Journal of Automation and Intelligence 4 (2025) 82–97

Contents lists available at ScienceDirect

Journal of Automation and Intelligence

Review article

A survey on Ultra Wide Band based localization for mobile autonomous machines☆

Ning Xu [a,b], Mingyang Guan [a,*], Changyun Wen [b]

[a] *Advanced Remanufacturing & Technology Centre (ARTC), Agency for Science, Technology and Research (A*STAR), 3 CleanTech Loop, #01-01 CleanTech Two, Singapore, 637143, Singapore*

[b] *School of Electrical and Engineering, Nanyang Technological University, 50 Nanyang Ave, Singapore, 639798, Singapore*

ARTICLE INFO

Keywords:
Ultra Wide Band
Localization
Mobile autonomous machines
Error mitigation
Optimization
Sensor fusion

ABSTRACT

The fast growth of mobile autonomous machines from traditional equipment to unmanned autonomous vehicles has fueled the demand for accurate and reliable localization solutions in diverse application domains. Ultra Wide Band (UWB) technology has emerged as a promising candidate for addressing this need, offering high precision, immunity to multipath interference, and robust performance in challenging environments. In this comprehensive survey, we systematically explore UWB-based localization for mobile autonomous machines, spanning from fundamental principles to future trends. To the best of our knowledge, this review paper stands as the pioneer in systematically dissecting the algorithms of UWB-based localization for mobile autonomous machines, covering a spectrum from bottom-ranging schemes to advanced sensor fusion, error mitigation, and optimization techniques. By synthesizing existing knowledge, evaluating current methodologies, and highlighting future trends, this review aims to catalyze progress and innovation in the field, unlocking new opportunities for mobile autonomous machine applications across diverse industries and domains. Thus, it serves as a valuable resource for researchers, practitioners, and stakeholders interested in advancing the state-of-the-art UWB-based localization for mobile autonomous machines.

1. Introduction

UWB technology has emerged as a leading solution for localization [1], offering accuracy, robustness, and adaptability in complex environments [2]. Significant advancements in electronics and signal processing have driven UWB from research laboratories into commercial applications [3,4]. Its deployment across various fields, such as industrial automation, robotics, and smart environments, highlights its versatility and paves the way for continued research and innovation [5–7].

At the same time, the rapid development of mobile autonomous machines has created an urgent demand for advanced localization systems. From traditional vehicles and mobile equipment to the latest unmanned autonomous or remotely operated vehicles such as Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), and Unmanned Surface Vehicles (USVs) [8–12], these technologies are transforming industries such as transportation, logistics, agriculture, environmental monitoring, and defense [13–15]. The growing need for precise and reliable localization to ensure the safe and efficient operation of these machines has further accelerated the advancement and adoption of localization technologies [16–18].

Challenges for localization of mobile autonomous machines arise from the need to maintain precise position estimation in complex and unpredictable conditions [19,20]. Applications often place these machines in environments with dynamic and unstructured elements, such as moving obstacles or human activity, which create uncertainty and disrupt localization [21]. Non-line-of-sight (NLOS) scenarios [22], multipath effects [23], and environmental interference, such as signal distortion from metallic surfaces or absorption by liquids [24,25], further complicate accuracy. Outdoor operations must contend with weather changes and uneven terrains, while indoor settings amplify signal reflections and interference [26]. Additionally, sensor noise, synchronization errors, and calibration difficulties pose significant hurdles [27], especially in large-scale or real-time applications.

The challenges necessitate the development of sophisticated error mitigation and optimization techniques to ensure accurate and reliable localization in real-world scenarios [28]. Continuously updated research works have been providing valuable insights into the strengths and limitations of the technology [29,30]. The rapid advancement of UWB technology has ushered in a new era of localization capabilities for mobile autonomous machines [31–33]. Table 1 summarizes the existing review literature for UWB-based localization in the past three years. These reviews, as well as the numerous research articles therein, demonstrate the current prosperity of UWB-based localization technology and the high demand for localization technology in various industries [1,4,34–47]. In Table 1, "Application Scenarios" documents specific application scenarios of localization the literature focuses on, while "Localization Object" records what kind of specific located objects the literature focuses on. Nevertheless, we feel that there is a lack of a comprehensive review focusing on mobile autonomous machines and summarizing how the evolving UWB-based localization technology contributes to mobile autonomous machines. A thorough understanding of the capabilities and limitations of existing UWB-based localization techniques is essential for ensuring safe, efficient, and effective operations of mobile autonomous machines in real-world environments.

This paper endeavors to provide an exhaustive overview of UWB-based localization techniques tailored for mobile autonomous machines, covering fundamental principles, ranging schemes, error mitigation and optimization methods, sensor fusion techniques, and future research directions. By shedding light on the advanced methods and their underlying principles, this paper serves as a guiding beacon for researchers, practitioners, and enthusiasts alike in the vibrant field of UWB-based localization. Fig. 1 illustrates a multi-layered circular framework summarizing the evolution of techniques related to UWB-based localization, showcasing their hierarchical and progressive relationships for various tasks in mobile autonomous machines. This hierarchical structure emphasizes the progression from basic UWB sensor technology to sophisticated applications in mobile autonomous systems, demonstrating the growing complexity and integration of UWB localization in various fields.

The remainder of this paper is organized as follows: Section 2 gives reviews of the fundamentals of UWB-based localization. The background, basic approaches of UWB-based localization techniques, advantages, and limitations have been summarized. Section 3 presents some typical reviews of the latest advancements in UWB ranging schemes and their direct impact on improving localization accuracy and reliability for mobile autonomous machines. Section 4 explores the integration of Artificial Intelligence (AI) techniques with UWB-based localization systems, emphasizing how AI enhances navigation, obstacle avoidance, and overall autonomy in mobile autonomous machines. Section 5 gives reviews of techniques and algorithms designed to mitigate errors inherent in UWB-based localization systems, focusing on their effectiveness in enhancing the robustness and precision of mobile autonomous machines. Section 6 discusses the synergies achieved by integrating UWB technology with other sensor modalities, highlighting how sensor fusion improves localization accuracy and supports diverse operational environments for mobile autonomous machines. Section 7 discusses some future research directions, and Section 8 concludes the paper.

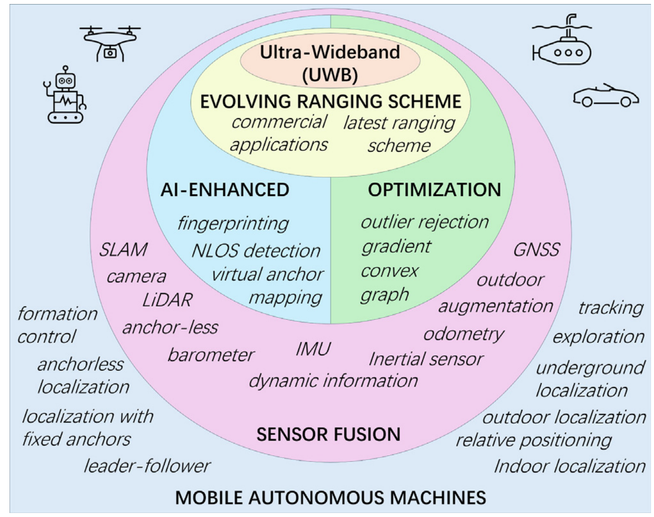


Fig. 1. The summary of the evolving techniques related to UWB-based localization and how they contribute to mobile autonomous machines.

2. UWB-based localization fundamentals

2.1. Background of UWB

UWB is a common Radio Frequency (RF) and perception technology [48]. The application of UWB for radar, communications, electronic warfare, and RF weaponization can be traced back to the last century [49–52]. The Defense Advanced Research Projects Agency (DARPA) for the first time defined UWB radar as "any radar whose fractional bandwidth is greater than 0.25, regardless of the center frequency or the signal time-bandwidth product" or occupies 1.5 GHz or more of the spectrum [52,53]. The fractional bandwidth in the definition is defined by:

$$B_f = \frac{2f_H - f_L}{f_H + f_L}, \tag{1}$$

where B_f is the fractional bandwidth, f_H is the upper frequency of the −10 dB emission point, and f_L is the lower frequency. Contrary to traditional Radio-Frequency Identification (RFID) systems that function

Table 1
Summary of recent surveys on UWB-based localization: Comparison of sensors, review focus, applications, and target objects.

Literature	Sensor	Review focus	Application scenarios	Localization object
Ridolfi et al. [34]	UWB	Self-calibration and collaborative localization	N.A.	N.A.
Obeidat et al. [35]	Various	Localization approach	Indoor	N.A.
Benouakta et al. [36]	UWB	Commercial evaluation boards and antenna influence	Industry	N.A.
Yang et al. [37]	IR-UWB	Human localization	N.A.	Human target
Elsanhoury et al. [4]	UWB	Localization approach	Indoor	N.A.
Sang et al. [38]	UWB	System models of specific schemes	N.A.	N.A.
Yu et al. [39]	UWB	Localization approach	Industrial IoT	Robots
Wang et al. [40]	UWB	Localization approach	Indoor	N.A.
Sesyuk et al. [41]	Various	Localization approach	Indoor	N.A.
Asaad et al. [42]	Various	Localization approach	IoT	N.A.
Rauf et al. [43]	Various	Filter-based localization approach	N.A.	UAVs
Coppens et al. [44]	UWB	Standards and organizations	N.A.	N.A.
Zhao et al. [45]	UWB	Personnel security management	N.A.	Human target
Zare et al. [46]	Various	Localization approach	Underground mining	N.A.
Panigrahi et al. [1]	Various	Localization approach	N.A.	Mobile robots
Yang et al. [47]	Various	Filter-based localization approach	Indoor	N.A.

within a single frequency band, UWB simultaneously sends signals across multiple bands of the radio spectrum [54].

In February 2002, the US Federal Communications Commission (FCC) for the first time "allocated 7.5 GHz (from 3.1 to 10.6 GHz [54]) of spectrum for unlicensed commercial UWB communication systems" [55] with the permission of technology commercialization. The issued ruling (FCC First Report and Order under Part 15 of the Commission's Rules Regarding Ultra-Wideband Transmission Systems [56]) expanded the use of UWB technology to consumer data communication with, at that time, the most extensive bandwidth allocation for any commercial terrestrial system [57]. The document outlined four categories for permissible UWB applications and established corresponding radiation masks and limitations for them. Compared to the definition given by DARPA, the FCC document reduced the −10 dB fractional bandwidth in the UWB definition from 0.25 to 0.20. The minimum bandwidth limit for UWB devices was reduced from 1.5 GHz to 500 MHz. Since then, a series of working groups: IEEE 802.15.3a, IEEE 802.15.3b-2006, and IEEE 802.15.4a-2007 [58–62] have been established by IEEE 802 standards committee to update the standards for the debate and development of UWB applications [63].

The commercial implementations compliant with the evolved standards have been devoted to market use, such as the products manufactured by Ubisense [64,65], BeSpoon [66], Decawave (acquired by Qorvo in 2020) [67], and Humatics [68]. Table 2 summarizes the latest notable commercial UWB products as well as their features and performance insights. These commercial solutions are extensively employed to address localization requirements in daily life and industrial settings, serving as fundamental tools for further advancements in precise positioning and localization research. Numerous studies in the field of UWB and sensor-fusion-based localization utilize commercial UWB sensors as standard experimental methods [69–72]

2.2. Basic UWB localization workflow for mobile autonomous machines

Unlike global positioning technologies such as Global Navigation Satellite System (GNSS), UWB-based localization technology does not require a large amount of resources, but only relies on signal transmission between multiple UWB sensors [29]. This feature makes UWB very suitable for flexible and versatile mobile autonomous machines. The fundamental principle of UWB-based localization is to obtain the relative relationship between two UWB sensors through signal transmission between them [54]. At this stage, different ranging schemes determine the content of the measurements of the UWB sensors, such as distance, angulation, hyperbolic distance difference [78,79]. The UWB sensor placed on the mobile autonomous machine that needs to be located is called a tag [80]. According to different application scenarios, tag localization can be further divided into fixed-anchored localization and anchor-less localization [81]. The former places many static UWB sensors in the environment around the tag, which are called anchors. Anchors, alternatively known as reference points or beacons, serve as stationary fixtures within the environment with pre-established coordinates [82]. They form the bedrock of the localization infrastructure, furnishing a stable spatial reference against which the positions of tags are globally located. On the other hand, in the case of anchor-less localization, there are no longer known global localization anchors in the environment [83]. By analyzing the relationship between UWB sensors, the local localization between tags can be calculated.

The measurement results are then analyzed and integrated into the position of the target object. Widely used approaches include trilateration and fingerprinting-based methods [84]. The former computes the position of a tag by intersecting the spheres of known distances emanating from reference points. According to the different ranging schemes, the triangulation-based localization methods can be divided into lateration and angulation techniques [85]. The latter, the fingerprinting-based methods, pre-map signal strength patterns across space during the offline/training phase, and perform localization through pattern recognition during the online phase, akin to matching a fingerprint to a database of known prints [86]. Other UWB-based localization algorithms applying to mobile autonomous machines include the centroid algorithm [78], the Smallest M-vertex Polygon (SMP) algorithm [54], the Nearest Neighbor (NN) method [87], the Multidimensional Scaling (MDS) [88,89], etc. The latest technology focuses on how to reduce errors in the integration process or fuse the results of UWB with those of other sensors.

2.3. Advantages and limitations of UWB for mobile autonomous machines

UWB technology offers numerous advantages that make it highly suitable for localizing mobile autonomous machines. Its unique impulse-like signal structure supports precise Time of Flight (TOF) and Time

Table 2
Overview of notable commercial UWB products: Comparison of features, applications, and performance insights.

Manufacturer	Product Name	Features and applications	Performance insights
Ubisense	Series 7000 industrial tag [64]	– Designed for industrial environments. – Used for tracking and localization of assets and personnel.	– Evaluated in industrial-like environments. – Offers reliable localization but prone to outliers in challenging conditions [66].
Ubisense	DIMENSION4 [65]	– High-precision real-time tracking system – Suitable for both indoor and industrial applications.	– Known for accuracy and adaptability in industrial applications.
BeSpoon	SpoonPhone [66]	– A smartphone integrated with UWB technology for localization and tracking. – First manufacturer that effectively incorporated the miniature IR-UWB system.	– Demonstrates good accuracy but slightly inferior to Decawave systems in industrial-like environments [73].
Decawave (now Qorvo)	DW1000 [67]	– High-precision UWB transceiver [73]. – Supports accurate localization in real-time systems. – Compliant to IEEE 802.15.4-2011.	– High accuracy for ranges over 1 m. – Economical, low price.
Decawave (now Qorvo)	DW3000 [74]	– Enhanced version of DW1000. – Designed for low-power applications with improved accuracy. – Compliant to both IEEE 802.15.4-2015 and IEEE 802.15.4z.	– Higher accuracy in distances < 1 m compared to DW1000. – Lower power consumption compared to DW1000. – Robust performance in LOS and NLOS conditions [75].
Humatics	P440 [76]	– Operates as a monostatic, bistatic, or multistatic radar. – High-precision product utilized for building comprehensive UWB datasets [68]. – Compliant to FCC Rule Part 15.519.	– Superior accuracy of < 2 cm and rates up to 125 Hz [77]. – Expensive price.

of Arrival (TOA) measurements, enabling high-accuracy position estimation [54]. Such a signal structure also provides higher resistance to multipath fading compared to narrow-band signals, providing reliable performance in cluttered environments, such as warehouses or factories [90]. Comparing to the other standard protocols of short-range wireless communications, such as Bluetooth, ZigBee, and Wi-Fi [91–93], the UWB has been affirmed to offer shorter transmission times, larger data payload sizes, higher energy efficiency, and higher maximum data rates [3]. UWB's low transmission power and minimal interference with other wireless systems operating in the same frequency band make it ideal for energy-efficient and cost-effective deployments [94]. Unlike visual or optical localization methods, UWB eliminates the need for optical calibration and image processing [48], making it a robust solution in varying lighting and environmental conditions. Its short-duration pulses can also penetrate walls and equipment [54], allowing consistent performance across diverse operational scenarios.

However, UWB-based localization is not without limitations, particularly when deployed in challenging environments often encountered by mobile autonomous machines. Dynamic and unstructured surroundings introduce constantly changing elements, such as moving objects and human activity, which can disrupt position estimation. UWB signals are particularly vulnerable to interference from metallic and liquid materials [54,94], leading to signal distortion and degraded performance in industrial or wet conditions. The NLOS scenarios and multipath reflections further complicate localization accuracy [48,95–97]. Additionally, system-level challenges, such as clock drift [98], frequency drift [99], antenna delay [100], and channel fading [101–103], add complexity, especially in large-scale operations requiring real-time updates. Multi-user interference (MUI) [104] and susceptibility to malicious attacks, such as jamming or spoofing [105,106], further highlight the need for auxiliary measures [107–109].

To overcome the limitations of UWB technology in localizing mobile autonomous machines, various complementary approaches are employed. Advanced ranging schemes enhance accuracy by addressing multipath interference and NLOS conditions. The AI techniques further compensate for environmental challenges by predicting and correcting errors, optimizing parameters, and improving navigation and obstacle avoidance in dynamic settings. Error mitigation techniques, including filters and optimization algorithms, reduce noise and system-level inaccuracies like clock drift and multipath effects. Additionally, sensor fusion frameworks integrate UWB with other sensor systems, combining their strengths to achieve precise, robust localization even in challenging environments. Together, these methods ensure reliable and high-performance localization for mobile autonomous machines in complex, dynamic environments. In the following sections, we will delve into the research advancements in these aspects.

3. ACCURACE: Improvement of UWB-base ranging schemes

As the foundation of UWB-based localization, calculating the relationship between two UWB sensors based on their signal transmission is crucial for achieving accurate localization. The latest advancements in UWB ranging schemes significantly enhance the localization accuracy and reliability of mobile autonomous machines. This section delves into the diverse array of UWB ranging schemes, and their contribution to the localization of mobile autonomous machines.

3.1. Conventional schemes & commercial applications

The conventional ranging schemes include assessing the attenuation of the emitted signal strength or the travel time [54]. The principle of the TOA is the simplest and most direct distance measurement method for the UWB sensor [110]. The TOA measures the one-way propagation time between the measuring unit and signal transmitter. The distance between the two items is then calculated according to the product of propagation time and the propagation velocity of the electromagnetic wave [111]. Despite its simplicity, the TOA-based ranging scheme exhibits notable shortcomings: It has high requirements for synchronization between all the transmitters and receivers in the system, and strict requirements for a timestamp in the transmitting signal for the measuring unit to identify [112].

The Two-Way Ranging (TWR) technique, also known as the Round Trip TOF technique, measures the TOF of the signal traveling from the anchor to the target tag and back [54]. Compared to the TOA-based one-way range scheme, the TWR-based scheme reduces the clock synchronization requirement [78]. The basic TWR-based scheme only uses one of the two UWB modules as the measuring unit. Therefore, it is also referred to as Single-Sided Two-Way Ranging (SS-TWR). The SS-TWR principle and its enhancements are presently the most prevalent UWB ranging strategy in use [113]. The most commonly used commercial UWB sensors for mobile machine localization, including the DW1000IC families, DW3000 IC families, and Humatics P440 Module, all support the TWR-based scheme.

The Time Difference of Arrival (TDOA) system is the foundation of the UWB-based localization, traced back to 2003 [114]. Currently, most of the commercial solutions of UWB-based localization systems are still equipped with TDOA-based ranging blocks, including the Ubisense Series, DW1000IC, DW3000IC, etc. The TDOA principle measures the time difference between the transmitter signal arriving at different reference points. Taking a 2-D space as an example, for each pair of reference points, the time difference of arrival restricts the possible transmitter positions to a hyperbola. The intersection of two or more hyperbolas measured via multiple pairs of reference points reveals the transmitter position [115]. The direct solutions to the hyperbolic TDOA equation require a large computational amount through nonlinear regression. The common calculation methods for TDOA estimation include the Generalized Cross-Correlation (GCC) [114], Least Squares (LS) method [116], Chan algorithm, and Taylor algorithm [54]. Compared with the TOA estimate, the TDOA estimate reduces the requirements for the synchronization of the mobile tag transmitter. Compared to the TWR techniques, the TDOA ranging is lower energy consuming and lower latency due to the one-way communication property [78]. Ref. [117] adopts the TDOA-based localization algorithm as it is "the most widely used, simple, and no additional hardware required".

Besides the propagation time which would suffer from the multipath effect, another method to estimate the distance between UWB modules is based on the Received Signal Strength (RSS) [118]. The RSS-based methods are also referred to as signal attenuation-based methods. It uses the attenuation of emitted signal strength to calculate the signal path loss due to propagation [119].

The Angle Of Arrival (AOA) estimation is a specific technique used to determine the angle from which a signal arrives at a receiver. This involves measuring the angles of arrival in azimuth and possibly elevation. The task can be achieved using either directional antennas or an array of antennas [54]. Another similar concept is the direction of arrival. The AOA estimation does not require time synchronization between measuring units [120]. The power consumption is also relatively low. However, it requires more complex hardware. The localization accuracy would reduce as the target moves away due to shadowing, multipath reflections, and limitations in angle measurements [78]. The Ubisense Series offers the capability to measure the 2-axis AOA of UWB signals.

The phase of arrival estimation, also known as the received signal phase estimation [121], determines the target object's location according to the carrier phase or phase difference. In addition to supporting TWR and TDOA, the DW3000 family can also be employed in the Phase Difference Of Arrival (PDOA) system [122].

Table 3 summarizes and compares the performance of key UWB ranging schemes, including TOA, TWR, TDOA, RSS, and AOA, along with their respective advantages, disadvantages, and commercial applications.

Table 3
Comparison of UWB-based ranging schemes: Advantages, disadvantages, and commercial applications.

Method	Advantages	Disadvantages	Commercial applications
TOA [110]	– Simple and direct method for distance measurement. – Provides high accuracy if time synchronization is achieved.	– Requires precise synchronization between all transmitters and receivers [112]. – High timestamp precision required.	–
TWR [54]	– Reduces clock synchronization requirements compared to TOA [78]. – Widely used in commercial systems. – Robust for real-world applications.	– Still requires synchronization, though less stringent. – Potential for high latency due to round-trip signal processing.	– DW1000 – DW3000 – Humatics P440
TDOA [114]	– Lower energy consumption and latency due to one-way communication. – Does not require synchronization of the mobile tag. – Widely used in commercial UWB systems.	– Requires complex calculation (nonlinear regression) to solve hyperbolic equations [116]. – High computational load.	– Ubisense DIMENSION4 – DW1000 – DW3000
RSS [118]	– Simple to implement. – Low power consumption. – Can operate in noisy environments.	– Susceptible to signal attenuation and multipath effects [119]. – Accuracy decreases with increasing distance.	–
AOA [120]	– Does not require time synchronization. – Low power consumption. – Can provide directional information for additional accuracy.	– Requires complex hardware (e.g., directional antennas or antenna arrays). – Accuracy decreases with target distance.	– Ubisense Series

3.2. Latest improved ranging schemes

For the popular and widely used ranging schemes, many targeted improvement and expansion plans have been proposed regarding their shortcomings. These solutions can have a direct impact on the accurate localization of mobile autonomous machines. For example, the TDOA technique heavily relies on precise and strict time synchronization between anchors. Ref. [123] uses a high-precision timer instead of initial synchronization to design a delay measurement-based TDOA ranging.

Another area that has received widespread attention and research is the TWR-based scheme. Specifically, the SS-TWR-based scheme confronts a large challenge to determine the exact delay and processing time. Ref. [124] proposes CFO-Corrected Single-Sided Two-Way Ranging (CC-SS-TWR), using the Carrier Frequency Offset (CFO) between the receiver and the transmitter to inherently estimate the relative clock offset, to reduce the ranging error of the SS-TWR scheme. The Symmetric Double-Sided Two-Way Ranging (SDS-TWR) scheme is another extension to mitigate the clock drift error [78]. Compared to the SS-TWR principle, the SDS-TWR scheme is achieved by transmitting one more reply message after the round trip [63]. While the SDS-TWR scheme can effectively mitigate clock and frequency drift errors [125, 126], it is important to note that the assumption of equally symmetric reply delay is overly idealistic and challenging to implement [63]. The SDS-TWR-based system may also be impacted by the “frequency drift occur during the crystal warm-up phase” [78], which is mainly caused by the instrument itself. Moreover, the SDS-TWR technique requires a long processing time [127]. An Asymmetric Double-Sided TWR (ADS-TWR) is designed to overcome the “susceptibility of TWR to crystal offsets and the increased ranging delay of SDS-TWR” [128]. Ref. [70] adopts the ADS-TWR scheme in the Self-Localization (SL) procedure. It also discusses the ADS-TWR procedure in the presence of antenna delays. Similar improved algorithms have been mentioned as the Alternative Double-Sided Two-Way Ranging (AltDS-TWR) [63,78] and Enhanced Asymmetric Double-Sided Two-Way Ranging (EADS-TWR) [127]. Ref. [129] proposes another alternative Double-Sided Two-Way Ranging (DS-TWR) scheme.

Besides the improvements, some conventional ranking schemes can also exert unexpected innovative effects based on their characteristics through targeted application: Ref. [130] adopts the TOA principle and implements it with the Ubisense UWB tag. With the single-way range measurement, any delay will be positive [131], which enables this work to propose its particle filter-based algorithm. Ref. [70] adopts the TDOA technique to localize the tags because the TDOA error eliminates the transmitting delay, leaving only the receiving antenna delay.

4. Strengthened: AI-enhanced UWB techniques

AI encompasses a wide array of technologies and methodologies aimed at enabling machines to perform tasks that typically require human intelligence [132]. These tasks include learning from data, recognizing patterns, making decisions, etc. The combination of AI with UWB-based localization leverages the strengths of both technologies to enhance the capabilities of mobile autonomous machines. AI algorithms can process and analyze the vast amounts of data generated by UWB sensors, identifying patterns and making predictions that improve localization accuracy and reliability. Machine learning models can be trained to recognize complex signal behaviors and compensate for environmental factors that affect UWB signals [133–135].

4.1. Enhancing the fingerprinting localization

AI algorithms improve the precision and accuracy of UWB-based localization by learning from data and adapting to environmental changes. For example, the RSS-based ranging scheme often relies on site-specific theoretical and empirical models. The fuzzy logic algorithms and AI algorithms help improve the performance of RSS-based localization. Besides the basic RSS indication, the wide bandwidth of UWB permits signal parameters with numerous degrees of freedom [136], leading to a sufficient database of evolving Channel Impulse Response (CIR) statistics, such as energy, delay spread, first path TOA [86], path gains, path delays [136], path loss magnitude [137], etc. These inherent advantages of UWB make it more potential to generate sufficient databases, so AI-enhanced UWB will have more room for development in the fingerprinting localization fields [125, 133]. Despite its reliance on extensive calibration and environmental factors, such techniques excel in scenarios where traditional geometric methods falter, such as in complex indoor environments with numerous obstructions.

Compared to other localization tasks, the localization requirements for mobile autonomous machines are more likely to occur in complex, multi-interference, even unknown environments. In such challenging environments, AI-enhanced UWB techniques are quite suited for deterministic fingerprinting tasks [125,136], such as the NLOS detection, LOS/NLSO classification [125], error mitigation [138], and other tasks that can be attributed to classical AI classification, regression, and prediction problems [95]. The thriving AI-enhanced UWB techniques have been widely applied to mobile autonomous machines, such as the feed-forward neural network [86], Support Vector Machine (SVM) [139], Multi-Class SVM (MC-SVM) [137], K-Nearest Neighbors

(KNN) [140], Decision Tree (DT) [141], Random Forests (RF) [142, 143], Convolutional Neural Network (CNN) [144–146], Long-Short Term Memory (LSTM) neural network [147,148], CNN-LSTM [149, 150], the probabilistic learning approach [151,152], etc.

In summary, AI techniques improve UWB-based fingerprinting localization by leveraging large datasets of CIR statistics, enabling precise localization in complex environments. AI algorithms such as CNN, LSTM, SVM, and probabilistic learning approaches enhance tasks like LOS/NLOS classification and error mitigation, making UWB localization highly adaptable to interference-prone settings.

4.2. Enhancing the mapping

For indoor environments where GPS signals are unreliable or unavailable, an ideal localization solution is to combine a high-precision UWB technology with a-priori available floorplan information [153]. Floorplan information provides a detailed map of the environment, including walls, rooms, and fixed obstacles. By integrating this data with UWB-based localization, the system can more accurately determine the position of a mobile autonomous machine by cross-referencing UWB signal data with known structural elements of the environment [154]. A-priori floorplans also enable the development of efficient navigation routes, avoiding obstacles and optimizing paths. This is particularly important in applications such as warehouse management, where mobile autonomous machines need to move efficiently to maximize productivity [155]. Furthermore, the floorplan information helps the system differentiate between various environments and adapt its behavior accordingly.

The AI techniques enhance these mapping and localization systems in several impactful ways: AI algorithms excel at integrating and interpreting diverse data sources [156]. By combining UWB signal data with floorplan information, AI can create a comprehensive and highly accurate map of the environment. Machine learning models can be trained to understand the relationship between signal characteristics and physical structures, improving localization accuracy [157]. Advanced algorithms can differentiate between static and dynamic obstacles, allowing mobile autonomous machines to plan safe and efficient routes [158]. Moreover, as mobile autonomous machines navigate through an indoor space, AI can continuously update the localization model based on new data, ensuring that the system remains accurate even as conditions change.

A typical example of the AI technique contributing to UWB-based mobile autonomous machine localization is the concept of Virtual Anchor (VA). With the Multipath Components (MPCs) of the UWB signals and the a-priori available floorplan information [159], the mirror-image virtual anchors are formed according to the reflection signals from the room walls or other reflecting surfaces [160]. The position of the agent can then be computed from these range estimates using statistical techniques. The VA technique increases the robustness and accuracy of the localization and reduces the requirements of LOS connection between anchors and target. The AI-enhanced UWB-based localization systems can significantly improve the effectiveness and utility of virtual anchors to dynamically adjust to environmental changes, process signals more accurately, and integrate seamlessly with existing infrastructure. The resulting improvements in accuracy, reliability, and scalability make AI-enhanced virtual anchors an invaluable tool for a wide range of applications, from indoor navigation and asset management to smart buildings and emergency response.

In a word, AI techniques enhance UWB mapping by integrating UWB signals with floorplan information for improved localization and navigation in GPS-denied environments. VAs based on MPCs use AI to dynamically adjust to environmental changes, enabling robust indoor navigation, obstacle avoidance, and route optimization in applications like warehouse management and emergency response.

5. Robustness: Error estimation & optimization

Section 4 introduces many of the latest AI-enhanced UWB-related technologies, which utilize the classification and decision-making capabilities of AI to analyze and categorize UWB measurement data, such as error classification [144] and NLOS detection [161]. These techniques often pair classification results with corresponding error mitigation and correction methods [162]. AI-based approaches typically rely on large datasets for training and validation [163]. However, practical UWB applications demand higher robustness and flexibility in error estimation and compensation, especially in dynamic and unpredictable real-world environments [164]. Beyond the AI-driven judgment-correction paradigm, recent advancements have introduced a range of error mitigation techniques that do not require prior data collection or training [165,166]. These methods significantly enhance the applicability of UWB localization in complex and uncertain settings [167]. For example, the Maximum Likelihood Estimation (MLE) has been applied to find the parameter values that maximize the likelihood of the observed UWB measurements given the model. It can be used to minimize the appropriate norm between the measuring distance and position difference for the triangulation method [138], or to form a Maximum A-Posteriori (MAP) estimator for the position-dependent channel estimation problem with prior floorplan information [159]. During this process, interference caused by the environment, such as the NLSO disturbance, can be considered as part of the estimation error. Recently, some more targeted error estimation and optimization techniques have been proposed for the UWB-based localization system in challenging environments.

5.1. Bayesian state–space estimation-based methods

The Bayesian state–space estimation, involving modeling the dynamics of a system using a state–space model, has been introduced to mobile target localization works. The model includes a dynamic process that describes how the state evolves and an observation model that relates the true state to the observed data. It combines Bayesian inference principles with the concept of a state–space model, making it a powerful approach for handling uncertainty and updating beliefs about the state of a system over time.

5.1.1. Kalman filter

The Kalman Filter (KF) and its improvements and extensions are widely used to estimate UWB measurement for mobile autonomous machines [160,168]. It recursively updates the estimate of the system's state based on the prior estimate, the dynamic model, and the observed measurements. The standard Kalman Filter originates from the recursive solution to the discrete data linear filtering problem in the 1960 s [169]. The employment of KF in the UWB-based localization system can be traced back to the 2000 s. It is particularly well-suited for linear systems with Gaussian noise [160,170]. The Kalman Filter works through a two-step recursive process: prediction and update [168,169]. In the prediction step, the filter uses the previous state estimate and the system's dynamic model (e.g., motion equations) to predict the current state. This prediction provides an estimate of the state at the current time step and an error covariance matrix that represents the uncertainty of this estimate.

$$\hat{x}_k^- = \boldsymbol{A}_{k-1}\hat{x}_{k-1} + \boldsymbol{B}_{k-1}u_{k-1}, \tag{2}$$

$$\boldsymbol{P}_k^- = \boldsymbol{A}_{k-1}\boldsymbol{P}_{k-1}\boldsymbol{A}_{k-1}^{\mathrm{T}} + \boldsymbol{Q}_{k-1}, \tag{3}$$

where $\hat{x}_k^-$ is the predicted state at time step k, $\boldsymbol{A}_{k-1}$ is the state transition matrix, $\hat{x}_{k-1}$ is the state estimate at time step $k-1$, $\boldsymbol{B}_{k-1}$ is the control coefficient matrix, and u_{k-1} is the control input, $\boldsymbol{P}_k^-$ is the predicted error covariance at time step k, $\boldsymbol{P}_{k-1}$ is the error covariance at time step $k-1$, and $\boldsymbol{Q}_{k-1}$ is the process noise covariance matrix.

Then in the measurement updating (correction) step, a new measurement is incorporated into the a-priori estimate to obtain an improved a-posteriori estimate.

$$\boldsymbol{K}_k = \boldsymbol{P}_k^- \boldsymbol{H}_k^{\mathrm{T}} (\boldsymbol{H}_k \boldsymbol{P}_k^- \boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{R}_k)^{-1}, \tag{4}$$

$$\hat{x}_k = \hat{x}_k^- + \boldsymbol{K}_k (z_k - \boldsymbol{H}_k \hat{x}_k^-), \tag{5}$$

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_k^-, \tag{6}$$

where $\boldsymbol{K}_k$ is the Kalman gain, $\boldsymbol{H}_k$ is the measurement matrix, $\boldsymbol{R}_k$ is the measurement noise covariance matrix, z_k is the actual measurement at time step k, $\boldsymbol{H}_k \hat{x}_k^-$ is the predicted measurement, and $\boldsymbol{I}$ is the identity matrix. The KF has the advantage of recursively conditioning the current estimate on all of the past measurements [169], which makes practical implementations much more feasible.

The classic KF can derive the optimal carrier state from linear stochastic difference equation. Nonetheless, practical localization systems inevitably exhibit varying degrees of nonlinearity, often arising from relationships such as the square or trigonometric functions within the state or observation equations [127]. In this case, Extended KF (EKF) is introduced to the UWB-based localization fields. The EKF is the KF that involves linearization of the current mean and covariance [169, 171]. Similar to the classic KF, EKF also consists of the time update equations and measurement update equations:

$$\hat{x}_{k+1}^- = f(x_k, u_k, 0), \tag{7}$$

$$\boldsymbol{P}_{k+1}^- = \boldsymbol{F}_k \boldsymbol{P}_k \boldsymbol{F}_k^{\mathrm{T}} + \boldsymbol{W}_k \boldsymbol{Q}_k \boldsymbol{W}_k^{\mathrm{T}}, \tag{8}$$

where $\boldsymbol{F}_k$ and $\boldsymbol{W}_k$ are the process Jacobians at step k, and $\boldsymbol{Q}_k$ is the process noise covariance at step k.

The EKFs are widely used in UWB-related localization solutions. Garcia et al. [172] use the EKF to mitigate NLOS. Benini et al. [69] adopted the EKF to improve the localization accuracy from the integration system based on IMU, UWB, and vision. Xu et al. [173] integrate the colored EKF and the colored Extended Unbiased Finite Impulse Response (EFIR) filter to reduce the colored measurement noise for UWB-based indoor localization.

Although the EKF algorithm relies solely on the first-order approximation within the Taylor expansion, it unavoidably introduces linearization errors [127]. Unscented KF (UKF) provides a more accurate estimation of nonlinear systems without the need for explicit linearization [174]. It achieves this by using sigma points, capturing the nonlinearities more effectively, and enhancing the filter's performance in complex and highly nonlinear systems [127]. Ref. [127] uses the UKF to couple the measurement of IMU and UWB for high-accuracy indoor localization and navigation. It also compares the performance between UKF and EKF. Ref. [175] uses the UKF to estimate the a-posteriori Probability Density Function (PDF) and therefore model the localization uncertainty.

5.1.2. Particle filter

Particle Filter (PF) is another kind of Bayesian state–space estimation-based method that is popular for UWB-based localization systems [176,177]. The PF uses a set of weighted particles to represent the posterior distribution and predicts the state forward in time. The PFs applied in the UWB-based localization field are mostly using Monte Carlo techniques [160]. Compared to the basic PF framework with Sequential Importance Sampling (SIS) form, the SMC form introduces additional techniques to address particle degeneracy issues and offers greater flexibility in resampling frequency. They are famous for providing a flexible and effective representation approach for nonlinear and nonGaussian dynamic systems [174,178]. Several other types of PFs and their variants also have extensive applications in the field of UWB-based localization. Meissner et al. [160] employ a Sampling-Importance-Resampling (SIR) PF to perform position estimates based on the CIR. Leitinger et al. [159] design the SIR-PF with the concept of Particle Swarm Global Optimization (PSO) to solve the highly multi-modal and non-convex MLE problem for agent position. The PFs applied to the localization field also include: the Auxiliary Particle Filter (APF) [179], Implicit Unscented Particle Filter (IUPF) [180], Rao-Blackwellized Particle Filter (RBPF) [181], Regularized Particle Filter (RPF) [182], etc.

5.2. Optimization based algorithms

UWB technology combined with optimization-based algorithms is another major category of technology that can make significant contributions to mobile autonomous machines. Popular optimization-based algorithms, such as gradient-based optimization algorithms, convex optimization algorithms, and graph optimization methods, can all contribute to the precise localization of mobile autonomous machines.

Graph optimization is a branch of optimization theory that deals with solving problems defined on graphs [183]. In large-scale mobile autonomous machine systems with multiple sensors or objects, graph optimization techniques can be easily applied to design the network topology. This involves selecting the subset of sensors to be active, determining communication links, and optimizing network connectivity to achieve desired localization performance [113,184]. It is very easy to define the mobile agents as vertices (nodes) and the communication between two UWB sensors as edges (connections) of the graph. The graph optimization methods help to remove the dependence on the kinematic model and the requirement of receiving concurrent multiple range measurements in the mobile autonomous machine system. Combining with other optimization algorithms, graph optimization has been a trend for UWB-based localization of mobile autonomous machines [185,186].

The convex optimization methods improve the quality of localization between mobile autonomous machines where the UWB estimation can be formulated as a convex program. Fundamental convex optimization techniques for UWB-based mobile agents localization include the LS algorithm [96,187], the Weighted LS (WLS) algorithm [188,189], etc. They are widely used in the triangulation localization methods [127,190]. Recently, advanced convex optimization methods have contributed to the improvement of mobile autonomous machines' UWB-based localization in more aspects: The Quadratically Constrained Quadratic Programming (QCQP) generally formulates the objective function and constraints using quadratic functions [191,192]. In the context of UWB-based localization where quadratic constraints naturally arise, QCQP can be used to formulate and solve optimization problems, providing a convex framework for efficient and reliable solutions [193,194]. The Second-Order Cone Programming (SOCP) is effective in handling problems with linear and second-order cone constraints [195–197]. It can be used to model distance constraints [198]. The Semidefinite Programming (SDP) [199,200] is particularly useful when dealing with non-convex constraints [201,202]. The convex optimization provides guarantees of finding the global optimum for convex problems, but its application in UWB-based localization may be limited by the nature of the problem.

The Gradient-based optimization methods can be used to iteratively refine the estimates of the device's position, leveraging information about the gradient of the objective function and quantifying the discrepancy between the UWB measurements and the predictions of the localization model. Regarding the UWB optimization tasks, the fundamental gradient-based optimization algorithm, such as the Gradient Descent (GD) algorithm [148,203], Stochastic Gradient Descent (SGD) [204], and Conjugate Gradient (CG) [205], have recently been gradually replaced by other algorithms that are more suitable for parallel computing and non-convex operations [206]. The gradient-based optimization algorithms recently involved in the UWB-based localization more as training algorithms for machine learning models [148, 207,208]. However, there are also some advanced gradient-based optimization algorithms being updated and improved to adapt to the increasing requirements of localization systems. For example, Nguyen et al. [209] proposes a "Localization in Riemannian Manifold Using a Conjugate Gradient (LRM-CG)" for the Euclidean distance matrix completion technique for the IoT network localization.

The Quasi-Newton method is a kind of nonlinear iterative optimization technique that has been continuously evolving for UWB-based localization estimation. They approximate the inverse Hessian matrix without explicitly computing it, allowing for faster convergence [210], which is suitable for the real-time localization of mobile autonomous machines. Mary et al. [211] applied the iterative Davidon–Fletcher–Powell (DFP) Quasi-Newton algorithm to precision automobile parking application. They also verified its progressiveness compared with the direct method. Besides the DFP quasi-Newton method, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) Quasi-Newton method [212] and Limited-Memory BFGS (L-BFGS) Quasi-Newton methods [213] are also widely used for UWB-based localization to improve the estimation accuracy and efficiency between the anchors and the autonomous mobile machines [214–216].

Other advanced gradient-based optimization methods can also contribute to mobile autonomous machines' UWB-based localization. For example, the Levenberg–Marquardt (LM) algorithm, the classical Gauss–Newton method with the Levenberg–Marquardt correction [217,218], is often used in UWB-based localization to optimize the parameters involved in non-linear models. Ref. [219] adopts the LM method with a known Jacobian to solve the optimal state estimation problem that minimizes the covariance of the UWB range measurement and processing noises to locate a flying robot with indirectly derived velocity constraints. The LM algorithm is famous for being stable, reliable, and rapidly converging, being particularly effective in situations where the Gauss–Newton method might encounter convergence issues [220,221]. Another example is the Newton–Raphson method [222]. It is suitable for well-behaved and smooth objective functions, which can be applied to enhance the UWB-based localization for mobile autonomous machines in scenarios where accurate second-order information is available [223,224].

Table 4 categorizes and summarizes the key optimization-based algorithms, including graph optimization, convex optimization, gradient-based methods, and Quasi-Newton methods. This table outlines their techniques, advantages, and applications, providing a clear reference to support the discussion on robustness and error estimation in UWB localization systems.

5.3. Threshold based outlier rejection

The outlier rejection techniques for UWB measurements are quite useful for mobile autonomous machine localization tasks, especially when considering mobile robots in extreme environments [170]. In addition to the AI-enhanced UWB technology introduced in Section 4, which can detect specific error circumstances, such as NLOS condition, another kind of advanced technique is the threshold-based outlier rejection algorithm. Its advantages are flexibility and adaptability. For mobile autonomous machines, such outlier rejection techniques can be flexibly combined with other error mitigation, optimization, and integration processes. Widely used outlier identification methods include statistical measures such as mean, median, standard deviation, or interquartile range to identify outliers [189]. Novelty outlier detection approaches have been proposed to improve the pure statistical analysis-based outlier deleting algorithms [225]. A recent trend involves identifying and discarding particularly conspicuous outliers based on overarching optimization and filtering strategies. The threshold can be fixed or dynamically adjusted based on factors such as signal strength or environmental conditions [226,227].

For instance, Nguyen et al. [228] calculate the variance of the UWB data in a sliding window as

$$\hat{\sigma}_k^2 = \frac{1}{K} \sum_{i=k-K+1}^{k} (\widetilde{d_i} - \bar{d}_k)^2, \tag{9}$$

where K is the window size, $\bar{d}_k$ is the mean value of K samples. When a new data $\widetilde{d}_{k+1}$ is received, if the new $\hat{\sigma}_{k+1}$ increases over a pre-defined threshold, the data is discarded.

Fang et al. [186] also employs a sliding trajectory window to control the number of constrained equations and introduces the threshold-based outlier rejection algorithm for the NLOS conditions. Specifically, the newly obtained range measurement d_{k+1} between the mobile target and one of the fixed anchors t^a_{k+1} at time $k+1$ is considered as an outlier if the following condition is satisfied:

$$|\hat{t}_k - t^a_{k+1}|^2 - d_{k+1} > \gamma \cdot \frac{v_{\max}}{f}, \tag{10}$$

where $\hat{t}^N_k$ is the estimated trajectory in the sliding window of time k, γ is the outlier rejection parameter, $v_{\max}$ is the maximum velocity of the mobile target, and f is the frequency of the UWB sensor.

Totally, threshold-based outlier rejection methods are not only robust but also highly adaptable to diverse applications. By leveraging dynamic thresholds and novel optimization techniques, these algorithms enhance the reliability and precision of UWB-based localization systems, even in challenging environments.

6. Integral: UWB fused other sensors

On the one hand, UWB-based localization stands out for its high accuracy, low cost, and low hardware requirements. However, on the other hand, UWB-based localization relies on the relative distance between different UWB sensors, which makes it only able to provide relative local positions. To obtain global localization information for mobile autonomous machines, a UWB-based localization system either depends on the fixed anchors with known global locations, or fuses with other sensors. Sensor fusion in the localization of mobile autonomous machines refers to integrating data from multiple sensors to enhance

Table 4
Summary of optimization-based algorithms: Techniques, advantages, and applications in UWB systems.

Algorithm type	Key techniques	Advantages	Applications
Graph Optimization [183]	– Defines agents as graph nodes [185]. – Edges represent communication links. – Optimizes network topology.	– Scalable for large systems [184]. – Reduces dependency on kinematic models. – Handles NLOS effectively.	– Multi-sensor systems. – Network design for localization [113].
Convex Optimization [187]	– LS [96], WLS [188] – QCQP [194], SOCP [195], SDP [199]	– Global optimal for convex problems. – Effective for triangulation [190]. – Handles non-convex constraints [201].	– Distance-based localization [198]. – Large-scale UWB networks.
Gradient-Based Methods [203]	– GD, SGD [204], CG [205] – LRM-CG [209] – LM [219], Newton–Raphson [222]	– Adaptable for non-linear models. – Suitable for real-time systems. – Parallel computing capabilities.	– Training ML models for UWB [148]. – Precise parameter optimization. – IoT network localization [209].
Quasi-Newton Methods [210]	– Nonlinear iterative optimization technique. – DFP [211], BFGS [212], L-BFGS [213] Quasi-Newton	– Approximates the inverse Hessian matrix without explicit computation, enabling faster convergence. – Suitable for nonlinear iterative optimization.	– Precision automobile parking [211]. – Real-time localization [214].

accuracy, reliability, and robustness [97,229]. Different sensors have their advantages and disadvantages. Effective sensor fusion can achieve localization effects that cannot be achieved by a single sensor. For dynamic mobile autonomous machines, UWB-based anchor-tag systems are often not enough for their localization requirements. To fully master their real-time dynamic tracking and localization, both the precise UWB data and the dynamic information from sensor fusion are indispensable. In this section, we will discuss the synergies achieved by integrating UWB technology with other sensor modalities, highlighting how sensor fusion improves localization accuracy and supports diverse operational environments for mobile autonomous machines. Table 5 summarizes the various UWB-related sensor-fusion solutions in mobile autonomous machine localization over the past three years. Mobile autonomous machines and mobile vehicles are studied as localization objects. Various application scenarios benefit from UWB-related sensor fusion, including underground mining, warehouses, multi-story buildings, and more. Different sensors and fusion solutions have been proposed to fit the specific requirements and challenges posed by the environment.

6.1. Fusion with dynamic information compensation

In addition to general localization methods, one major way to locate mobile autonomous machines is to use their real-time dynamic information for localization and state estimation. Sensors that can achieve this include inertial sensors, odometry systems, barometers, etc. They are all crucial components for the localization of mobile autonomous machines, functioning by recording dynamic real-time data, which is essential for estimating the machine's position and movement over time. Inertial sensors measure acceleration and angular velocity, providing information on the mobile autonomous machine's orientation and linear movement. Specifically, an Inertial Measurement Unit (IMU) provides measurements of specific force (acceleration) and angular rate (rotation) along three axes (X, Y, Z) [231,233,243]. Micro-Electro-Mechanical Systems Inertial Navigation System (MEMS-INS) incorporates MEMS sensors for measuring the inertial properties of a moving object [244]. Odometry systems track the mobile autonomous machine's displacement through wheel rotations or leg movements, translating these into distance traveled and changes in position [245]. Barometers measure atmospheric pressure to determine altitude changes, which can be critical for navigating varied terrains or multi-level environments [246].

These sensors are typically compact, lightweight, and can be integrated seamlessly into mobile robotic platforms. They offer high temporal resolution, ensuring continuous and precise tracking of the mobile autonomous machine's movements. However, each type of sensor is also subject to certain limitations, such as drift in inertial sensors, cumulative error in odometry, and sensitivity to environmental changes in barometers. By fusing with the UWB sensors, the overall accuracy and reliability of localization can be efficiently improved. The UWB distance measurements are particularly valuable during the initialization process, providing accurate initial estimates of device positions relative to anchors before other sensors [230,233,247]. Furthermore, the UWB distance measurements can reduce the drift issues, leading to a localization system with higher accuracy. The fusion results are highly beneficial for mobile autonomous machines. Jao et al. [248] tightly coupling fused the IMUs, UWB modules, and barometers with a foot-mounted localization system. The integration of UWB beacons serves to confine the propagation of position errors in foot-mounted INS, obviating the necessity for beacon surveying. Xu et al. [249] adopt UWB-ranging results to correct the measurement errors of IMUs in the proposed tightly integrated model. Vandermeeren et al. [234] skillfully utilize the close relationship between shopping cart acceleration and stroller step length, combining the step detection algorithm, People Dead Reckoning (PDR) algorithm, and IMU measurement data. UWB ranging results and the PDR algorithm are then merged with the filter-based optimization algorithms to complement each other when their localization quality declines. Si et al. [232] develop the UWB credibility factor to evaluate the UWB measurements and adjust the fusion weight of UWB information before fusing the IMUs' and UWB measurements. Feng et al. [230] propose an SVM-base NLOS detection algorithm and assign different filter-based fusion solutions for the UWB and IMU to different environmental conditions. There are also Refs. [233,241,250] that adopt a similar detection-fusion framework.

In a word, dynamic information from sensors like IMUs, odometry systems, and barometers complements UWB localization. These sensors provide real-time data for position and movement estimation. Fusing their outputs with UWB mitigates sensor limitations (e.g., drift) and improves accuracy and reliability, particularly for dynamic positioning systems.

6.2. Fusion with SLAM

Simultaneous Localization and Mapping (SLAM) is particularly suitable for mobile autonomous machines due to its ability to concurrently build a map of an unknown environment while determining the mobile autonomous machine's precise location within that map. This dual capability is essential for mobile autonomous machines operating in dynamic or unstructured environments where pre-existing maps are unavailable or unreliable [251]. SLAM algorithms utilize the visual information from visual sensors, such as kinds of cameras [235,252,253], LiDAR (Light Detection and Ranging) [254], etc [81,236]. SLAM algorithms use this visual information to build and continuously update a map of the environment while simultaneously keeping track of the robot's position within this map [229,255,256].

By combining SLAM with UWB, the strengths of both technologies are leveraged: SLAM's ability to create detailed maps and handle dynamic environments is complemented by UWB's high-precision

Table 5
Summary of recent localization solutions based on UWB-related sensor fusion: Comparison of sensor types, applications, and fixed base station usage.

Literature	Fused sensor types	Localization objects	Fixed BS
Feng et al. [230]	UWB + IMU	Mobile BS	Yes
Li et al. [231]	UWB + IMU	Quadcopters	N.A.
Si et al. [232]	UWB + IMU	Underground mobile equipment	Yes
Sun et al. [233]	UWB + IMU + Odometer	Turtlebot3	Yes
Vandermeeren et al. [234]	UWB + IMU + PDR	Shopping cart	Yes
Liu et al. [81]	UWB + IMU + LiDAR	UGVs	Yes
Nguyen et al. [235]	UWB + IMU + Monocular camera	UGVs	Yes
Gerwen et al. [229]	UWB + IMU + SLAM camera + Sonar + ArUco markers	UAVs	N.A.
Nguyen et al. [228], Goudar et al. [236]	UWB + VIO	Quadcopters	N.A.
Chen et al. [237]	UWB + IR	MSTAR dataset	N.A.
Huang et al. [238]	UWB + GNSS	Mobile tag	Yes
Niu et al. [239]	UWB + RTK GPS	USV	Yes
Kang et al. [240]	UWB + Laser-based depth camera	Mobile robot	N.A.
Gao et al. [241]	UWB + MEMS-INS	Vehicle	N.A.
Brunacci et al. [242]	UWB + Magnetic RS	Quadcopters	N.A.
Csik et al. [84]	UWB + WiFi + ISM frequency band	APs	Yes

localization data. This fusion helps in mitigating errors and uncertainties associated with each system, resulting in improved accuracy and reliability of the mobile autonomous machine's localization [257]. The integration of UWB can also enhance SLAM's performance in environments where traditional visual or LIDAR-based methods may struggle, such as in low-light or featureless areas. Thus, the synergy between SLAM and UWB provides a more comprehensive and resilient localization solution, essential for the effective operation of mobile autonomous machines in diverse and challenging environments [258]. Liu et al. [81] tightly-coupled fuse the LiDAR-Inertial Odometry (LIO) system with the UWB modules. The UWB technique helps the LIO system to correct long-term state drift. Specifically, the UWB ranging results are input into the anchor selection module to initialize the Inertial Navigation System (INS). The estimation from the INS propagation algorithm is fed back for UWB modules' outlier removal processing and the incorporation of the uncertainty-aware module. The latter provides accurate covariance in observation information, which enables the multimodal state estimation system to achieve reliable estimates. Nguyen et al. [235] fused the UWB with the state-of-art Visual-Inertial Odometry (VIO) system. They formulate an optimization problem over the data window to solve the UWB underutilized issue due to the data rate incompatibility issue with UWB-camera sensors.

In a word, SLAM enables mobile machines to map environments and localize simultaneously. Combining UWB with SLAM leverages UWB's precision and SLAM's adaptability to challenging environments (e.g., low light). This synergy improves localization in dynamic or unstructured spaces.

6.3. Fusion with GNSS

GNSS is crucial for mobile autonomous machines as it provides accurate and reliable global localization, enabling mobile autonomous machines to navigate large-scale outdoor environments with ease. The most well-known GNSS systems include: Global Positioning System (GPS), Global Navigation Satellite System (GLONASS), Galileo, BeiDou, etc [239,259]. GNSS provides global positioning information but can suffer from accuracy issues in urban environments, indoors, or under dense foliage where satellite signals may be obstructed or reflected.

By integrating UWB with GNSS, mobile autonomous machines can achieve improved localization accuracy and reliability across various challenging environments. UWB technology excels in providing precise distance measurements between devices, enabling robust localization even in GPS-denied areas or environments with multipath interference. The combination of GNSS and UWB allows mobile autonomous machines to leverage the global coverage of GNSS for initial positioning while refining their location estimates with UWB's precise distance measurements. This fusion approach enhances the overall localization system's accuracy, robustness, and capability to operate seamlessly in diverse and challenging real-world scenarios, making it well-suited for a wide range of mobile robotic applications. Rapinski et al. [216] utilize the UWB sensors as the ground-based nodes located in the vicinity of the receiver to form an augmentation network for the GNSS.

In summary, GNSS provides global positioning but struggles in environments like urban areas or indoors. UWB complements GNSS by refining positioning with precise distance measurements, offering robust performance in GPS-challenged conditions. This fusion enhances accuracy and reliability for diverse outdoor and indoor applications, benefiting large-scale navigation tasks.

7. Future trend

The future of mobile autonomous machines is increasingly intertwined with the advancements in UWB technology and its related techniques, promising significant contributions across various domains. As the UWB technology continues to evolve, several emerging trends are shaping the future of UWB-based localization for mobile autonomous machines. These trends hold promise for enhancing accuracy, efficiency, and scalability in diverse application scenarios. In this section, we highlight some of the key trends that are expected to drive advancements in UWB-based localization for mobile autonomous machines in the coming years.

7.1. Trend 1: Integration of machine learning and artificial intelligence

One of the most significant trends in UWB-based localization for mobile autonomous machines is the integration of machine learning and AI techniques. Machine learning algorithms enhance localization accuracy and robustness by adapting to dynamic environments. AI, particularly large generative AI (GenAI) models, is expected to improve decision-making and adaptability in localization systems, enabling autonomous, self-evolving networks [260]. The advent of 6G technologies, including THz communications and reconfigurable intelligent surfaces, will further advance UWB localization in critical applications such as emergency response [261]. Additionally, the integration of AI with fog computing will enhance real-time data processing and energy efficiency for mobile autonomous systems [262].

7.2. Trend 2: Edge computing and distributed processing

Another emerging trend is the adoption of edge computing and distributed processing architectures for high-precision localization. By leveraging computational resources at the network edge, localization computations can be offloaded from centralized servers to distributed nodes, reducing latency and improving responsiveness in real-time applications. This is particularly important for clustered mobile autonomous machines, as it can increase the flexibility and mobility of individuals in the cluster. The integration of 6G technologies, such as network function virtualization and intelligent edge modules, is expected to further enhance scalability and support complex multi-agent operations in dynamic environments [263]. Edge computing also enables efficient data aggregation, processing, and decision-making closer to the source, enhancing scalability and reliability in large-scale deployment scenarios [264].

7.3. Trend 3: Multi-modal fusion and sensor integration

The integration of multiple sensor modalities, including UWB, inertial sensors, vision systems, and environmental sensors, is becoming increasingly prevalent in UWB-based localization systems [265]. Multi-modal sensor fusion techniques enable complementary information from different sensors to be combined synergistically, improving localization accuracy, robustness, and reliability in challenging environments. The target is to fuse diverse sensor data and achieve higher levels of accuracy and resilience across a wide range of operating conditions [266].

7.4. Trend 4: Standardization and interoperability

With the growing adoption of UWB technology in various industries and applications for mobile autonomous machine localization tasks, there is a growing need for standardization and interoperability to ensure compatibility and seamless integration across different platforms and ecosystems [267]. Standardization efforts, such as those led by industry consortia and standards organizations, aim to define common protocols, interfaces, and data formats, facilitating interoperability and enabling broader adoption in the marketplace [268]. Furthermore, the development of federated learning and explainable AI models will help automate processes, optimize performance, and reduce overhead, contributing to the future standardization of UWB-based mobile localization systems [269].

7.5. Trend 5: Privacy, security, and ethical considerations

Future trends in UWB-based localization for mobile autonomous machines will emphasize privacy, security, and ethical considerations. As these systems become more integrated into everyday applications, there is an increasing focus on safeguarding sensitive data collected by UWB technology. Advances in privacy-enhancing technologies, such as differentially private algorithms, will be crucial in safeguarding data in dynamic environments. Research in differential privacy, such as the use of time-varying noise and stochastic approximation methods, highlights the importance of balancing privacy with system accuracy [270, 271]. Moving forward, the development of advanced security protocols, privacy-enhancing technologies, and clear ethical guidelines will be essential to guarantee the responsible and secure deployment of UWB-based localization in mobile autonomous machines. These efforts will promote secure, transparent, and ethical use in real-world applications, mitigating potential privacy risks.

In conclusion, these emerging trends are set to shape the future of UWB-based localization for mobile autonomous machines, driving improvements in accuracy, efficiency, scalability, and ethical considerations. By embracing these trends and adopting advanced technologies, UWB-based localization systems can unlock new possibilities and tackle challenges across various application domains.

8. Conclusion

In this paper, we have provided a comprehensive survey of UWB-based localization techniques for mobile autonomous machines. Beginning with an introduction to UWB technology and its historical context, we delve into the fundamental principles of UWB-based localization, exploring its advantages and disadvantages in various applications. We explore the latest advancements in UWB ranging schemes, highlighting how these innovations have significantly enhanced localization accuracy and reliability, thereby supporting more precise navigation for autonomous machines. The integration of AI with UWB systems is examined in detail, demonstrating how AI can substantially improve navigation, obstacle avoidance, and overall autonomy, transforming UWB-based localization from a precise localization tool into an intelligent navigation solution.

Furthermore, we review various optimization techniques designed to address and mitigate errors within UWB-based localization systems. These techniques are crucial for enhancing the robustness and precision of localization, ensuring that mobile autonomous machines can operate effectively even in challenging environments. The survey also delve into sensor fusion, where UWB technology is combined with other sensor modalities such as LiDAR, cameras, and IMUs. This integration creates a more resilient and accurate localization system capable of supporting diverse operational environments.

Lastly, we discuss future research directions, identifying key areas that hold promise for further advancements in UWB-based localization and its applications in mobile autonomous machines. The potential for continued innovation in this field is vast, driven by ongoing developments in AI, sensor technology, and optimization algorithms.

In conclusion, this survey paper offers a comprehensive overview of UWB-based localization techniques for mobile autonomous machines, encompassing various aspects ranging from fundamental principles to advanced optimization strategies. By synthesizing existing research and highlighting key advancements and challenges in the field, we hope to provide valuable insights for researchers and practitioners aiming to develop and deploy UWB-based localization solutions in real-world applications.

CRediT authorship contribution statement

Ning Xu: Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Mingyang Guan:** Writing – review & editing, Supervision, Conceptualization. **Changyun Wen:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research/project is supported by A*STAR (C221518005).

Data availability

Data will be made available on request.

References

[1] P.K. Panigrahi, S.K. Bisoy, Localization strategies for autonomous mobile robots: A review, J. King Saud Univ.- Comput. Inf. Sci. 34 (8) (2022) 6019–6039.

[2] F. Mazhar, M.G. Khan, B. Sällberg, Precise indoor positioning using UWB: A review of methods, algorithms and implementations, Wirel. Pers. Commun. 97 (3) (2017) 4467–4491.

[3] J.-S. Lee, Y.-W. Su, C.-C. Shen, A comparative study of wireless protocols: Bluetooth, UWB, ZigBee, and wi-fi, in: IECON 2007-33rd Annual Conference of the IEEE Industrial Electronics Society, Ieee, 2007, pp. 46–51.

[4] M. Elsanhoury, P. Mäkelä, J. Koljonen, P. Välisuo, A. Shamsuzzoha, T. Mantere, M. Elmusrati, H. Kuusniemi, Precision positioning for smart logistics using ultra-wideband technology-based indoor navigation: A review, IEEE Access 10 (2022) 44413–44445.

[5] F. Khan, A. Ghaffar, N. Khan, S.H. Cho, An overview of signal processing techniques for remote health monitoring using impulse radio UWB transceiver, Sensors 20 (9) (2020) 2479.

[6] D. Minoli, B. Occhiogrosso, Ultrawideband (UWB) technology for smart cities IoT applications, in: 2018 IEEE International Smart Cities Cconference, ISC2, IEEE, 2018, pp. 1–8.

[7] J. San Martín, A. Cortés, L. Zamora-Cadenas, B.J. Svensson, Precise positioning of autonomous vehicles combining UWB ranging estimations with on-board sensors, Electronics 9 (8) (2020) 1238.

[8] C. Zhou, S. Gu, Y. Wen, Z. Du, C. Xiao, L. Huang, M. Zhu, The review unmanned surface vehicle path planning: Based on multi-modality constraint, Ocean Eng. 200 (2020) 107043.

[9] V. Chamola, P. Kotesh, A. Agarwal, N. Gupta, M. Guizani, et al., A comprehensive review of unmanned aerial vehicle attacks and neutralization techniques, Ad Hoc Netw. 111 (2021) 102324.

[10] M.A. Kamel, X. Yu, Y. Zhang, Formation control and coordination of multiple unmanned ground vehicles in normal and faulty situations: A review, Annu. Rev. Control. 49 (2020) 128–144.

[11] S. Bandari, L. Nirmala Devi, A multi-objective approach for optimal target coverage UAV placement: Hybrid heuristic formulation, J. Control. Decis. (2024) 1–17.

[12] T. Zhang, H. Wang, W. Che, Q. Li, Adaptive event-triggered path following control for networked autonomous vehicles under aperiodic denial-of-service attacks, J. Control. Decis. (2023) 1–18.

[13] F. Ahmed, J. Mohanta, A. Keshari, P.S. Yadav, Recent advances in unmanned aerial vehicles: A review, Arab. J. Sci. Eng. 47 (7) (2022) 7963–7984.

[14] Y. Liu, H.-N. Dai, Q. Wang, M.K. Shukla, M. Imran, Unmanned aerial vehicle for internet of everything: Opportunities and challenges, Comput. Commun. 155 (2020) 66–83.

[15] N.A. Ubina, S.-C. Cheng, A review of unmanned system technologies with its application to aquaculture farm monitoring and management, Drones 6 (1) (2022) 12.

[16] E. Balestrieri, P. Daponte, L. De Vito, F. Lamonaca, Sensors and measurements for unmanned systems: An overview, Sensors 21 (4) (2021) 1518.

[17] R. Dainelli, P. Toscano, S.F. Di Gennaro, A. Matese, Recent advances in unmanned aerial vehicle forest remote sensing-A systematic review. Part I: A general framework, Forests 12 (3) (2021) 327.

[18] F. Xia, H. Song, H. Dou, Fog removal and enhancement method for UAV aerial images based on dark channel prior, J. Control. Decis. 10 (2) (2023) 188–197.

[19] I. Ullah, D. Adhikari, H. Khan, M.S. Anwar, S. Ahmad, X. Bai, Mobile robot localization: Current challenges and future prospective, Comput. Sci. Rev. 53 (2024) 100651.

[20] M.B. Alatise, G.P. Hancke, A review on challenges of autonomous mobile robot and sensor fusion methods, IEEE Access 8 (2020) 39830–39846.

[21] P. Hoppenot, E. Colle, Localization and control of a rehabilitation mobile robot by close human-machine cooperation, IEEE Trans. Neural Syst. Rehabil. Eng. 9 (2) (2001) 181–190.

[22] I. Ullah, D. Adhikari, H. Khan, S. Ahmad, C. Esposito, C. Choi, Optimizing mobile robot localization: Drones-enhanced sensor fusion with innovative wireless communication, in: IEEE INFOCOM 2024-IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPS, IEEE, 2024, pp. 1–6.

[23] V.N. Ekambaram, K. Ramchandran, R. Sengupta, Collaborative high-accuracy localization in mobile multipath environments, IEEE Trans. Veh. Technol. 65 (10) (2013) 8414–8422.

[24] T. Ahmad, X.J. Li, B.-C. Seet, A self-calibrated centroid localization algorithm for indoor ZigBee WSNs, in: 2016 8th IEEE International Conference on Communication Software and Networks, ICCSN, IEEE, 2016, pp. 455–461.

[25] P. Merriaux, Y. Dupuis, R. Boutteau, P. Vasseur, X. Savatier, Robust robot localization in a complex oil and gas industrial environment, J. Field Robot. 35 (2) (2018) 213–230.

[26] T. Conceição, F. Neves dos Santos, P. Costa, A.P. Moreira, Robot localization system in a hard outdoor environment, in: ROBOT 2017: Third Iberian Robotics Conference: Volume 1, Springer, 2018, pp. 215–227.

[27] A. Hornung, K.M. Wurm, M. Bennewitz, Humanoid robot localization in complex indoor environments, in: 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, 2010, pp. 1690–1695.

[28] L. Barbieri, M. Brambilla, A. Trabattoni, S. Mervic, M. Nicoli, UWB localization in a smart factory: Augmentation methods and experimental assessment, IEEE Trans. Instrum. Meas. 70 (2021) 1–18.

[29] J.P. Queralta, C.M. Almansa, F. Schiano, D. Floreano, T. Westerlund, UWB-based system for UAV localization in GNSS-denied environments: Characterization and dataset, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2020, pp. 4521–4528.

[30] W. Shule, C.M. Almansa, J.P. Queralta, Z. Zou, T. Westerlund, UWB-based localization for multi-UAV systems and collaborative heterogeneous multi-robot systems, Procedia Comput. Sci. 175 (2020) 357–364.

[31] M. Zhao, T. Chang, A. Arun, R. Ayyalasomayajula, C. Zhang, D. Bharadia, Uloc: Low-power, scalable and cm-accurate UWB-tag localization and tracking for indoor applications, Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 5 (3) (2021) 1–31.

[32] F. Che, A. Ahmed, Q.Z. Ahmed, S.A.R. Zaidi, M.Z. Shakir, Machine learning based approach for indoor localization using ultra-wide bandwidth (UWB) system for industrial internet of things (IIoT), in: 2020 International Conference on UK-China Emerging Technologies, UCET, IEEE, 2020, pp. 1–4.

[33] M. Ridolfi, S. Van de Velde, H. Steendam, E. De Poorter, Analysis of the scalability of UWB indoor localization solutions for high user densities, Sensors 18 (6) (2018) 1875.

[34] M. Ridolfi, A. Kaya, R. Berkvens, M. Weyn, W. Joseph, E.D. Poorter, Self-calibration and collaborative localization for UWB positioning systems: A survey and future research directions, ACM Comput. Surv. 54 (4) (2021) 1–27.

[35] H. Obeidat, W. Shuaieb, O. Obeidat, R. Abd-Alhameed, A review of indoor localization techniques and wireless technologies, Wirel. Pers. Commun. 119 (2021) 289–327.

[36] A. Benouakta, F. Ferrero, L. Lizzi, R. Staraj, Advancements in industrial RTLSs: A technical review of UWB localization devices emphasizing antennas for enhanced accuracy and range, Electronics 13 (4) (2024) 751.

[37] D. Yang, Z. Zhu, J. Zhang, B. Liang, The overview of human localization and vital sign signal measurement using handheld IR-UWB through-wall radar, Sensors 21 (2) (2021) 402.

[38] C.L. Sang, M. Adams, M. Hesse, U. Rückert, Bidirectional UWB localization: A review on an elastic positioning scheme for GNSS-deprived zones, IEEE J. Indoor Seamless Position. Navig. (2023).

[39] Y. Xianjia, L. Qingqing, J.P. Queralta, J. Heikkonen, T. Westerlund, Applications of UWB networks and positioning to autonomous robots and industrial systems, in: 2021 10th Mediterranean Conference on Embedded Computing, MECO, IEEE, 2021, pp. 1–6.

[40] F. Wang, H. Tang, J. Chen, Survey on NLOS identification and error mitigation for UWB indoor positioning, Electronics 12 (7) (2023) 1678.

[41] A. Sesyuk, S. Ioannou, M. Raspopoulos, A survey of 3D indoor localization systems and technologies, Sensors 22 (23) (2022) 9380.

[42] S.M. Asaad, H.S. Maghdid, A comprehensive review of indoor/outdoor localization solutions in IoT era: Research challenges and future perspectives, Comput. Netw. 212 (2022) 109041.

[43] A. Rauf, M.J. Irshad, M. Wasif, Z. Mehmood, T. Kiren, N. Siddique, A state of the art in simultaneous localization and mapping (SLAM) for unmanned ariel vehicle (UAV): A review, Electr. Control. Commun. Eng. 18 (1) (2022) 50–56.

[44] D. Coppens, A. Shahid, S. Lemey, B. Van Herbruggen, C. Marshall, E. De Poorter, An overview of UWB standards and organizations (IEEE 802.15. 4, FiRa, Apple): Interoperability aspects and future research directions, IEEE Access 10 (2022) 70219–70241.

[45] R. Zhao, H. Li, W. Zhu, B. Wei, C. Zheng, Q. Lin, A review of UWB positioning technology applications in personnel security management, in: Third International Conference on Digital Signal and Computer Communications (DSCC 2023), vol. 12716, SPIE, 2023, pp. 265–274.

[46] M. Zare, R. Battulwar, J. Seamons, J. Sattarvand, Applications of wireless indoor positioning systems and technologies in underground mining: A review, Min. Met. Explor. 38 (6) (2021) 2307–2322.

[47] T. Yang, A. Cabani, H. Chafouk, A survey of recent indoor localization scenarios and methodologies, Sensors 21 (23) (2021) 8086.

[48] X. He, L. Mo, Q. Wang, An attention-assisted UWB ranging error compensation algorithm, IEEE Wirel. Commun. Lett. 12 (3) (2022) 421–425.

[49] G. Lu, G. Yang, J. Wang, X. Jing, The study on detection of the life signals of human subject based on micropower UWB radar, Chin. Med. Equip. J. (1989).

[50] B. Ottersten, R. Roy, T. Kailath, Signal waveform estimation in sensor array processing, in: Twenty-Third Asilomar Conference on Signals, Systems and Computers, 1989, vol. 2, IEEE Computer Society, Los Alamitos, CA, USA, 1989, pp. 787–791.

[51] McCorkle, Focusing of synthetic aperture ultra wideband data, in: IEEE 1991 International Conference on Systems Engineering, 1991, pp. 1–5.

[52] C. Fowler, J. Entzminger, J. Corum, Assessment of ultra-wideband (UWB) technology, IEEE Aerosp. Electron. Syst. Mag. 5 (11) (1990) 45–49.

[53] J.D. Taylor, Introduction to Ultra-Wideband Radar Systems, CRC Press, 2020.

[54] H. Liu, H. Darabi, P. Banerjee, J. Liu, Survey of wireless indoor positioning techniques and systems, IEEE Trans. Syst. Man, Cybern. Part C (Appl. Rev.) 37 (6) (2007) 1067–1080.

[55] G.R. Aiello, G.D. Rogerson, Ultra-wideband wireless systems, IEEE microwave magazine 4 (2) (2003) 36–47.

[56] F.C. Commission, et al., FCC 02-48–First Report and Order: Revision of Part 15 of the Commission's Rules Regarding Ultra-Wideband Transmission Systems, vol. 22, Washington, DC, 2002, released April.

[57] I. Oppermann, M. Hämäläinen, J. Iinatti, UWB: Theory and Applications, John Wiley & Sons, 2004.

[58] I..W. Group, et al., Part 15.4: Wireless medium access control (MAC) and physical layer (PHY) specifications for low-rate Wireless Personal Area networks (LR-WPANs), in: ANSI/ IEEE Std, vol. 802, (4) 2006.

[59] I..L.S. Committee, et al., IEEE standard for high data rate wireless multi-media networks–amendment 2: 100 gb/s wireless switched point-to-point physical layer, in: IEEE Std, vol. 802, 2017, pp. 1–55.

[60] I..L.S. Committee, et al., IEEE standard for IEEE amendment to part 15.3: Wireless medium access control (MAC) and physical layer (PHY) specifications for high rate wireless personal area networks (WPAN): Amendment to MAC sublayer, in: IEEE Std 802.15.3b-2005 (Amendment to IEEE Std 802.15.3-2003), 2006, pp. 1–169.

[61] L.S. Committee, et al., IEEE Standard for Information Technology–Local and Metropolitan Area Networks–Specific Requirements–Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs), Minneapolis, MN, USA, 2006, pp. 1–320.

[62] I..L.S. Committee, et al., IEEE standard for low-rate wireless networks–amendment 1: Enhanced ultra wideband (UWB) physical layers (PHYs) and associated ranging techniques, in: IEEE Std 802.15.4z-2020 (Amendment to IEEE Std 802.15.4-2020), 2020, pp. 1–174.

[63] D. Neirynck, E. Luk, M. McLaughlin, An alternative double-sided two-way ranging method, in: 2016 13th Workshop on Positioning, Navigation and Communications, WPNC, IEEE, 2016, pp. 1–4.

[64] M. Van Der Sluis, B. De Klerk, E.D. Ellen, Y. De Haas, T. Hijink, T.B. Rodenburg, Validation of an ultra-wideband tracking system for recording individual levels of activity in broilers, Animals 9 (8) (2019) 580.

[65] L. Barbieri, M. Brambilla, A. Trabattoni, S. Mervic, M. Nicoli, UWB localization in a smart factory: Augmentation methods and experimental assessment, IEEE Trans. Instrum. Meas. 70 (2021) 1–18.

[66] A.R.J. Ruiz, F.S. Granja, Comparing ubisense, bespoon, and decawave UWB location systems: Indoor performance analysis, IEEE Trans. Instrum. Meas. 66 (8) (2017) 2106–2117.

[67] J. Sidorenko, V. Schatz, N. Scherer-Negenborn, M. Arens, U. Hugentobler, DecaWave ultra-wideband warm-up rrror correction, IEEE Trans. Aerosp. Electron. Syst. 57 (1) (2020) 751–760.

[68] T.-M. Nguyen, S. Yuan, M. Cao, Y. Lyu, T.H. Nguyen, L. Xie, Ntu viral: A visual-inertial-ranging-lidar dataset, from an aerial vehicle viewpoint, Int. J. Robot. Res. 41 (3) (2022) 270–280.

[69] A. Benini, A. Mancini, S. Longhi, An IMU/UWB/Vision-Based extended Kalman filter for mini-UAV localization in indoor environment using 802.15. 4a wireless sensor network, J. Intell. Robot. Syst. 70 (2013) 461–476.

[70] M. Piavanini, L. Barbieri, M. Brambilla, M. Cerutti, S. Ercoli, A. Agili, M. Nicoli, A self-calibrating localization solution for sport applications with UWB technology, Sensors 22 (23) (2022) 9363.

[71] H. Nurminen, T. Ardeshiri, R. Piché, F. Gustafsson, A NLOS-robust TOA positioning filter based on a skew-t measurement noise model, in: 2015 International Conference on Indoor Positioning and Indoor Navigation, IPIN, IEEE, 2015, pp. 1–7.

[72] S. Mastrolembo Ventura, P. Bellagente, S. Rinaldi, A. Flammini, A.L. Ciribini, Enhancing safety on construction sites: A UWB-based proximity warning system ensuring GDPR compliance to prevent collision hazards, Sensors 23 (24) (2023) 9770.

[73] A.R. Jiménez, F. Seco, Comparing decawave and bespoon UWB location systems: Indoor/outdoor performance analysis, in: 2016 International Conference on Indoor Positioning and Indoor Navigation, IPIN, IEEE, 2016, pp. 1–8.

[74] G.I. Hapsari, R. Munadi, B. Erfianto, I.D. Irawati, Accuracy improvement for indoor positioning using decawave on ESP32 UWB pro with display and regression, J. Robot. Control. (JRC) 5 (3) (2024) 851–862.

[75] T. Polonelli, S. Schläpfer, M. Magno, Performance comparison between decawave DW1000 and DW3000 in low-power double side ranging applications, in: 2022 IEEE Sensors Applications Symposium, SAS, IEEE, 2022, pp. 1–6.

[76] A. Chowdhury, T. Das, S. Rani, A. Khasnobish, T. Chakravarty, Activity rcognition using ultra wide band range-time scan, in: 2020 28th European Signal Processing Conference, EUSIPCO, IEEE, 2021, pp. 1338–1342.

[77] L. Luo, F. Peng, L. Dong, Improved multi-sensor fusion dynamic odometry based on neural networks, Sensors 24 (19) (2024) 6193.

[78] M. Qian, K. Zhao, B. Li, A. Seneviratne, An overview of ultra-wideband technology and performance analysis of UWB-TWR in simulation and real environment, in: CEUR Workshop Proceedings, vol. 3248, 2022, p. 2022.

[79] Y. Qi, C.B. Soh, E. Gunawan, K.-S. Low, A. Maskooki, An accurate 3D UWB hyperbolic localization in indoor multipath environment using iterative taylor-series estimation, in: 2013 IEEE 77th Vehicular Technology Conference, VTC Spring, IEEE, 2013, pp. 1–5.

[80] V. Brunacci, A. De Angelis, G. Costante, P. Carbone, Development and analysis of a UWB relative localization system, IEEE Trans. Instrum. Meas. (2023).

[81] H. Liu, S. Pan, P. Wu, K. Yu, W. Gao, B. Yu, Uncertainty-aware UWB/LiDAR/INS tightly-coupled fusion pose estimation via filtering approach, IEEE Sens. J. (2024).

[82] S. Monica, G. Ferrari, UWB-based localization in large indoor scenarios: Optimized placement of anchor nodes, IEEE Trans. Aerosp. Electron. Syst. 51 (2) (2015) 987–999.

[83] H. Premachandra, R. Liu, C. Yuen, U.-X. Tan, UWB radar SLAM: An anchorless approach in vision denied indoor environments, IEEE Robot. Autom. Lett. (2023).

[84] D. Csik, Á. Odry, P. Sarcevic, Fingerprinting-based indoor positioning using data fusion of different radiocommunication-based technologies, Machines 11 (2) (2023) 302.

[85] M. Ciężkowski, S. Romaniuk, A. Wolniakowski, Apparent beacon position estimation for accuracy improvement in lateration positioning system, Measurement 153 (2020) 107400.

[86] L. Yu, M. Laaraiedh, S. Avrillon, B. Uguen, Fingerprinting localization based on neural networks and ultra-wideband signals, in: 2011 IEEE International Symposium on Signal Processing and Information Technology, ISSPIT, IEEE, 2011, pp. 184–189.

[87] L. Cheng, H. Zhang, D. Wei, J. Zhou, An indoor tracking algorithm based on particle filter and nearest neighbor data fusion for wireless sensor networks, Remote. Sens. 14 (22) (2022) 5791.

[88] D. Wui, L. Bao, M. Du, R. Li, Design and evaluation of localization rotocols and algorithms in wireless sensor networks using UWB, in: 2008 IEEE International Performance, Computing and Communications Conference, IEEE, 2008, pp. 18–25.

[89] W. Cui, C. Wu, W. Meng, B. Li, Y. Zhang, L. Xie, Dynamic multidimensional scaling algorithm for 3-D mobile localization, IEEE Trans. Instrum. Meas. 65 (12) (2016) 2853–2865.

[90] C.-D. Wann, H.-C. Chin, Hybrid TOA/RSSI wireless location with unconstrained nonlinear optimization for indoor UWB channels, in: 2007 IEEE Wireless Communications and Networking Conference, IEEE, 2007, pp. 3940–3945.

[91] I. Association, et al., 802.15. 1-2005-IEEE standard for information technology–local and metropolitan area networks–specific requirements–Part 15.1a: Wireless medium access control (MAC) and physical layer (PHY) specifications for Wireless Personal Area networks (WPAN), 2005, pp. 1–700.

[92] S.C. Ergen, ZigBee/IEEE 802.15. 4 Summary, vol. 10, (17) UC Berkeley, 2004, p. 11, September.

[93] E. Ferro, F. Potorti, Bluetooth and wi-fi wireless protocols: a survey and a comparison, IEEE Wirel. Commun. 12 (1) (2005) 12–26.

[94] I. Oppermann, L. Stoica, A. Rabbachin, Z. Shelby, J. Haapola, UWB wireless sensor networks: UWEN-a practical example, IEEE Commun. Mag. 42 (12) (2004) S27–S32.

[95] K. Yu, K. Wen, Y. Li, S. Zhang, K. Zhang, A novel NLOS mitigation algorithm for UWB localization in harsh indoor environments, IEEE Trans. Veh. Technol. 68 (1) (2018) 686–699.

[96] S. Marano, W.M. Gifford, H. Wymeersch, M.Z. Win, NLOS identification and mitigation for localization based on UWB experimental data, IEEE J. Sel. Areas Commun. 28 (7) (2010) 1026–1035.

[97] W. Jiang, Z. Cao, B. Cai, B. Li, J. Wang, Indoor and outdoor seamless positioning method using UWB enhanced multi-sensor tightly-coupled integration, IEEE Trans. Veh. Technol. 70 (10) (2021) 10633–10645.

[98] S. Zhao, X.-P. Zhang, X. Cui, M. Lu, Optimal two-way TOA localization and synchronization for moving user devices with clock drift, IEEE Trans. Veh. Technol. 70 (8) (2021) 7778–7789.

[99] F. Dong, C. Shen, J. Zhang, S. Zhou, A TOF and Kalman filtering joint algorithm for IEEE802.15.4a UWB locating, in: 2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference, 2016, pp. 948–951.

[100] A. Foudazi, H.R. Hassani, et al., Small UWB planar monopole antenna with added GPS/GSM/WLAN bands, IEEE Trans. Antennas and Propagation 60 (6) (2012) 2987–2992.

[101] H. Liu, R.C. Qiu, Z. Tian, Error performance of pulse-based ultra-wideband MIMO systems over indoor wireless channels, IEEE Trans. Wirel. Commun. 4 (6) (2005) 2939–2944.

[102] D.L. Goeckel, Q. Zhang, Slightly frequency-shifted reference ultra-wideband (UWB) radio, IEEE Trans. Commun. 55 (3) (2007) 508–519.

[103] S. Duan, R. Su, C. Xu, Y. Chen, J. He, Ultra-wideband radio channel characteristics for near-ground swarm robots communication, IEEE Trans. Wirel. Commun. 19 (7) (2020) 4715–4726.

[104] S. Sharma, Y. Hong, UWB receiver via deep learning in MUI and ISI scenarios, IEEE Trans. Veh. Technol. 69 (3) (2020) 3496–3499.

[105] J. He, X. Gong, Resilient path planning of unmanned aerial vehicles against covert attacks on ultra-wideband sensors, IEEE Trans. Ind. Inform. (2023).

[106] H. Chen, A. Dhekne, Spoofing evident and spoofing deterrent localization using ultra-wideband (UWB) active-passive ranging, IEEE J. Indoor Seamless Position. Navig. (2023).

[107] F. Khan, S. Azou, R. Youssef, P. Morel, E. Radoi, O.A. Dobre, An IR-UWB multi-sensor approach for collision avoidance in indoor environments, IEEE Trans. Instrum. Meas. 71 (2022) 1–13.

[108] B. Wang, H. Song, W. Rhee, Z. Wang, Overview of ultra-wideband transceivers-system architectures and applications, Tsinghua Sci. Technol. 27 (3) (2021) 481–494.

[109] X. Fang, H. Fan, L. Liu, B. Wang, Decentralized adaptive fault-tolerant control of interconnected systems with sensor faults, J. Control. Decis. (2023) 1–17.

[110] N.A. Alsindi, B. Alavi, K. Pahlavan, Measurement and modeling of ultrawideband TOA-based ranging in indoor multipath environments, IEEE Trans. Veh. Technol. 58 (3) (2008) 1046–1058.

[111] B. Alavi, K. Pahlavan, Modeling of the TOA-based distance measurement error using UWB indoor radio measurements, IEEE Commun. Lett. 10 (4) (2006) 275–277.

[112] B. Choi, K. La, S. Lee, UWB TDOA/TOA measurement system with wireless time synchronization and simultaneous tag and anchor positioning, in: 2018 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications, CIVEMSA, IEEE, 2018, pp. 1–6.

[113] S. Zheng, Z. Li, Y. Liu, H. Zhang, X. Zou, An optimization-based UWB-IMU fusion framework for UGV, IEEE Sens. J. 22 (5) (2022) 4369–4377.

[114] D.P. Young, C.M. Keller, D.W. Bliss, K.W. Forsythe, Ultra-wideband (UWB) transmitter location using time difference of arrival (TDOA) techniques, in: The Thrity-Seventh Asilomar Conference on Signals, Systems & Computers, 2003, vol. 2, IEEE, 2003, pp. 1225–1229.

[115] J. Xu, M. Ma, C.L. Law, Position estimation using UWB TDOA measurements, in: 2006 IEEE International Conference on Ultra-Wideband, IEEE, 2006, pp. 605–610.

[116] Y. Cheng, T. Zhou, UWB indoor positioning algorithm based on TDOA technology, in: 2019 10th International Conference on Information Technology in Medicine and Education, ITME, IEEE, 2019, pp. 777–782.

[117] X. Kong, X. Li, X. Song, Y. Tian, D. Kong, An accurate and reliable positioning methodology for land vehicles in tunnels based on UWB/INS integration, Meas. Sci. Technol. 33 (9) (2022) 095107.

[118] G. Kia, L. Ruotsalainen, J. Talvitie, Toward accurate indoor positioning: An RSS-based fusion of UWB and machine-learning-enhanced WiFi, Sensors 22 (9) (2022) 3204.

[119] J. Tian, M. Yang, X. Li, S. Zou, T. Chao, Improvement of RSS-based measurement based on adaptive Kalman filter considering the anisotropy on antenna in dynamic environment, IEEE Trans. Instrum. Meas. 72 (2023) 1–13.

[120] M. Naseri, A. Shahid, E. De Poorter, Adapting UWB AOA estimation towards unseen environments using transfer learning and data augmentation, Internet Things 27 (2024) 101298.

[121] Á. De-La-Llana-Calvo, J.-L. Lázaro-Galilea, A. Gardel-Vicente, D. Rodríguez-Navarro, I. Bravo-Muñoz, F. Espinosa-Zapata, Characterization of multipath effects in indoor positioning systems by AOA and POA based on optical signals, Sensors 19 (4) (2019) 917.

[122] T. Margiani, S. Cortesi, M. Keller, C. Vogt, T. Polonelli, M. Magno, Angle of arrival and centimeter distance estimation on a smart UWB sensor node, IEEE Trans. Instrum. Meas. 72 (2023) 1–10.

[123] X. Li, K. Pahlavan, M. Latva-aho, M. Ylianttila, Comparison of indoor geolocation methods in DSSS and OFDM wireless LAN systems, in: Vehicular Technology Conference Fall 2000. IEEE VTS Fall VTC2000. 52nd Vehicular Technology Conference (Cat. No. 00CH37152), vol. 6, IEEE, 2000, pp. 3015–3020.

[124] I. Dotlic, A. Connell, M. McLaughlin, Ranging methods utilizing carrier frequency offset estimation, in: 2018 15th Workshop on Positioning, Navigation and Communications, WPNC, IEEE, 2018, pp. 1–6.

[125] V. Tran, Z. Dai, N. Trigoni, A. Markham, DeepCIR: Insights into CIR-based data-driven UWB error mitigation, in: 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2022, pp. 13300–13307.

[126] Z. Niu, H. Yang, L. Zhou, M.F. Taha, Y. He, Z. Qiu, Deep learning-based ranging error mitigation method for UWB localization system in greenhouse, Comput. Electron. Agric. 205 (2023) 107573.
[127] D. Feng, C. Wang, C. He, Y. Zhuang, X.-G. Xia, Kalman-filter-based integration of IMU and UWB for high-accuracy indoor positioning and navigation, IEEE Internet Things J. 7 (4) (2020) 3133–3146.
[128] Y. Jiang, V.C. Leung, An asymmetric double sided two-way ranging for crystal offset, in: 2007 International Symposium on Signals, Systems and Electronics, IEEE, 2007, pp. 525–528.
[129] M.A. Shalaby, C.C. Cossette, J.R. Forbes, J. Le Ny, Calibration and uncertainty characterization for ultra-wideband two-way-ranging measurements, in: 2023 IEEE International Conference on Robotics and Automation, ICRA, IEEE, 2023, pp. 4128–4134.
[130] N. Zhou, L. Lau, R. Bai, T. Moore, A robust detection and optimization approach for delayed measurements in UWB particle-filter-based indoor positioning, NAVIGATION: J. Inst. Navig. 69 (2) (2022).
[131] G. Shen, R. Zetik, O. Hirsch, R.S. Thomä, Range-based localization for UWB sensor networks in realistic environments, EURASIP J. Wirel. Commun. Netw. 2010 (2009) 1–9.
[132] Z. Chen, W. Zhao, L. Deng, Y. Ding, Q. Wen, G. Li, Y. Xie, Large-scale self-normalizing neural networks, J. Autom. Intell. (2024).
[133] S. Djosic, I. Stojanovic, M. Jovanovic, T. Nikolic, G.L. Djordjevic, Fingerprinting-assisted UWB-based localization technique for complex indoor environments, Expert Syst. Appl. 167 (2021) 114188.
[134] E. Bogdani, D. Vouyioukas, N. Nomikos, Localization error modeling of hybrid fingerprint-based techniques for indoor ultra-wideband systems, Telecommun. Syst. 63 (2016) 223–241.
[135] B. Song, S. Zhang, J. Long, Q. Hu, et al., Fingerprinting localization method based on TOA and particle filtering for mines, Math. Probl. Eng. 2017 (2017).
[136] C. Steiner, A. Wittneben, Efficient training phase for ultrawideband-based location fingerprinting systems, IEEE Trans. Signal Process. 59 (12) (2011) 6021–6032.
[137] R. Bharadwaj, A. Alomainy, S.K. Koul, Experimental investigation of body-centric indoor localization using compact wearable antennas and machine learning algorithms, IEEE Trans. Antennas and Propagation 70 (2) (2021) 1344–1354.
[138] H. Wymeersch, S. Maranò, W.M. Gifford, M.Z. Win, A machine learning approach to ranging error mitigation for UWB localization, IEEE Trans. Commun. 60 (6) (2012) 1719–1728.
[139] A.G. Ferreira, D. Fernandes, S. Branco, A.P. Catarino, J.L. Monteiro, Feature selection for real-time NLOS identification and mitigation for body-mounted UWB transceivers, IEEE Trans. Instrum. Meas. 70 (2021) 1–10.
[140] H. Xu, Y. Ding, P. Li, R. Wang, Y. Li, An RFID indoor positioning algorithm based on Bayesian probability and K-nearest neighbor, Sensors 17 (8) (2017) 1806.
[141] F. Zhu, K. Yu, Y. Lin, C. Wang, J. Wang, M. Chao, Robust LOS/NLOS identification for UWB signals using improved fuzzy decision tree under volatile indoor conditions, IEEE Trans. Instrum. Meas. (2023).
[142] Y. Yang, L. Zhang, J. Xu, D. Li, J. Bao, J. Tan, Cooperative indoor localization system based UWB and random forest algorithm in complicated underground NLOS scenario, in: 2022 9th International Conference on Digital Home, ICDH, IEEE, 2022, pp. 271–276.
[143] C. Huang, A.F. Molisch, R. He, R. Wang, P. Tang, B. Ai, Z. Zhong, Machine learning-enabled LOS/NLOS identification for MIMO systems in dynamic environments, IEEE Trans. Wirel. Commun. 19 (6) (2020) 3643–3657.
[144] J. Wang, K. Yu, J. Bu, Y. Lin, S. Han, Multi-classification of UWB signal propagation channels based on one-dimensional wavelet packet analysis and CNN, IEEE Trans. Veh. Technol. 71 (8) (2022) 8534–8547.
[145] Z. Cui, Y. Gao, J. Hu, S. Tian, J. Cheng, LOS/NLOS identification for indoor UWB positioning based on morlet wavelet transform and convolutional neural networks, IEEE Commun. Lett. 25 (3) (2020) 879–882.
[146] J. Fontaine, M. Ridolfi, B. Van Herbruggen, A. Shahid, E. De Poorter, Edge inference for UWB ranging error correction using autoencoders, IEEE Access 8 (2020) 139143–139155.
[147] D.-H. Kim, A. Farhad, J.-Y. Pyun, UWB positioning system based on LSTM classification with mitigated NLOS effects, IEEE Internet Things J. 10 (2) (2022) 1822–1835.
[148] Y.-Y. Chen, S.-P. Huang, T.-W. Wu, W.-T. Tsai, C.-Y. Liou, S.-G. Mao, UWB system for indoor positioning and tracking with arbitrary target orientation, optimal anchor location, and adaptive NLOS mitigation, IEEE Trans. Veh. Technol. 69 (9) (2020) 9304–9314.
[149] C. Jiang, J. Shen, S. Chen, Y. Chen, D. Liu, Y. Bo, UWB NLOS/LOS classification using deep learning method, IEEE Commun. Lett. 24 (10) (2020) 2226–2230.
[150] A. Abbasi, H. Liu, Novel CNN and hybrid CNN-LSTM algorithms for UWB SNR estimation, in: 2021 IEEE 11th Annual Computing and Communication Workshop and Conference, CCWC, IEEE, 2021, pp. 0637–0641.
[151] C. Mao, K. Lin, T. Yu, Y. Shen, A probabilistic learning approach to UWB ranging error mitigation, in: 2018 IEEE Global Communications Conference, GLOBECOM, IEEE, 2018, pp. 1–6.
[152] F. Che, Q.Z. Ahmed, J. Fontaine, B. Van Herbruggen, A. Shahid, E. De Poorter, P.I. Lazaridis, Feature-based generalized Gaussian distribution method for nlos detection in ultra-wideband (UWB) indoor positioning system, IEEE Sens. J. 22 (19) (2022) 18726–18739.
[153] N. Rajagopal, P. Lazik, N. Pereira, S. Chayapathy, B. Sinopoli, A. Rowe, Enhancing indoor smartphone location acquisition using floor plans, in: 2018 17th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN, IEEE, 2018, pp. 278–289.
[154] P. Meissner, E. Leitinger, K. Witrisal, UWB for robust indoor tracking: Weighting of multipath components for efficient estimation, IEEE Wirel. Commun. Lett. 3 (5) (2014) 501–504.
[155] S. Sbîrnă, L.-S. Sbîrnă, Optimization of indoor localization of automated guided vehicles using ultra-wideband wireless positioning sensors, in: 2019 23rd International Conference on System Theory, Control and Computing, ICSTCC, IEEE, 2019, pp. 504–509.
[156] F.-H. Chang, Y.-S. Huang, L.-C. Fu, et al., Spatial graph-based localization and navigation on scaleless floorplan, IEEE Robot. Autom. Lett. (2024).
[157] A.R. Khairuddin, M.S. Talib, H. Haron, Review on simultaneous localization and mapping (SLAM), in: 2015 IEEE International Conference on Control System, Computing and Engineering, ICCSCE, IEEE, 2015, pp. 85–90.
[158] W. Osamy, A.M. Khedr, A. Salim, A.I. Al Ali, A.A. El-Sawy, Coverage, deployment and localization challenges in wireless sensor networks based on artificial intelligence techniques: a review, IEEE Access 10 (2022) 30232–30257.
[159] E. Leitinger, M. Fröhle, P. Meissner, K. Witrisal, Multipath-assisted maximum-likelihood indoor positioning using uwb signals, in: 2014 IEEE International Conference on Communications Workshops, ICC, IEEE, 2014, pp. 170–175.
[160] P. Meissner, T. Gigl, K. Witrisal, UWB sequential Monte Carlo positioning using virtual anchors, in: 2010 International Conference on Indoor Positioning and Indoor Navigation, IEEE, 2010, pp. 1–10.
[161] J. Fontaine, F. Che, A. Shahid, B. Van Herbruggen, Q.Z. Ahmed, W.B. Abbas, E. De Poorter, Transfer learning for UWB error correction and (N)LOS classification in multiple environments, IEEE Internet Things J. (2023).
[162] H. Yang, Y. Wang, S. Xu, J. Bi, H. Jia, C.K. Seow, UWB ranging errors mitigation with novel CIR feature parameters and two-step NLOS identification, Sensors 24 (5) (2024).
[163] E. Dehmollaian, B. Etzlinger, P. Peterseil, A. Springer, AI-enhanced UWB-based localisation in wireless networks, in: Intelligent Secure Trustable Things, Springer, 2024, pp. 201–216.
[164] Q. Liu, Y. Zhao, Z. Yin, Z. Wu, WDMA-UWB indoor positioning through channel classification-based NLOS mitigation approach, IEEE Sens. J. (2024).
[165] Q. Wang, M.-s. Chen, G.-q. Wang, K. Li, Y.-c. Lin, Z.-H. Li, C.-Z. Zhang, A novel NLOS identification and error mitigation method for UWB ranging and positioning, IEEE Commun. Lett. (2023).
[166] X. Zhu, J. Yi, J. Cheng, L. He, Adapted error map based mobile robot UWB indoor positioning, IEEE Trans. Instrum. Meas. 69 (9) (2020) 6336–6350.
[167] X. Xu, X. Liu, B. Zhao, B. Yang, An extensible positioning system for locating mobile robots in unfamiliar environments, Sensors 19 (18) (2019) 4025.
[168] J.A. Corrales, F.A. Candelas, F. Torres, Hybrid tracking of human operators using IMU/UWB data fusion by a Kalman filter, in: Proceedings of the 3rd ACM/IEEE International Conference on Human Robot Interaction, 2008, pp. 193–200.
[169] G. Bishop, G. Welch, et al., An introduction to the Kalman filter, in: Proc SIGGRAPH, Course, vol. 8, (27599–23175) 2001, p. 41.
[170] S. Wang, Z. Wu, A. Lim, Denoising, outlier/dropout correction, and sensor selection in range-based positioning, IEEE Trans. Instrum. Meas. 70 (2021) 1–13.
[171] G. Guan, G. Chen, An improved LSE-EKF optimisation algorithm for UAV UWB positioning in complex indoor environments, J. Control. Decis. 10 (4) (2023) 547–559.
[172] E. García, P. Poudereux, Á. Hernández, J. Ureña, D. Gualda, A robust UWB indoor positioning system for highly complex environments, in: 2015 IEEE International Conference on Industrial Technology, ICIT, IEEE, 2015, pp. 3386–3391.
[173] Y. Xu, Y.S. Shmaliy, S. Bi, X. Chen, Y. Zhuang, Extended Kalman/UFIR filters for UWB-based indoor robot localization under time-varying colored measurement noise, IEEE Internet Things J. (2023).
[174] S. Konatowski, P. Kaniewski, J. Matuszewski, Comparison of estimation accuracy of EKF, UKF and PF filters, Annu. Navig. (23) (2016) 69–87.
[175] V. Magnago, P. Corbalán, G.P. Picco, L. Palopoli, D. Fontanelli, Robot localization via odometry-assisted ultra-wideband ranging with stochastic guarantees, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS, IEEE, 2019, pp. 1607–1613.
[176] J. González, J.-L. Blanco, C. Galindo, A. Ortiz-de Galisteo, J.-A. Fernández-Madrigal, F.A. Moreno, J.L. Martinez, Mobile robot localization based on ultra-wide-band ranging: A particle filter approach, Robot. Auton. Syst. 57 (5) (2009) 496–507.
[177] X. Wang, F. Gao, J. Huang, Y. Xue, UWB/LiDAR tightly coupled positioning algorithm based on ISSA optimized particle filter, IEEE Sens. J. (2024).
[178] D.B. Jourdan, J.J. Deyst, M.Z. Win, N. Roy, Monte Carlo localization in dense multipath environments using UWB ranging, in: 2005 IEEE International Conference on Ultra-Wideband, IEEE, 2005, pp. 314–319.

[179] N. Zhou, L. Lau, R. Bai, T. Moore, Evolutionary-inspired strategy for particle distribution optimization in auxiliary particle filtering algorithm based indoor positioning, in: 2021 International Conference on Indoor Positioning and Indoor Navigation, IPIN, IEEE, 2021, pp. 1–8.

[180] L. Cheng, Z. Zhao, Y. Shi, Y. Lu, Implicit unscented particle filter based indoor fusion positioning algorithms for sensor networks, Alex. Eng. J. 94 (2024) 104–119.

[181] T. Deissler, J. Thielecke, UWB SLAM with rao-blackwellized Monte Carlo data association, in: 2010 International Conference on Indoor Positioning and Indoor Navigation, IEEE, 2010, pp. 1–5.

[182] J.M. Pak, C.K. Ahn, Y.S. Shmaliy, P. Shi, M.T. Lim, Accurate and reliable human localization using composite particle/FIR filtering, IEEE Trans. Hum.- Mach. Syst. 47 (3) (2016) 332–342.

[183] Q. Wu, Y. Xiong, Q. Zhang, Z. Guo, X.-G. Xia, Z. Li, Joint routing and topology formation in multihop UWB networks, IEEE J. Sel. Areas Commun. 24 (4) (2006) 843–849.

[184] M. Wang, L. Li, J. Liu, R. Chen, Neural network aided factor graph optimization for collaborative pedestrian navigation, IEEE Trans. Intell. Transp. Syst. (2023).

[185] S. Zheng, Z. Li, Y. Yin, Y. Liu, H. Zhang, P. Zheng, X. Zou, Multi-robot relative positioning and orientation system based on UWB range and graph optimization, Measurement 195 (2022) 111068.

[186] X. Fang, C. Wang, T.-M. Nguyen, L. Xie, Graph optimization approach to range-based localization, IEEE Trans. Syst. Man, Cybern.: Syst. 51 (11) (2020) 6830–6841.

[187] L. Taponecco, A.A. D'Amico, U. Mengali, Joint TOA and AOA estimation for UWB localization applications, IEEE Trans. Wirel. Commun. 10 (7) (2011) 2207–2217.

[188] İ. Güvenç, C.-C. Chong, F. Watanabe, H. Inamura, NLOS identification and weighted least-squares localization for UWB systems using multipath channel statistics, EURASIP J. Adv. Signal Process. 2008 (2007) 1–14.

[189] H. Yang, Y. Wang, C.K. Seow, M. Sun, M. Si, L. Huang, UWB sensor-based indoor LOS/NLOS localization with support vector machine learning, IEEE Sens. J. 23 (3) (2023) 2988–3004.

[190] M. Camp, H. Garbe, Parameter estimation of double exponential pulses (EMP, UWB) with least squares and nelder mead algorithm, IEEE Trans. Electromagn. Compat. 46 (4) (2004) 675–678.

[191] J.A. Momoh, R. Adapa, M. El-Hawary, A review of selected optimal power flow literature to 1993. I. Nonlinear and quadratic programming approaches, IEEE Trans. Power Syst. 14 (1) (1999) 96–104.

[192] Z.-Q. Luo, N.D. Sidiropoulos, P. Tseng, S. Zhang, Approximation bounds for quadratic optimization with homogeneous quadratic constraints, SIAM J. Optim. 18 (1) (2007) 1–28.

[193] S. Yousefi, X.-W. Chang, B. Champagne, Mobile localization in non-line-of-sight using constrained square-root unscented Kalman filter, IEEE Trans. Veh. Technol. 64 (5) (2014) 2071–2083.

[194] F. Shu, S. Yang, Y. Qin, J. Li, Approximate analytic quadratic-optimization solution for TDOA-based passive multi-satellite localization with earth constraint, IEEE Access 4 (2016) 9283–9292.

[195] Y. Liu, L. Zhang, L. Ye, Z. Nie, Q.H. Liu, Synthesis of sparse arrays with frequency-invariant-focused beam patterns under accurate sidelobe control by iterative second-order cone programming, IEEE Trans. Antennas and Propagation 63 (12) (2015) 5826–5832.

[196] G. Naddafzadeh-Shirazi, M.B. Shenouda, L. Lampe, Second order cone programming for sensor network localization with anchor position uncertainty, IEEE Trans. Wirel. Commun. 13 (2) (2013) 749–763.

[197] S. Tomic, M. Beko, R. Dinis, Distributed RSS-based localization in wireless sensor networks based on second-order cone programming, Sensors 14 (10) (2014) 18410–18432.

[198] W. Wang, G. Wang, F. Zhang, Y. Li, Second-order cone relaxation for TDOA-based localization under mixed LOS/NLOS conditions, IEEE Signal Process. Lett. 23 (12) (2016) 1872–1876.

[199] T.H. Nguyen, L. Xie, Estimating odometry scale and UWB anchor location based on semidefinite programming optimization, IEEE Robot. Autom. Lett. 7 (3) (2022) 7359–7366.

[200] R. Zheng, G. Wang, K. Ho, Accurate semidefinite relaxation method for elliptic localization with unknown transmitter position, IEEE Trans. Wirel. Commun. 20 (4) (2020) 2746–2760.

[201] C.R. Berger, M. Eisenacher, S. Zhou, F.K. Jondral, Improving the UWB pulse-shaper design using nonconstant upper bounds in semidefinite programming, IEEE J. Sel. Top. Signal Process. 1 (3) (2007) 396–404.

[202] H. Chen, G. Wang, Z. Wang, H.-C. So, H.V. Poor, Non-line-of-sight node localization based on semi-definite programming in wireless sensor networks, IEEE Trans. Wirel. Commun. 11 (1) (2011) 108–116.

[203] W. Zhao, J. Panerati, A.P. Schoellig, Learning-based bias correction for time difference of arrival ultra-wideband localization of resource-constrained mobile robots, IEEE Robot. Autom. Lett. 6 (2) (2021) 3639–3646.

[204] D.T.A. Nguyen, H.-G. Lee, E.-R. Jeong, H.L. Lee, J. Joung, Deep learning-based localization for UWB systems, Electronics 9 (10) (2020) 1712.

[205] Z. Gao, Y. Jiao, W. Yang, X. Li, Y. Wang, A method for UWB localization based on CNN-SVM and hybrid locating algorithm, Information 14 (1) (2023) 46.

[206] F. Ge, Y. Shen, Single-anchor ultra-wideband localization system using wrapped PDoA, IEEE Trans. Mob. Comput. 21 (12) (2021) 4609–4623.

[207] L. Nosrati, M.S. Fazel, M. Ghavami, Improving indoor localization using mobile UWB sensor and deep neural networks, IEEE Access 10 (2022) 20420–20431.

[208] Z. Hajiakhondi-Meybodi, A. Mohammadi, M. Hou, K.N. Plataniotis, DQLEL: Deep Q-learning for energy-optimized LoS/NLoS UWB node selection, IEEE Trans. Signal Process. 70 (2022) 2532–2547.

[209] L.T. Nguyen, J. Kim, S. Kim, B. Shim, Localization of IoT networks via low-rank matrix completion, IEEE Trans. Commun. 67 (8) (2019) 5833–5847.

[210] K. Yu, I. Oppermann, Performance of UWB position estimation based on time-of-arrival measurements, in: 2004 International Workshop on Ultra Wideband Systems Joint with Conference on Ultra Wideband Systems and Technologies. Joint UWBST & IWUWBS 2004 (IEEE Cat. No. 04EX812), IEEE, 2004, pp. 400–404.

[211] G.I. Mary, V. Prithiviraj, UWB localization techniques for precision automobile parking system, in: 2008 10th International Conference on Electromagnetic Interference & Compatibility, IEEE, 2008, pp. 621–626.

[212] A. Chehri, P. Fortier, P.M. Tardif, UWB-based sensor networks for localization in mining environments, Ad Hoc Netw. 7 (5) (2009) 987–1000.

[213] B. Van Herbruggen, S. Luchie, J. Fontaine, E. De Poorter, Multi-hop self-calibration algorithm for ultra-wideband (UWB) anchor node positioning, IEEE J. Indoor Seamless Position. Navig. (2023).

[214] P.N. Beuchat, H. Hesse, A. Domahidi, J. Lygeros, Enabling optimization-based localization for IoT devices, IEEE Internet Things J. 6 (3) (2019) 5639–5650.

[215] F. Yin, C. Fritsche, F. Gustafsson, A.M. Zoubir, EM-and JMAP-ML based joint estimation algorithms for robust wireless geolocation in mixed LOS/NLOS environments, IEEE Trans. Signal Process. 62 (1) (2013) 168–182.

[216] J. Rapinski, A. Janowski, The optimal location of ground-based GNSS augmentation transceivers, Geosciences 9 (3) (2019) 107.

[217] K. Levenberg, A method for the solution of certain non-linear problems in least squares, Quart. Appl. Math. 2 (2) (1944) 164–168.

[218] D.W. Marquardt, An algorithm for least-squares estimation of nonlinear parameters, J. Soc. Ind. Appl. Math. 11 (2) (1963) 431–441.

[219] W. Dong, Y. Li, X. Sheng, X. Zhu, Trajectory estimation of a flying robot with a single ranging beacon and derived velocity constraints, IEEE Trans. Ind. Electron. 70 (5) (2022) 5024–5033.

[220] Y. Rong, D.W. Bliss, Remote sensing for vital information based on spectral-domain harmonic signatures, IEEE Trans. Aerosp. Electron. Syst. 55 (6) (2019) 3454–3465.

[221] N. Chernov, C. Lesort, Least squares fitting of circles, J. Math. Imaging Vision 23 (2005) 239–252.

[222] R. Nakamura, H. Hadama, Target localization using multi-static UWB sensor for indoor monitoring system, in: 2017 IEEE Topical Conference on Wireless Sensors and Sensor Networks, WiSNet, IEEE, 2017, pp. 37–40.

[223] X. Zhuge, A.G. Yarovoy, T. Savelyev, L. Ligthart, Modified Kirchhoff migration for UWB MIMO array-based radar imaging, IEEE Trans. Geosci. Remote Sens. 48 (6) (2010) 2692–2703.

[224] Q. Zhang, S. Song, Parsimonious correlated nonstationary models for real baseband UWB data, IEEE Trans. Veh. Technol. 54 (2) (2005) 447–455.

[225] L. Cheng, H. Chang, K. Wang, Z. Wu, Real time indoor positioning system for smart grid based on UWB and artificial intelligence techniques, in: 2020 IEEE Conference on Technologies for Sustainability, SusTech, IEEE, 2020, pp. 1–7.

[226] M. Martalò, S. Perri, G. Verdano, F. De Mola, F. Monica, G. Ferrari, Improved UWB TDoA-based positioning using a single hotspot for industrial IoT applications, IEEE Trans. Ind. Inform. 18 (6) (2021) 3915–3925.

[227] Y. Gao, H. Jing, M. Dianati, C.M. Hancock, X. Meng, Performance analysis of robust cooperative positioning based on GPS/UWB integration for connected autonomous vehicles, IEEE Trans. Intell. Veh. 8 (1) (2022) 790–802.

[228] T.H. Nguyen, L. Xie, Relative transformation estimation based on fusion of odometry and UWB ranging data, IEEE Trans. Robot. (2023).

[229] J. Vanhie-Van Gerwen, K. Geebelen, J. Wan, W. Joseph, J. Hoebeke, E. De Poorter, Indoor drone positioning: Accuracy and cost trade-off for sensor fusion, IEEE Trans. Veh. Technol. 71 (1) (2021) 961–974.

[230] D. Feng, J. Peng, Y. Zhuang, C. Guo, T. Zhang, Y. Chu, X. Zhou, X.-G. Xia, An adaptive IMU/UWB fusion method for NLOS indoor positioning and navigation, IEEE Internet Things J. (2023).

[231] K. Li, Z. Cao, U.D. Hanebeck, Continuous-time ultra-wideband-inertial fusion, IEEE Robot. Autom. Lett. (2023).

[232] L. Si, Z. Wang, D. Wei, J. Gu, P. Zhang, Fusion positioning of mobile equipment in underground coal mine based on redundant IMUs and UWB, IEEE Trans. Ind. Inform. (2023).

[233] J. Sun, W. Sun, J. Zheng, Z. Chen, C. Tang, X. Zhang, A novel UWB/IMU/Odometer-Based robot localization system in LOS/NLOS mixed environments, IEEE Trans. Instrum. Meas. (2024).

[234] S. Vandermeeren, H. Steendam, PDR/UWB based positioning of a shopping cart, IEEE Sens. J. 21 (9) (2021) 10864–10878.

[235] T.H. Nguyen, T.-M. Nguyen, L. Xie, Range-focused fusion of camera-IMU-UWB for accurate and drift-reduced localization, IEEE Robot. Autom. Lett. 6 (2) (2021) 1678–1685.

[236] A. Goudar, W. Zhao, A.P. Schoellig, Range-visual-inertial sensor fusion for micro aerial vehicle localization and navigation, IEEE Robot. Autom. Lett. 9 (1) (2023) 683–690.

[237] D. Chen, G. Xiong, L. Wang, W. Yu, Variable length sequential iterable convolutional recurrent network for UWB-IR vehicle target recognition, IEEE Trans. Geosci. Remote Sens. 61 (2023) 1–11.

[238] O. Huang, H. Rao, Z. Zhang, R. Gu, H. Xu, G. Jia, Boosting research for carbon neutral on edge UWB nodes integration communication localization technology of IoV, IEEE Trans. Sustain. Comput. (2023).

[239] M. Niu, G. Wen, H. Shen, Y. Lv, G. Chen, Stochastic event-triggered sequential fusion filtering for USV cooperative localization, IEEE Trans. Aerosp. Electron. Syst. (2023).

[240] H. Kang, W. Zhang, Y. Ge, H. Liao, B. Huang, J. Wu, R.-J. Yan, I.-M. Chen, A high-accuracy hollowness inspection system with sensor fusion of ultra-wide-band radar and depth camera, Robotica 41 (4) (2023) 1258–1274.

[241] H. Gao, X. Li, X. Song, A fusion strategy for vehicle positioning at intersections utilizing UWB and onboard sensors, Sensors 24 (2) (2024) 476.

[242] V. Brunacci, A. De Angelis, Fusion of UWB and magnetic ranging systems for robust positioning, IEEE Trans. Instrum. Meas. (2023).

[243] M. Zhang, X. Xu, Y. Chen, M. Li, A lightweight and accurate localization algorithm using multiple inertial measurement units, IEEE Robot. Autom. Lett. 5 (2) (2020) 1508–1515.

[244] Q. Xu, X. Li, C.-Y. Chan, Enhancing localization accuracy of MEMS-INS/GPS/In-Vehicle sensors integration during GPS outages, IEEE Trans. Instrum. Meas. 67 (8) (2018) 1966–1978.

[245] B. Zhou, H. Fang, J. Xu, UWB-IMU-odometer fusion localization scheme: Observability analysis and experiments, IEEE Sens. J. 23 (3) (2022) 2550–2564.

[246] J. Li, Y. Wang, Z. Chen, L. Ma, S. Yan, Improved height estimation using extended Kalman filter on UWB-barometer 3D indoor positioning system, Wirel. Commun. Mob. Comput. 2021 (2021) 1–13.

[247] R. Ali, R. Liu, A. Nayyar, B. Qureshi, Z. Cao, Tightly coupling fusion of UWB ranging and IMU pedestrian dead reckoning for indoor localization, IEEE Access 9 (2021) 164206–164222.

[248] C.-S. Jao, D. Wang, C. Chen, E. Sangenis, J. Grasso, S.S. Kia, A.M. Shkel, Augmented UWB-ZUPT-SLAM utilizing multi-sensor fusion, IEEE J. Indoor Seamless Position. Navig. (2023).

[249] Y. Xu, Y.S. Shmaliy, C.K. Ahn, T. Shen, Y. Zhuang, Tightly coupled integration of INS and UWB using fixed-lag extended UFIR smoothing for quadrotor localization, IEEE Internet Things J. 8 (3) (2020) 1716–1727.

[250] A. Liu, S. Lin, J. Wang, X. Kong, A novel loosely coupling fusion approach of ultra-wideband and wheel odometry for indoor localisation, Electronics 12 (21) (2023) 4499.

[251] J. Tiemann, A. Ramsey, C. Wietfeld, Enhanced UAV indoor navigation through SLAM-augmented UWB localization, in: 2018 IEEE International Conference on Communications Workshops, ICC Workshops, IEEE, 2018, pp. 1–6.

[252] Y. Wu, F. Tang, H. Li, Image-based camera localization: An overview, Vis. Comput. Ind. Biomed. Art 1 (2018) 1–13.

[253] H. Song, W. Choi, H. Kim, Robust vision-based relative-localization approach using an RGB-depth camera and LiDAR sensor fusion, IEEE Trans. Ind. Electron. 63 (6) (2016) 3725–3736.

[254] R.W. Wolcott, R.M. Eustice, Visual localization within LiDAR maps for automated urban driving, in: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, 2014, pp. 176–183.

[255] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, A. Torralba, Learning deep features for discriminative localization, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2921–2929.

[256] C. Deng, J. Wei, W. Ma, Z. Zhao, J. Qin, An indoor intelligent care system based on the fusion of vision and UWB heterogeneous sensors, in: 2023 IEEE International Conference on Unmanned Systems, ICUS, IEEE, 2023, pp. 1708–1713.

[257] Y. Song, M. Guan, W.P. Tay, C.L. Law, C. Wen, UWB/LiDAR fusion for cooperative range-only SLAM, in: 2019 International Conference on Robotics and Automation, ICRA, 2019, pp. 6568–6574.

[258] M. Guan, C. Wen, Autonomous exploration using UWB and LiDAR, J. Autom. Intell. 2 (1) (2023) 51–60.

[259] S. Goel, A. Kealy, V. Gikas, G. Retscher, C. Toth, D.-G. Brzezinska, B. Lohani, Cooperative localization of unmanned aerial vehicles using GNSS, MEMS inertial, and UWB sensors, J. Surv. Eng. 143 (4) (2017) 04017007.

[260] L. Bariah, Q. Zhao, H. Zou, Y. Tian, F. Bader, M. Debbah, Large generative AI models for telecom: The next big thing? IEEE Commun. Mag. (2024).

[261] A. Alnoman, A.S. Khwaja, A. Anpalagan, I. Woungang, Emerging AI and 6G-based user localization technologies for emergencies and disasters, IEEE Access (2024).

[262] A. Benfradj, A. Thaljaoui, T. Moulahi, R.U. Khan, A. Alabdulatif, P. Lorenz, et al., Integration of artificial intelligence (AI) with sensor networks: Trends, challenges, and future directions, J. King Saud Univ.- Comput. Inf. Sci. 36 (1) (2024) 101892.

[263] H. Ibn-Khedher, M. Laroui, M. Alfaqawi, A. Magnouche, H. Moungla, H. Afifi, 6G-edge support of internet of autonomous vehicles: A survey, Trans. Emerg. Telecommun. Technol. 35 (1) (2024) e4918.

[264] Y. Shang, Z. Li, S. Li, Z. Shao, L. Jian, An information security solution for vehicle-to-grid scheduling by distributed edge computing and federated deep learning, IEEE Trans. Ind. Appl. (2024).

[265] X. Wang, Z. Sun, A. Chehri, G. Jeon, Y. Song, Deep learning and multi-modal fusion for real-time multi-object tracking: Algorithms, challenges, datasets, and comparative study, Inf. Fusion 105 (2024) 102247.

[266] N. Cohen, I. Klein, Inertial navigation meets deep learning: A survey of current trends and future directions, Results Eng. (2024) 103565.

[267] A. Shoomal, M. Jahanbakht, P.J. Componation, D. Ozay, Enhancing supply chain resilience and efficiency through internet of things integration: Challenges and opportunities, Internet Things (2024) 101324.

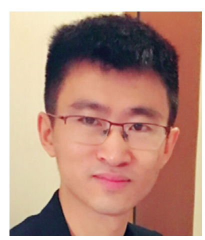
[268] M. Yang, K. Jiang, B. Wijaya, T. Wen, J. Miao, J. Huang, C. Zhong, W. Zhang, H. Chen, D. Yang, Review and challenge: High definition map technology for intelligent connected vehicle, Fundam. Res. (2024).

[269] C. Yeh, Y.-S. Choi, Y.-J. Ko, I.-G. Kim, Standardization and technology trends of artificial intelligence for mobile systems, Comput. Commun. 213 (2024) 169–178.

[270] J. Wang, J. Ke, J.-F. Zhang, Differentially private bipartite consensus over signed networks with time-varying noises, IEEE Trans. Autom. Control (2024).

[271] J. Wang, J.-F. Zhang, Differentially private distributed stochastic optimization with time-varying sample sizes, IEEE Trans. Autom. Control (2024).

Ning Xu received the B.E. degree from Xi'an Jiaotong University (XJTU), China, in 2020, and M.S. degree from Nanyang Technological University (NTU), Singapore in 2022. She is currently working toward a Ph.D. degree in electrical engineering at NTU, Singapore. Since October 2022, she has been with Advanced Remanufacturing and Technology Centre (ARTC), A*STAR, Singapore. Her current research interests include robotic control policy, artificial intelligence technology, and related engineering applications.



Mingyang Guan received the B.S. and M.S. degree from Xi'an Jiaotong University, China, in 2010 and 2013, respectively, and the Ph.D. degree from Nanyang Technological University, Singapore in 2020. Since January 2021, he has been with Advanced Remanufacturing and Technology Centre (ARTC), A*STAR, Singapore, where he is currently a senior scientist. His current research interests include multi-robot systems, deep reinforcement learning, and sensor fusion SLAM. He has been working as the track chair in several international conferences, i.e. ICIEA, and IECON.

Changyun Wen received the B.Eng. degree from Xi'an Jiaotong University, China, in 1983 and the Ph.D. degree from the University of Newcastle, Australia in 1990. From August 1989 to August 1991, he was a Postdoctoral Fellow at University of Adelaide, Australia. Since August 1991, he has been with Nanyang Technological University, Singapore, where he is a Full Professor. His main research activities are in the areas of control systems and applications, cyber–physical systems, smart grids, autonomous systems.

Prof Wen is a Fellow of IEEE and Fellow of the Academy of Engineering, Singapore. He was a member of IEEE Fellow Committee from January 2011 to December 2013 and a Distinguished Lecturer of IEEE Control Systems Society from 2010 to 2013. Currently he is the co-Editor-in-Chief of IEEE Transactions on Industrial Electronics, Associate Editor of Automatica (from Feb 2006) and Executive Editor-in-Chief of Journal of Control and Decision. He also served as an Associate Editor of IEEE Transactions on Automatic Control from 2000 to 2002, IEEE Transactions on Industrial Electronics from 2013 to 2020 and IEEE Control Systems Magazine from 2009 to 2019. He has been actively involved in organizing international conferences playing the roles of General Chair (including the General Chair of IECON 2020 and IECON 2023), TPC Chair (e.g. the TPC Chair of Chinese Control and Decision Conference since 2008) etc.

He was the recipient of a number of awards, including the Prestigious Engineering Achievement Award from the Institution of Engineers, Singapore in 2005, and the Best Paper Award of IEEE Transactions on Industrial Electronics in 2017. He was listed as a Highly Cited Researcher by Clarivate in each year from 2020 to 2024.