing the channel statistics parameters, such as mean delay, excess delay, amplitude and SNR. When the faulty observable is identified, it can be excluded from further analysis to improve the positioning accuracy.

Various methods can be used for mitigating NLOS errors, such as outlier detection, PFs, ML and weighted least squares (WLS). The authors in [177] proposed an NLOS identification technique based on multipath channel statistics, such as the kurtosis, the mean excess delay spread and the RMS delay spread. A likelihood ratio test was conducted for LOS and NLOS identification. Smaller weights were assigned to the measurements, which were likely biased. The authors analysed the WLS method, which deployed the likelihood
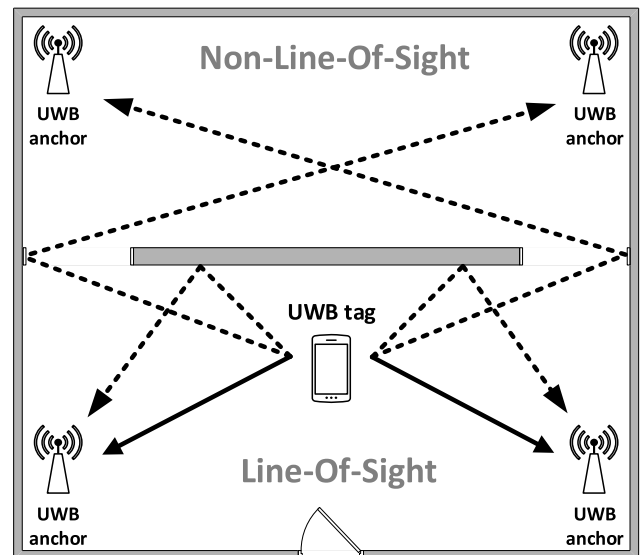

FIGURE 8. NLOS and LOS situations in UWB positioning system. The anchors in the left and right upper corners do not have a LOS connection to the tag, but the signal is received only through reflections, and therefore, the flight time is longer than expected, and the distance estimate fails. The anchors in the lower corners receive the LOS signal first.

functions obtained from the multipath components of the received signal. Recently, ML has been extensively applied for NLOS identification and error mitigation, which is presented in Section VIII-A.

A commercial solution was coined by Decawave (Qorvo) in [178] for systems that contain the DW1000 chips. This embedded resolution comprises the use of additional registers to assign a level of confidence to the received timestamps. Afterwards, it post-processes accumulators to allow the identification of a falsely detected first path, hence, identifying NLOS situations.

VI. RECENT ADVANCES IN UWB POSITIONING LITERATURE
The main contribution of this paper is that it summarises the most recent advances in UWB positioning literature that have spanned the previous five years; hence, we provide a compact summary, as shown in Tables 4–9. The tables categorise each article concerning the publication year, ranging methods used, applied algorithms, whether they use the fusion-based technique and field of application, as well as a summarised description explaining the rationale, methodology and findings for each article. In addition, several other articles are summarised as in-text review outside the table, which can be found in the relevant sections.

VII. ADVANCES IN SENSOR FUSION TECHNIQUES
Sensor fusion is a computational procedure to combine the measurements from multiple sources such that the output information after fusion is maximized [179].

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TABLE 4. Summary of UWB literature: General methodology development.

Ref	Year	Ranging method	Algo-rithm	Multi-sensor	Application	More information
[192]	2020	TOA	LS trilatera-tion	-	General	Improved the UWB positioning accuracy in low SNR situations by proposing a modified leading edge detection algorithm in addition to LS trilateration filtering.
[140]	2020	TW-TOF	KF, MLE	-	2D & 3D posi-tioning	A comparative study employing various signal processing and AI techniques to identify measurement outliers. LOS/NLOS classifiers were investigated in both 2D and 3D localisation.
[173]	2018	TWR, TDOA	ELPSO	-	2D & position-ing, 3D	Developed an ensemble learning particle swarm optimisation (ELPSO) method for UWB indoor positioning. The system optimised the positions of 36 tags in which the final estimated values converged after 20 iterations, which outperformed other PSO methods.
[194]	2018	AOD, AOA, TOA, RSS	RiMAX	-	2D & 3D posi-tioning	Developed a novel positioning algorithm using an extension to the RiMAX algorithm and based on the geometrical properties of the propagation path of the UWB signal. The performances of numerous ranging techniques were compared and exploited to achieve channel sounding measurements. The proposed method achieved an overall accuracy of 0.26 m in LOS and 0.90 m in NLOS.
[194]	2019	TOF	TSML-WLS	Wi-Fi	2D & 3D posi-tioning	Investigated the performance of Wi-Fi as an IPS when it cooperated with UWB-IPS. Experimental results showed increased accuracy when Wi-Fi access points were gradually replaced with UWB beacons (20-30 cm per replacement). The proposed hybrid approach achieved an efficient compromise between positioning accuracy and infrastructure costs.
[141]	2020	TW-TOF	KF, MLE	-	2D & 3D posi-tioning	Proposed a real-time indoor positioning system for smart grids by employing UWB as IPS. The proposed framework is based on AI techniques to detect the measurement outliers caused by NLOS conditions and hence improve the positioning accuracy of smart grid components.
[195]	2020	TOA	Trilateration, LSTM	-	2D positioning	Achieved high localisation accuracy (MAE = 0.7 m) by using two LSTM algorithm networks to mitigate the effect of NLOS measure-ments.
[191]	2019	TOA	PUFIR	INS	2D positioning	Introduced the problem of missing UWB measurements and proposed a fusion with INS augmented by a predictive unbiased finite impulse response (PUFIR) filter. The authors compared its performance with three other filters: KF, an ordinary UFIR and a predictive Kalman filter (PKF). The results showed that the PUFIR filter yielded less RMSE (0.5 m), more robustness than KF and a reliable navigation accuracy (maximum error = 2.28 m) amid missing UWB range measurements.
[189]	2018	TOA	EFIR	INS	2D positioning	Proposed a federated EFIR algorithm to fuse UWB and INS measure-ments. The real test results showed that the EFIR filter outperformed the conventional federated EKF.
[196]	2020	TOA, TDOA	MLP, CNN	-	2D positioning	Proposed a transfer learning-based UWB NLOS identification scheme for an unmeasured environment. The proposed hybrid method showed better NLOS identification accuracy (98.33 %) at 48 times faster training time than conventional ML algorithms MLP and CNN.
[142]	2020	TOA	SVD-FDCKF	IMU	2D positioning	Proposed an IMU/UWB multi-sensor system using the singular value decomposition federated derivative cubature Kalman filter (SVD)-FDCKF, which continuously corrects the IMU through UWB posi-tioning observables to avoid the accumulation of IMU drift errors in a short time.
[143]	2016	TOA	LS, EKF, PF	-	2D positioning	Simulated the distance measurements using RTT and compared the estimation performance of PF against those of LS and EKF. Results showed that the PF output is more reliable than other algorithms but on account of computational complexity.
[197]	2020	TDOA	WKNN-LSTM	-	2D positioning	The LSTM model was used to predict UWB measurements, which were later used to fix the actual ones. The corrected UWB measure-ments were fed to the WKNN model, and hence, the localisation was obtained. This method resulted in high precision accuracy of 20 cm.
[125]	2020	TOA	Chan-Taylor	-	3D positioning	The research focuses on mitigating the effect of NLOS error on indoor 3D positioning by achieving RMSE error of 0.2 m.

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TABLE 5. Summary of UWB literature: NLOS mitigation and integration with fingerprinting.

Ref	Year	Ranging method	Algo-rithm	Multi-sensor	Application	More information
[75]	2019	TOA	LSE-Taylor	-	Multi-users in dense environments	Developed waveform division multiple access (WDMA)-based UWB positioning for dense multipath and NLOS environments. The proposed (WUB-IP) method was complemented by a transfer learning approach (SHLA) to mitigate NLOS. The WUP-IP method showed a high precision positioning scheme (RMSE < 2 cm) compared to other methods (RMSE > 10 cm).
[198]	2018	TOA	WLS, IVM	-	NLOS identification	Proposed a novel ML NLOS identification method using WLS and IVM algorithms. The tests showed that IVM had better positioning accuracy (in terms of RMSE and CDF) than RVM and SVM.
[199]	2019	TW-TOF	ECTSRLS	-	NLOS mitigation	Developed an equality constrained Taylor series robust least squares (ECTSRLS) technique followed by a fuzzy comprehensive evaluation (FCE) to mitigate the effects of NLOS situations. The FCE-ECTSRLS method is used for channel identification to select the optimal set of ranges for the position estimation. The experimental results showed that the proposed method outperformed other algorithms by RMSE = 0.602 to 1.063 m.
[200]	2021	AltDS-TWR	LS trilatera-tion	-	Fingerprinting positioning	Presented the Fingerprinting-Assisted UWB-based localisation (FAUL) method to improve the accuracy of UWB localisation in complex indoor environments. FAUL combines fingerprinting and weighted trilateration techniques to reduce the localisation error (accuracy > 95%) when LOS situations are minimal.
[201]	2020	TW-TOF	CNN	-	Fingerprinting positioning	Utilized an ML model (CNN) to improve the accuracy of fingerprinting measurements. The data were divided as 70% for training and 30% for testing, and the CNN method outperformed SVM and random forest algorithms.

TABLE 6. Summary of UWB literature: IoT.

Ref	Year	Ranging method	Algo-rithm	Multi-sensor	Application	More information
[202]	2018	TOA	LS, CI, TSML	-	IoT	Derived a statistical model based on an LS algorithm to improve the performance of the estimated pairwise distances before forwarding to the localisation algorithms. The method was validated against two algorithms: CI and TSML. The results showed a significant improvement in performance within scenarios of varying geometry, such as IoT scenarios.
[203]	2018	TOA	-	RFID	Industrial + IoT	Highlighted the numerous attempts made to utilize UWB in various environments, including the outer space. Experiments carried out by [208] showed that the UWB/RFID method could achieve up to 4 cm accuracy.
[205]	2017	TOA	Tri-lateration	RFID	IoT, energy harvesting	Highlighted the characteristics of energy-autonomous tags that can achieve centimetre-level positioning accuracy. The authors demonstrated the UWB-RFID backscatter method, a promising candidate for precise positioning.
[79]	2018	TDOA, TWR	-	-	Tracking in dense environments	Investigated the capability of UWB Decawave DW1000 chip to support numerous tags simultaneously in dense environments. The authors concluded that the proposed method (TDOA-TDMA) can support up to 6171 tags (updates per second), outperforming other combinations of methods.

As sensor technology becomes more sophisticated (and owing to its erroneous nature), multi-sensor fusion has been trending recently. The reliance on multiple measurement devices in positioning applications can result in fewer uncertainties, and greater reliability and accuracy than depending on a single measurement sensor [180]. Numerous tracking systems can be fused with a UWB system to produce more accurate and reliable estimations. Common examples of these systems are GNSSs, inertial navigation systems (INSs), dead reckoning (DR), visual map matching (VMM) and computer vision. The optimal positioning estimations that result from fusing multiple positioning methods follow a unified framework, which is illustrated in Figure 9.

GNSSs (e.g. GPS, GLONASS and Galileo) provide satellite-based positioning estimations for outdoor environments within an acceptable error range. However, the signal suffers from multiple degradation factors, such as multipath fading, path loss and shadowing, which reduce its applicability in indoor positioning applications [147], [181].

INSs are highly reliable positioning systems, as they are not influenced by external factors. However, they accumulate significant errors over time [182], [183]. The main role of

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TABLE 7. Summary of UWB literature: Autonomous systems.

Ref	Year	Ranging method	Algorithm	Multi-sensor	Application	More information
[144]	2020	DS-TWR	EKF	DR	AGV control	Proposed a fusion-based UWB/DR localisation technique to achieve 10 cm tracking accuracy for AGVs in harsh industrial environments.
[206]	2020	TOA, TDOA	GD, LS	-	AGV	Developed a low-cost UWB localisation system that provided precise positioning for AGVs using gradient descent and LS algorithms. The proposed method was validated against RTK data, and the result was a robust system capable of localisation both indoors and outdoors.
[183]	2019	TOA	LS, SHFAF	INS	Autonomous robots	Proposed an INS/UWB/SHFAF method to deal with the time-varying noise, which accounts for the positioning errors of indoor autonomous robots. Through simulations and experiments, the proposed method achieved high positioning performance in terms of accuracy and robustness in dense environments.
[186]	2017	TOA	IAKF, AR	INS	Mobile robots	Tested an INS/UWB sensor fusion approach to tackle the problem of accumulated errors for tracking indoor mobile robots in real-time. A 2D kinematic model, improved adaptive Kalman filter (IAKF) algorithm and AR algorithm were used to identify the estimated position outliers. The results showed that IAKF outperformed the KF algorithm with an improved error of 0.24 m.
[136]	2019	TOA	EKF, UKF, PF	-	Robot localisation	Presented and compared the performances of EKF, UKF and PF in positioning mobile robots. The simulation results showed that the PF performed fastest in the low-speed mode (1 m/s), while UKF performed fastest at higher speeds (2-10 m/s).
[147]	2020	TDOA	FKF	GNSS, DR, VMM	Intelligent transportation	Designed the fusion positioning algorithm of GNSS/UWB/DR with a federated Kalman filter (FKF). The results obtained from both the simulation and real vehicle testing showed that the proposed intelligent vehicle localisation accuracy was improved (MAE < 0.88 m). The positioning accuracy could be improved, and an adaptive information distribution coefficient was established based on the FKF.
[207]	2021	TOA	MLKF	-	UAV 3D positioning	Indoor localisation of a fleet of vehicles using UWB. The measurements involved the calculation of inter-vehicle distance, which improved the overall positioning accuracy by 60 percent.
[149]	2018	DS-TWR	EKF	IMU	UAV 3D positioning	Proposed a 3D attitude and pose estimation method for small UAVs involving the use of IMU, UWB and EKF filtering. The best RMSE values achieved for attitude and pose were 1.93° and 0.19 m, respectively.
[208]	2017	TW-TOF	LMA multilateration	-	UAV tracking	Developed a numerical method which involved the use of UWB technology and Levenberg-Marquardt algorithm (LMA) to track and control UAVs. The analysis results showed that an improved accuracy on decimetre order could be achieved for the 3D-positioning of UAVs.
[32]	2020	TOA, TDOA	Cost function	GNSS, LoRa	UAV traffic management	Proposed a high-precision prototype for a UAV traffic management (UTM) system. Besides GPS, the authors used a novel method comprising an IR-calibrated UWB (Decawave) in addition to the LoRa module. The proposed cost function reduced the GPS positioning error from 4.03 to 1.73 cm.
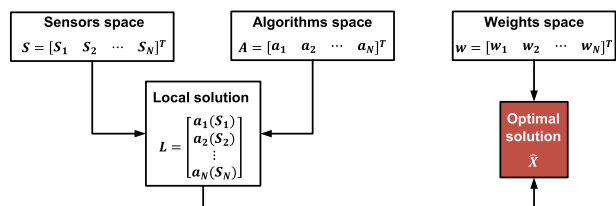
FIGURE 9. Fusion-based positioning framework, adapted from [179], [180].

UWB precise positioning technology is to refine INS errors by tightening the position estimate to the absolute coordinate system, while an INS provides more accurate delta position updates in the short term, making the integrated INS/UWB system more accurate and robust [26], [76]. An IMU differs from an INS as it is not an integrated dynamic system as an INS. However, IMU units are the main building block of an INS [184]. IMUs can still be used independently in fusion-based localisation endeavours, but INSs have recently been widely adopted in positioning systems.

A. SENSOR FUSION POSITIONING IN TRANSPORTATION APPLICATIONS

As cooperative positioning is a crucial element in intelligent transportation systems (ITSs), the authors in [185] developed a cooperative scheme supported by vehicle-to-infrastructure (V2I) communications as a prototype implementation of an

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TABLE 8. Summary of UWB literature: Industrial applications.

Ref	Year	Ranging method	Algo-rithm	Multi-sensor	Application	More information
[34]	2020	TW-TOF	EKF, ESKF	IMU	Coal mine robots	Developed an IMU/UWB-based localisation system to equip CMRs with reliable estimations that improved navigation in underground tunnels. UWB measurements were filtered by EKF, which were federated with IMU measurements through the ESKF algorithm. Small-scale experiments showed improved robustness but less positioning accuracy (RMSE = 0.562 m).
[191]	2019	TDOA, AOA	KF	SINS	Coal mines	Proposed the SINS/UWB method, in which both measurements were fed to a Kalman filter to fuse the estimated position and speed. The results showed that the tightly coupled model and the decision tree model could produce accurate positioning during partial and total node failure situations. The maximum error of the SINS/UWB multimodel method was 0.93 m, accumulated in 327 s.
[149]	2020	ADS-TWR-MTMA	WLM, WLS, KF	IMU	Underground Mines	A numerical analysis using simulation data to validate the impact of using fusion-based method (UWB/IMU) to improve the localisation accuracy in underground Mines.
[209]	2020	TOA	Chan	-	Substation safety monitoring	Investigated the feasibility of a test environment that employs UWB positioning in 500 kV substation operation monitoring. Despite the high costs and shielding problem, the experimental results showed positioning accuracy of 0.15-0.3 m in the UWB substation monitoring environment.
[90]	2017	AOA, TDOA	PF	-	Industrial warehouse	Conducted a comparative study between commercial UWB providers such as BeSpoon, Ubisense and Decawave. The authors concluded that the Decawave system outperformed other systems in terms of reliability and accuracy owing to its advanced antennas.

TABLE 9. Summary of UWB literature: Pedestrian positioning.

Ref	Year	Ranging method	Algo-rithm	Multi-sensor	Application	More information
[145]	2019	TW-TOF	EKF, K-means	-	Body wearable sensors	Investigated the effect of UWB wearable location with respect to the body on the overall positioning accuracy. The method involved the use of smoothing, filtering and clustering. The experimental results showed that placing the UWB wearable tag on the human chest produced the largest positioning error due to the highest NLOS component, while placing it on the forehead yielded the best accuracy.
[146]	2017	TOA	EKF, EFIR	-	Human localisation	Compared the performances of EKF and EFIR estimators for human localisation based on UWB. The results showed that EFIR performed better than LS and EKF algorithms, with MAE values of 0.19 and 0.54 m for the north and east directions, respectively.
[210]	2017	TOA	PF, ZUPT	IMU	Pedestrian positioning	Proposed a fusion-based method, IMU/UWB, through PF and ZUPT algorithms to achieve precise positioning for pedestrians. The results showed that the proposed method demonstrated high precision under NLOS conditions using fewer particles.
[148]	2020	TOA, TDOA	PF, EKF, ZUPT	INS	Pedestrian tracking	The UWB observables were treated by joint particle filtering, while the INS data were filtered by the ZUPT algorithm. Both UWB and INS errors were loosely fused by EKF, resulting in improved accuracy (MAE = 0.35 m) and better adaptability in robust environments.
[211]	2020	TDOA	SWA	-	Shopping mall	The TDOA ranging technique and sliding window algorithm (SWA) were used to track a moving stroller in a shopping mall down to 20 cm RMSE positioning error.
[51]	2018	TOA	PF, EKF	-	Sports athletes tracking	Investigated the performance of UWB tracking for athletic activities, such as running, walking with varying speeds and accelerations and jumping. The tests involved PF and EKF algorithms, which showed an acceptable accuracy of approximately 20 cm.
[212]	2019	SDS-TWR	-	-	Track indoor cyclists	Studied the feasibility of employing UWB for tracking indoor athletes (cyclists). The authors investigated various configuration setups to conclude the best positioning accuracy, best anchor height in LOS, least energy consumption and the most convenient spot for athletes to mount the mobile UWB tag. The experimental results showed that UWB positioning is viable for tracking indoor cyclists.

ITS. This method comprises a tightly coupled sensor-fused GPS/UWB/INS algorithm built upon an error detection unit, in addition to a robust Kalman filter. The UWB component acts as a refining agent for noisy GPS measurements.

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The results showed that the fusion of UWB with GPS/INS improved the overall positioning accuracy of the vehicles down to a sub-metre level with an added pseudo-range gross error in different scenarios (the highest positioning error was 0.78 m) and, thus, increased the system reliability.

In ITSs, various low-cost positioning systems can be fused to improve the overall accuracy and reliability, as demonstrated in [147]. The authors used a federated Kalman filter (FKF) to combine GNSS, UWB, DR and visual map matching (VMM) in one framework, which the authors called an 'intelligent positioning strategy'. VMM is a common method in GNSS positioning, which uses pre-stored maps to correct the fusion error. Three input sources to VMM were propagated: (i) result of GNSS/UWB/DR fusion, (ii) captured images from a vehicle camera and (iii) pre-stored visual map repository, sampled by frame and pose. The integrated GNSS/UWB/DR/VMM strategy was tested in a simulation environment and a real-vehicle test platform on a university campus. The results of both tests showed that the framework improved the accuracy (MAE 0.9 m) and system reliability.

Intelligent logistics (also known as smart logistics) have recently adopted AGV robots which possess key transportation capabilities to maximise the efficiency of logistics traffic. The authors in [139] developed an INS/UWB integrated approach along with an interactive multiple model (IMM) algorithm that involves dual Kalman filters in both LOS and NLOS situations by combining their probabilities through a Markov chain transform. The INS and UWB position errors were fused, and the error covariance was updated using another Kalman filter, which compared the INS measurements against the UWB estimated values. Finally, the Kalman filter yielded the estimated position as the output and proceeded to the weighted fusion step. The results showed that the proposed INS/UWB-IMM method reduced the influence of a LOS/NLOS mixed situation; the average localisation error obtained was 0.2 m.

B. FUSION-BASED POSITIONING IN INDOOR APPLICATIONS

Fusion-based indoor positioning has recently gained significant attention due to advances made in wireless sensor networks, enhancements achieved in positioning technologies and its optimisation capabilities [180]. Another tightly coupled technique was presented by [186], where the authors used an INS/UWB sensor fusion approach to address the problem of accumulated errors in inertial navigation systems, which can localise and track indoor mobile robots in real-time. A 2D kinematic model of a mobile robot was developed for positioning and tracking, in addition to an autoregressive algorithm, to accommodate a third-order error equation for the gyroscope and accelerometer. In addition, an IAKF algorithm was developed, and a covariance matching method was used to identify the estimated position outliers. The results showed that IAKF outperformed the KF algorithm, and the error of the INS/UWB integrated
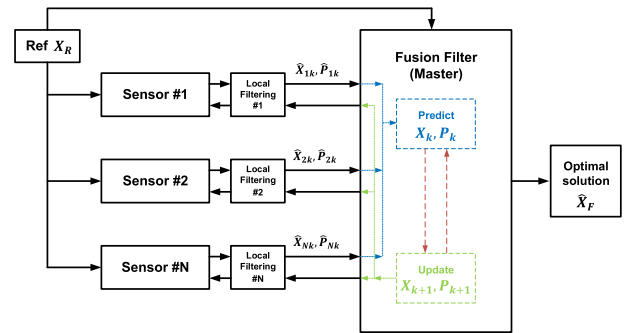
FIGURE 10. Structure of the federated Kalman filters.

system was improved to 0.24 m, which is an acceptable level for the practical requirements of the system model.

The concept of an FKF filter in multi-sensor data fusion has been implemented as a group of sub-filters corresponding to each sensor measurement in addition to the master combining filter, which regularly fuses sensor data to achieve optimal estimations [187], [188]. The concept of federal filters is illustrated in Figure 10. The authors of [189] adopted a federated extended finite impulse response (EFIR) filter as the sub-filter to fuse INS/UWB measurements between the reference nodes and target tag. Another EFIR was used as the master filter to achieve optimal position estimation based on the sub-filter outputs to mitigate the INS error.

The results obtained from [189] showed that the EFIR sub-filter approach was more accurate (RMSE = 0.45 m) and robust than the normal FEKF. In [190], the same authors introduced the problem of missing UWB measurements and proposed the combination of an INS augmented by a predictive unbiased finite impulse response (PUFIR) filter. The performance of the proposed method was compared with those of the other three filters: the Kalman filter, an ordinary UFIR and a PKF. Although the ordinary UFIR filter performed the worst, the PUFIR filter yielded a smaller RMSE (0.5 m) and more robustness than the Kalman filter and yielded reliable navigation accuracy (maximum error = 2.28 m) amid temporary missing UWB range measurements.

The authors of [183] addressed the multipath effect during NLOS situations on a UWB signal in dense, complicated environments for the indoor navigation of autonomous robots. The authors introduced an adaptive filter called Sage-Husa fuzzy adaptive filter (SHFAF) for outlier detection. Such filters assume that the noise is time-varying, especially in an NLOS situation, in contrast to Kalman filters, which assume time-invariant noise. In a SHFAF, noise covariance is estimated by adjusting the innovation weight adaptively, which results in more accurate estimations (88.2% of the time, the positioning error is less than 0.2 m) and enhanced robustness, as demonstrated by the simulation and experimental results.

C. FUSION-BASED POSITIONING IN EXTREME CONDITIONS

GNSS signal is not available in underground mines, and all positioning systems in those conditions are prone to signal deterioration and multipath effects. Being quite tolerant against multipath propagation, UWB positioning has been used in Coal mine robots (CMRs) for precise underground positioning to function in excavation, mining and security control rescue tasks. The authors of [34] developed an IMU/UWB-based localisation system to equip CMRs with reliable Estimations, which can mitigate the navigation uncertainties in underground tunnels. The UWB measurements were propagated into an EKF. Subsequently, its output was federated with IMU measurements through an ESKF to realise six-degree-of-freedom state estimations. The estimates were compared with LiDAR odometry methods. The simulations and small-scale experiments exhibited improved robustness but slightly decreased positioning accuracy for the proposed fusion method ESKF-UWB over EKF-UWB. The authors attributed these results to two reasons: (i) the EKF method did not comprise orientation errors, or (ii) the crawler robot suffered movement vibrations, generating additional IMU noise. This implementation is yet to be investigated on a larger scale.

The strap-down inertial navigation system (SINS) is commonly employed in Chinese coal mines to measure the position and attitude of a shearer on rails; however, it suffers from the accumulation of error drifts over time. Hence, the authors of [191] proposed an integrated SINS/UWB system through a multimodel intelligent fault-tolerant algorithm to refine the positioning errors by switching between a tightly coupled model and a decision tree model based on the working state of UWB anchors. The switching was performed by assessing the ability of all anchor nodes to accurately measure the range between each stationary node and the mobile node. Afterwards, the determined UWB epochs, along with SINS estimations were fed to a Kalman filter to obtain the final position and speed. The results showed that the tightly coupled model could accurately localise the shearer amid partial node failure. In contrast, the decision tree model could produce accurate positioning during total node failure situations. The maximum SINS/UWB multimodel method error was 0.93 m, accumulated in 327 s.

VIII. ADVANCES IN MACHINE LEARNING APPROACHES IN PRECISION POSITIONING

The multilateration techniques directly estimate the position of an agent using distance observables with a direct signal propagation model. The reliability of the estimation can be increased using a dynamic state model, which in addition to current observations, uses the previous positions in estimations as well through Bayesian statistics (e.g. Kalman- and PF-based solutions). These are the most common methods and are particularly functional inside a controlled positioning infrastructure. While plain multilateration and dynamic state models have been the most common methods for positioning estimation, more advanced ML models have become increasingly popular due to their increased calculation capacity and advances in ML methods. They are used for positioning in situations in which simple models do not work efficiently (e.g. due to heavy nonlinearities, abruptly changing conditions, heterogeneous information sources, skewed noise distribution or non-convexity). Typical reasons for using ML are to increase robustness, allow adaptation to changes, implement a collaborative or model-free positioning system, use heterogeneous information sources or select the most useful features for positioning. These methods allow the use of ad hoc observations not originally intended for positioning, such as optical images and RSSs from Wi-Fi base stations. Often traditional positioning algorithms are supplemented with ML methods.

ML methods have been found helpful in many use cases, some of which are listed in the following subsections. Moreover, a summary that describes the properties, strategies and purposes of the reviewed ML algorithms is presented in Table 10.

A. RESOLVING NLOS UNCERTAINTY

UWB systems that are augmented by ML approaches play an important role in resolving NLOS situations. For instance, the basic ML algorithms, such as a *naïve* Bayesian filter and gradient descent algorithms were adopted by [213] and [206], respectively, to address NLOS conditions by recognising measurement outliers, hence improving the overall accuracy. Using large datasets, the authors of [106] proposed a radar system augmented by a multiclass support vector machine algorithm to localise and identify targets by specifying the location within the building rooms, which reduced the uncertainty associated with NLOS. A similar approach with a novel NLOS identification algorithm based on an import vector machine (IVM) algorithm, along with a feature selection strategy was proposed by [198].

The suitable performance of neural network deep-learning approaches have also been rising in dominance in the most recent UWB literature (in a span of the past three years). In [196], the use of a multilayer perceptron, with transfer learning and convolutional neural networks (CNNs) as NLOS classifiers, not only enhanced the overall training accuracy from 44% to 98% but also achieved faster training times than those achieved using CNNs alone in an unmeasured environment. Another neural network approach was presented in [195], where the authors employed a long short-term memory (LSTM) algorithm for predicting the user position based on the received TOA measurements. This LSTM approach resulted in a 7 cm accuracy, which outperformed several other techniques, including the recurrent neural network (RNN) method. The ML methods can be used to increase the robustness of the well-known model-based traditional methods, such as Kalman filter [214].

TABLE 10. Summary of machine learning methods used for positioning.

Algorithm	Purpose	Strategy	Properties	Ref.
Naïve Bayesian filter	NLOS mitigation	Outlier detection	Accuracy in terms of the area under curve (AUC) is 87%	[213]
LS + thresholding	NLOS mitigation	Outlier detection	Penalize the quadratic error (cost function)	[206]
CNN	NLOS mitigation	Outlier detection	Transfer learning, 98% accuracy	[194]
SVM	UWB radar	Venue detection	Correction rate > 95%	[106]
LSTM	Robust positioning	Analysing mean error and hyper-parameters	Mean error 6-7 m, less than with other methods tested	[195]
Multi PF	Adaptive positioning	Change channel model when NLOS is detected	RMS positioning error 20 m in 2000 m field	[215]
Reinforced learning + PF	Adaptive positioning	Change PF mode according to success / failure	Accurate and fast recovery for positioning errors	[216]
PF + ML based data fusion	Collaborative positioning	Peer to peer data fusion	Works during main positioning system outage	[217], [218]
PF + ML autocalibration	Collaborative positioning	Automatic configuration	Autocalibration, adaptive time slot protocol	[220], [221]
Ensemble regression and deep learning	Model-free positioning	Fingerprinting	Based on scanning a map of observables	[224], [225]

B. ADAPTIVE POSITIONING

The parameters of the prediction models can be tuned or changed according to the change in the operating conditions detected by ML models, for example, when an agent moves from outdoors to indoors or the detection of NLOS situations. Some researchers have been able to improve the positioning accuracy by using various dynamic-state models simultaneously and selecting the most suitable model according to the conditions detected by the ML model [215]. Neural networks and reinforced learning methods allow even more flexible adaptation to the changing environment [216].

C. COLLABORATIVE POSITIONING

Collaborative positioning means that agents share information with each other while performing positioning. The solution does not necessarily conform to the preconditions of the static or dynamic state model-based methods, as the noise distribution might be skewed, and the problem might be non-convex. Therefore, traditional optimisation methods might not find the global optimum.

Hoang et.al. studied collaborative positioning of vehicles using onboard GNSS, IMU, odometer and UWB for inter-vehicle distance measurement. They formed an ad hoc communication network using the ITS-G5 standard for collaborative positioning [217]. The data fusion was performed using Bayesian frameworks with EKF and PF for pre-processing and data fusion, and they noticed that the PF outperformed the EKF. The experimental result showed that collaborative positioning using

vehicle-to-vehicle communication could secure accurate positioning during GNSS outage in some cases [217].

The noise in DGNSS observables is not Gaussian, and the collaborative positioning problem is not convex. Therefore, the ML approach was used to create a cognitive PF for positioning for industrial IoT purposes [218]. They also noticed that if the noise probability distribution of the sensor data can be properly estimated and used in particle weight computation, the positioning accuracy can be further improved.

Infrastructure-free multi-robot localisation using UWB and PF [219]–[221], including functionality for system autocalibration [105], has been extensively studied. Both relative position and orientation of robots can be obtained by attaching several UWB requesters and responders in robots and measuring ranges using TW-TOA [222].

D. MODEL-FREE POSITIONING

In many cases, ML is used for solving problems without pre-defined models, which can be particularly useful when using ad hoc information for positioning. Inside positioning infrastructure, model-based methods are often more efficient than model-free methods. ML learns the model of the problem domain by itself based on the optimal information gain. In addition to positioning itself, ML can also be used for studying the problem and revealing the hidden dependencies between variables. For example, Wi-Fi fingerprint-based positioning is implemented with ML [223]. Nonlinear ensemble regression methods, such as random regression trees and deep learning, can be efficient in this domain [224], [225].

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E. DEVELOPMENTS IN MISCELLANEOUS APPLICATIONS

With the rapid development of ML approaches in various sectors, there is a growing need to investigate and analyse ML suitability for localisation applications. In the case of location-based services, ML is growing in popularity as it can produce accurate positioning information for navigational purposes. An ML approach can support the achievement of better positioning performance both outdoors and indoors [226]. This positioning system allows real-time tracking and tracing of goods and enables the optimisation of logistics processes in many application areas [227]. In an indoor warehouse scenario, an ML algorithm allowed, for the first time, a monocular optical positioning application [227].

The authors of [228] proposed a visible light positioning (VLP) algorithm, which is based on ML and works to measure the relative distance between the receiving and transmitting ends of the camera. The combination of VLP systems and dual-function ML algorithms enables an increase in positioning accuracy by reducing the negative effect and eliminating low-intensity reflective signals [229]. In this approach, the position is determined by a proposed triangulation algorithm. The authors of [230] proposed an automated visual positioning system using deep learning, which aids to correctly place a workpiece on a fixture. This approach requires template matching across the image in which the template is compared with the local pixels.

ML methods are also used in fingerprint-based algorithms to enhance the precision and robustness of indoor positioning. The advancement of fingerprint localisation technology is a promising method for indoor positioning in various applications [231]. The authors of [232] developed a fingerprint-based localisation method, which is combined with ML and a heterogeneous feature fusion model. Another promising positioning method is smartphone-based indoor tracking, exploiting opportunistic sensing and machine learning techniques, e.g. SLAM. The SLAM method offers a new intelligent filtering approach to maintain good positioning performance [233].

F. SUMMARY

The research interest towards ML methods in positioning has been continuously increasing during the last five years [234]. ML facilitates the use of more data sources for positioning and development of collaborative positioning schemes, which are too complex for traditional methods. ML plays an important role in developing future location-based services by seamlessly using many available positioning infrastructure and other information sources [234].

IX. DISCUSSION

As UWB is a relatively new standard, the maturity in chip production is rapidly increasing. New accurate and affordable UWB hardware has been recently introduced by Decawave and NXP for industrial applications, and UWB chips are included in recent phone models and other consumer products

by the biggest mobile phone manufacturers. This development has made UWB an attractive technology for indoor positioning purposes. Recent UWB positioning systems support decimetre-level accuracy and 60 m distance [105].

Most of the positioning algorithms used with UWB are the same, which have been used for positioning for decades, including multilateration, LS solution, Kalman filtering and particle filtering, but the increased popularity and lowering prices of UWB positioning are also attracting new application areas, solutions and algorithms. While traditional approaches are still optimal for the standard multilateration problem, different ML methods have been proposed to cover special situations, such as the use of heterogeneous data, detection of outliers, mitigation of NLOS situations and automatic adaptation to changing conditions. Automatically calibrated multi-robot positioning systems with collaborative positioning and pose estimation methods have been proposed to assist in controlling industrial robots, drones or cars [159], [235]. Multi-sensor fusion has been studied for increasing the reliability and availability of the positioning service and ML methods to allow seamless roaming between positioning systems and the use of signals of opportunity together with actual positioning observables. Similarly, collaborative positioning can increase the positioning reliability under difficult conditions.

The recent literature in UWB positioning for smart logistics contains adaptation of UWB positioning to many new application areas and increasing the flexibility and reliability using new algorithms.

In the future, low-earth orbit (LEO) satellites can be used to provide an additional mode for both outdoor, and indoor navigation [236]. We intend to implement our proposed positioning system (mobile App), which involves the use of GNSSs, inertial sensors and UWB for smart logistics applications and researching the possibility of using LEO-based positioning observables fused with other available information.

X. CONCLUSION

Due to its versatility, accuracy and robustness, UWB technology is considered an efficient and reliable localisation method for implementing smart logistics. The wide adoption of UWB in location-based services confirms its ability to make an effective compromise among the cost, resource budget and precision. This paper summarises the most recent studies that have adopted UWB in sensitive applications that require high precision positioning in which UWB has successfully reduced the localisation error to a few centimetres. UWB advances for location provision are foreseen to grow as the adoption of this technology in mass-market devices increases via standards and related developments. UWB will likely not only be providing location solutions for special industrial applications but also consumer devices in the future. Moreover, this paper presents a compact review that focuses on using multi-sensor fusion-based systems in specific applications. We highlight the use of inertial sensors, remote sensing devices, visual sensors and other RF-based navigational sensors to achieve seamless navigation under various conditions.

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Additionally, we present a higher perspective on the algorithms used for either single-sensor systems or multi-sensor fusion systems, such as Kalman filter, LS, PF, federated filter structure and ML methods. We have designed the architecture of this article to be a compact tutorial for researchers seeking an overall view on UWB positioning technology, aiming to make it a landmark article on the literature track of UWB.

CONFLICT OF INTERESTS
The authors declare no conflict of interests.

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