A COMPREHENSIVE REVIEW OF INDOOR LOCALIZATION: SOLUTIONS, ARCHITECTURES, CHALLENGES, AND FUTURE DIRECTIONS

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ABSTRACT

The concept of indoor localization has become a fundamental technology of contemporary location-based services in areas like smart buildings, healthcare, emergency response, logistics, and Industry 4.0. Nevertheless, indoor settings are extremely difficult compared to outdoor settings where Global Navigation Satellite Systems (GNSS) can offer good positioning, indoor settings are still a challenge with multipath propagation, Non-Line-of-Sight (NLoS) effects, signal attenuation and dynamic environment variations. The need to overcome these constraints is the main issue that inspired this work. The objective of the research is to both present a cohesive and detailed overview of the indoor localization systems, including their development, mathematical basis and the new technological trends in their development. To do this, the research employs a systematic review approach that incorporates the viewpoints of wireless communications, artificial intelligence, and computational architectures. These include important technological advances of early Radio Frequency Identification (RFID) systems to current Wireless Fidelity (Wi-Fi), Bluetooth Low Energy (BLE), Ultra-Wideband (UWB), and emerging technologies of Visible Light Communication (VLC) and hybrid sensor-fusion systems. Geometric (trilateration, triangulation, ToA, TDoA, AoA), fingerprinting, and probabilistic filtering methods (Kalman and particle filters) are mathematically modelled and discussed, as well as machine learning-improved localization models. The study findings indicate that there is no best localization method that will always be optimal; instead, the performance is a trade-off between accuracy, infrastructure needs, and environmental sturdiness. Under favourable conditions, UWB-based systems can be used to achieve sub-decimetre accuracy, and Wi-Fi and BLE fingerprinting techniques can be used to achieve meter-level accuracy with greater versatility in the complex indoor environment. Moreover, hybrid methods that combine sensor fusion, machine learning, and adaptive algorithms can enhance the localization performance in NLoS and dynamic scenarios rather than in a single way. On the basis of these results, the paper suggests the application of interdisciplinary, data-driven, and hybrid localization structures integrating geometric, fingerprinting, and learning-based approaches. The systems of the future must be focused on the ease of scaling and environmental flexibility and privacy protection using methods like federated learning, edge intelligence, and secure data sharing. As a set of enablers in the development of a ubiquitous, high-precision indoor positioning and seamless indoor-outdoor navigation, emerging technologies, such as 5G/6G-enabled Joint Communication and Sensing (JCAS), Reconfigurable Intelligent Surfaces (RIS), and AI-driven localization, are identified.

Keywords: Real-time localization system; Indoor localization; Indoor positioning; Hybrid localization architectures; RTLS

1 INTRODUCTION

Indoor localization has become a core competency to a broad domain of systems and services, which need spatial awareness in GNSS denied areas. Its applications can be used in various fields and areas, such as smart buildings, where it can be used to provide occupancy-sensitive climate and lighting control, optimize energy, track assets within hospitals or factories, or help analyse space utilization alongside the IoT platforms [1]. In healthcare, accurate indoor localization allows to track critical devices, monitor patient flow and staff location in case of an emergency, which lowers retrieval time and enhances workflow and patient safety [2, 3]. It is also important to note that emergency response activities also depend on precise indoor location to assist occupants in the evacuation process, assist first-responder teams to navigate intricate layouts, and improve situational awareness in time-sensitive situations [3, 4]. A combination of these applications requires centimetre to millimetre level precision, instant updates, support to environmental variations, and intensive security of sensitive location information [2]. Even though GNSS is ubiquitous outdoors, it has fundamental limitations in use indoors. The attenuation of signals transmitted by the satellites of the navigation system is extremely high because of concrete, metal, and glass, which often makes it difficult to directly receive them inside standard buildings [5, 6]. The signals in numerous instances are overshadowed by multipath reflections that distort timing measurements and cause the notable varying errors [7, 8]. Loss of accuracy caused by poor geometric dilution of precision on the small number of visible satellites even in cases where faint signals are observed, further affects accuracy to such a point that most indoor services are not served with an acceptable level of accuracy [5]. Although the use of a highly sensitive receivers or hybrid GNSS-augmented solutions can work well around the perimeter of buildings, the general opinion in literature is that GNSS alone is not capable of providing a reliable and fine-grained indoor positioning in practical deployment, and thus the innovation of a diverse ecosystem of alternative and complementary solutions is encouraged [2, 7]. Modern indoor localization systems have goals other than simple position estimations. The spatial resolution needed by certain applications, such as the room-level navigation and the millimetre-level accuracy asset tracking, has led to the exploration of technologies, such as, Ultra-Wideband (UWB), Channel State Information (CSI), fingerprinting and positioning capability in 5G and beyond wireless networks [2, 9]. Energy efficiency and cost-effectiveness are also equally critical, particularly with battery-powered tags or smartphones with several methods being able to utilize current infrastructure like Wireless Fidelity (WiFi) or Bluetooth Low Energy (BLE) with the intention of minimizing both deployment and maintenance costs [2, 10]. Resilience to changing conditions, that is, the mobility of people, the mobility of furniture or structures are another key condition and this has been approached by adaptive fingerprint updates [11], crowdsourced mapping [12] and machine learning models that can generalize under device heterogeneity [2, 11, 13, 14]. The operation of low latency is important in navigation, Augmented Reality (AR), robotics, and emergency, which is why edge computing, lightweight inference models, and efficient sensor fusion pipelines are used [10]. The main aspects of user trust and regulatory compliance are privacy and security, and therefore, the system design should include privacy-preserving algorithms, local processing, and encryption [2]. The review paper provides an overview of the existing methodologies and architectures suggested to be used in indoor localization including both legacy and state-of-the-art. It explores geometric and array-based methods which include Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) and trilateration or triangulation, which give interpretable answers when measurements are favourable [2]. It addresses the concept of fingerprinting and database-based approaches such as the Received Signal Strength (RSS) and the CSI modalities that have been combined with pattern matching or Machine Learning (ML), and rely on the existing infrastructure and eliminate the multipath effects at the expense of data collection and calibration [2, 14]. Hybrid and sensor fusion systems have been surveyed based on their capability to combine Inertial Measurement Units (IMUs), barometers, cameras and RF signals to provide robust, high-level continuous tracking in diverse applications by probabilistic filters, or through optimization methods [2]. Lastly, the paper identifies the use of AI-inspired and network-native localization schemes that leverage deep and federated learning and utilizes the positioning features of the contemporary wireless networks, especially 5G and beyond wireless communications with massive MIMO, beamforming, and Reconfigurable Intelligent Surfaces (RIS) [9, 15]. Offering an overview of the existing state of affairs and focusing on the technological direction toward strong and widespread indoor positioning, this review will focus on understanding of theoretical basis, comparison, the analysis of practical factors like cost of deployment, scalability, and privacy.

2 METHODOLOGY

At the time this review was written, the work adhered to the guidelines of Preferred Reporting Items of Systematic Reviews and Meta-Analyses [16] to make this process transparent, reproducible, and comprehensive in terms of the literature selection and synthesis process. Its methodological framework consisted of five consecutive steps, i.e., formulation of research questions, development of a search strategy, use of inclusion and exclusion criteria, systematic study selection, and systematic data extraction and synthesis.

2.1 Research Questions

The research questions were constructed with the purpose of mapping the technological development and the methodology of the field of the indoor localization. There were four guiding questions: Which are the most common indoor localization technologies, and what are the mathematical principles of these technologies? What are the practical and theoretical limitations in relation to real-world deployments and what have been done to address them? How are the next-generation indoor positioning systems being influenced by emerging technologies, such as UWB or mmWave localization, RIS, CSI fingerprinting, 6G joint sensing, and edge or federated fusion? The following questions were aimed at reflecting the historical developments of localization as well as the state-of-the-art innovations, that is, hardware, algorithms, and architectural paradigms.

2.2 Search Strategy

The search of the literature was systematic and carried out primarily using four large scientific databases with known high-quality and peer-reviewed research output: MDPI, IEEE Xplore, ScienceDirect (Elsevier) and SpringerLink. Additional cross-referencing of Wiley online library, Taylor and Francis online and ACM were used to reduce publication bias. In order to capture the technological development of the field in a sufficient way, the time span was broadened to capture the period since 1995 and 2025. The reasons why this time duration was chosen are: RFID and infrared-based RTLS were first proposed as the basis of indoor localization in the early 1990s; WiFi, BLE, and UWB became the top wireless modalities of the 2000s; and The 2010s saw AI-driven edges, edge-intelligent and 6G-capable systems. The retention of seminal pre-1990 work included that work which presented fundamental mathematical formulations or novel system architectures (e.g., early radar and infrared localization research). The Boolean operators (“AND”, “OR”) and truncation characters (") were used in the search to identify variations of the terms. The keyword query was a mix of both technological and methodological terms that included: “indoor localization”, “indoor positioning”, “fingerprinting”, “ToA”, “TDoA”, “RFID”, “WiFi”, “Bluetooth Low Energy” or “BLE”, “Ultra-Wideband”, or “UWB”, “visible light communication” or “VLC”, “sensor fusion”, “Kalman filter”, “machine learning”, “deep learning”, “edge computing”, “federated learning”, “geometric localization”, “5G”, and “6G”.

2.3 Inclusion and Exclusion Criteria

Inclusion criteria as delineated hereunder were established to bring in relevancy and quality. These included: Research that specifically targeted indoor localization or positioning; Research in English and in peer reviewed journals or conferences (MDPI, IEEE, Elsevier, ACM, Springer, Wiley, or similar publications); Measures of quantitative or comparative performance (e.g., accuracy, latency, or power efficiency); Written system architectures, mathematical modelling, or algorithms. Exclusion criteria as adopted in this review paper included: Works that focused on outdoor utilizing GNSS positioning; Work that was inaccessible in full texts; Gave only conceptual or speculative arguments with no empirical proof. Additionally, the inclusion criteria also onboarded state-of-the-art conference papers that covered indoor localization.

2.4 Selection and Screening of Studies

The obtained search results were deduped using EndNote. The screening was done in two phases, which are: title and abstract filtering to eliminate obviously unrelated works, and; full-text evaluation to determine methodological soundness. All the articles were evaluated by two independent reviewers. The consensus was always used to solve any dispute and a third reviewer was used when necessary to achieve objectivity. The number of records identified, screened, excluded, and ultimately included in the study was documented in a PRISMA flow diagram as shown in Figure 1 to ensure complete audit transparency [16].

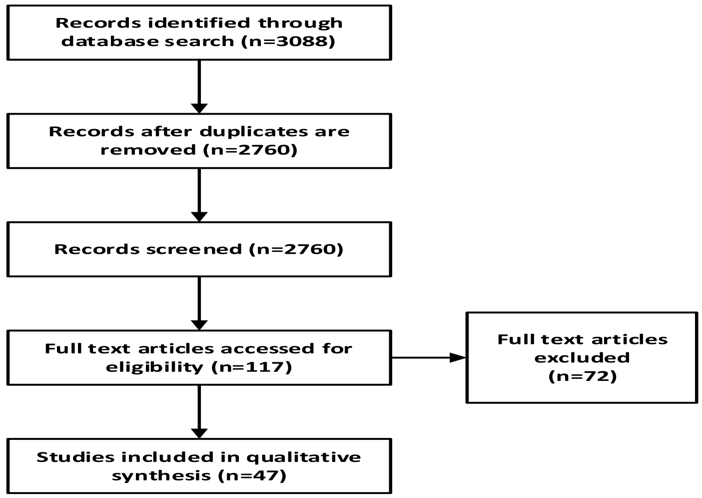

Figure 1. PRISMA Flow Diagram Delineating the Identification, Screening, Eligibility and Included Literature.

2.5 Data Extraction and Synthesis

The following attributes were captured by a structured data extraction form: Bibliographic (authors, year, venue); Localization technology and system architecture (WiFi, BLE, UWB, VLC, hybrid, AI-based, etc.); Basic mathematical or algorithmic models (e.g., ToA, TDoA, AoA, RSSI, Kalman or Particle Filter, CNN, RNN); Measures of reported performance (accuracy, coverage, latency, or computational load), and; determined issues and suggested ways of mitigation. Additionally, to describe the technological world development and to emphasize the cross-cutting tendencies in several decades and technologies, the comparative tables and timeline charts were created.

2.6 Rationale for the Time Frame (1995-2025)

The extended period of time (1995-2025) accounts for historical roots and new innovations. Initial research foundations were set with baseline architectures (RFID), then WiFi and UWB were brought in as RTLS in the 2000s, and more recently, AI-based sensor fusion, edge intelligence, and 6G-based systems were also explored. This timeline considered balances breadth (including three decades of technological progress) and depth (including a detailed analysis of mathematical models, the development of algorithms, and architectures on a systems level). The multi-publisher inclusion prevents the bias in favor of one particular outlet and guarantees that the contributions of across the aforementioned databases are balanced.

3 EVOLUTION AND EMERGING TECHNOLOGIES IN INDOOR LOCALIZATION

The history of indoor localization technologies can be seen as a progressive process of evolving the legacy RFID systems to much smarter, hybrid, and AI-based systems. Every new technological generation has helped to enhance the accuracy, scalability, robustness and contextual awareness of the indoor positioning systems. Discussed hereunder is a technology timeline of indoor localization technologies.

3.1 Early Development (1940-1990): RFID and Infrared System

Early active RFID systems, Infrared Real-Time Location Systems (RTLS) are the predecessors of indoor localization. The novelty of the British IFF System (Identification Friend or Foe) in the 1940s involved the principle of defining and finding objects through active transponders, although in a high-altitude or outdoor environment. This was the conceptual foundation of tracking radio or optical signals of assets and personnel indoors [17]. The development of RFID-based indoor localization started in the late 1980s and early 1990s, based on the principle that tags (active or passive) and readers can be used to sense proximity or reads and deduce location. These common models associate range with Received Signal Strength Indicator (RSSI) or phase/reader-tag read rate. As an example, simplified propagation models take the form of a variant of the Friis transmission equation as show in Eq. (1) [18]:

$$P_r(d) = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^2 \tag{1}$$

where $P_r(d)$ denoted the received power at distance, d, P_t delineated the transmit power, $G_t G_r$ represented the transmit and receiving gains of the antenna, respectively, λ denotes the wavelength. However later studies made it clear that indoor settings are far from being within the assumptions of the free-space but are subject to multipath and shadowing, which constrained the accuracy of RSSI-only localization. Hybrid systems added reference tags to enhance stability; such as the three-dimensional indoor RFID localization system proposed by [19] had a localization error of about 1.08 m on average in controlled laboratory conditions which proved not only a step forward but also a continuing challenge of early RFID techniques. Simultaneously, infrared (IR) Real-Time Location Systems (RTLS) developed to be used as an alternative to the outdoor localization in the clinical and secure facilities. The localization of the IR is based on the fact that the infrared signals cannot pass through the walls of the rooms, which allows localizing it on the rooms or zone level. Other IR systems used geometrical representations like simple AoA relationships. This is mathematically represented using Eq. (2):

$$x = x_0 + h.\tan(\theta), \qquad y = y_0 \tag{2}$$

In limited two-dimensional configurations, there is not much literature that documents finer-grained IR algorithmic implementations of the 1980s and 1990s. The modern reviews state that IR RTLS is primarily a legacy technology, whose functionality is good in the clear Line-of-Sight (LOS) scenarios but grossly diminishes when blocked by furniture, human bodies, or light source. IR systems were efficient in controlled environments, but were dense deployments and had an occlusion and orientation limit [17, 18]. In general, these early RFID and IR systems demonstrated the principle of indoor tracking and positioning and were limited by a rough accuracy, dependence on the sensitivity to the environmental change, and the burden on the infrastructure. Their shortcomings influenced the design intention of the further developments in the WiFi, UWB, BLE, VLC, and multi-sensor fusion technologies that subsequently characterized contemporary localization of high precision indoors. Table 1 outline the observation from literature that delineates the evolution of indoor localization technologies from the 1940s to the 1990s.

Table 1. Evolution of Indoor Localization Technologies.

Ref	Approach/ Focus	Methodology	Accuracy	Advantages	Limitation
[19]	Active RFID using RSSI and reference tags	RSSI distance model with hybrid kNN triangulation and weighted averaging	~1.0m - 1.2m	Simple implementation; scalable in small spaces	Requires dense reader deployment; sensitive to multipath
[6]	Early hybrid positioning framework	RF-based theoretical model combining Friis and path loss equations	1-3m	Provides theoretical basis for radio positioning models	Poor performance under NLoS; needs calibration per environment
[20]	Overview of IR RTLS performance	Empirical range estimation from light intensity attenuation	0.3-3m (LoS)	Immune to RF interference; high accuracy indoors	Limited coverage; requires dense deployment; sensitive to obstruction

3.2 Wireless Era (1995-2010): WiFi, RFID and Bluetooth

The Wireless Era is a critical era of indoor localization, as it is marked by the substitution of dedicated hardware (for example, infrared or specialized RFID systems) with those technologies that make use of the existing wireless communication infrastructure. WiFi, RFID and Bluetooth Low Energy (BLE) emerged between 1995 and 2010, and provide the enablers of Real-Time Location Systems (RTLS), increasing accessibility, scalability, and cost-efficiency in the use of Real-time positioning over an indoor environment.

3.2.1 Wireless Fidelity Based Localization

As a result of the popularization of wireless access points (APs) during the early 2000s, WiFi fingerprinting became one of the most researched approaches to positioning indoors. In the simplest variant, WiFi localization can be performed using the log-distance path-loss model to determine the distance between the Access Point and the receiver [6, 21] as shown in Eq. (3):

$$P_r(d) = P_r(d_0) - 10\text{nlog}_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{3}$$

where *d* represents the received signal power (dBm), d_0 delineates the power at reference distance, *n* signifies the path-loss is the shadowing factor (a zero-mean Gaussian random variable). Analytical models later gave way to fingerprinting, which is the mapping of RSSI signatures onto the spatial coordinates with the help of statistical or machine-learning algorithms like k-Nearest Neighbor (k-NN), Support Vector Machines (SVM), or Gaussian Mixture Models (GMM) [3]. In dense AP environments, WiFi fingerprinting was found to be accurate to sub- meters up to 3m, but performance declined under environmental dynamics, device heterogeneity and multipath fading [19].

3.2.2 Radio Frequency Identification Based Localization

Historically, as WiFi took over the infrastructure-based localization, RFID systems were evolving in the same direction, they offered object-centric and inventory-based tracking solutions. There were active and passive RFID systems. Active RFID tags periodically operated identification beacons, which allowed time- or signal-strength-based localization. Passive RFID was based on backscattered signals; range was estimated based on the Received Signal Strength Indicator (RSSI) or phase angle, or the most likely location zone could be identified. One of the propagation models typically used in RFID system is mathematically represented using Eq. (4):

$$d = d_0 \times \frac{P_r(d_0) - P_r(d)}{10n} \quad (4)$$

In order to enhance spatial accuracy, researchers used RSSI fingerprinting or hybrid multilteration with probabilistic estimation. Experiments demonstrated the accuracies to 0.2m -1.5m as possible in a laboratory environment [22]. Nevertheless, tag orientation, reader density, and environmental clutter had a strong influence on performance [23].

3.2.3 Bluetooth Low Energy Localization

In 2010, with the release of Bluetooth 4.0, Bluetooth Low Energy (BLE) technology was presented that supports low-power beacon-based indoor positioning. BLE localization is conceptually similar to WiFi and RFID, with the RSSI-distance relationship being [24-26] mathematically obtained using Eq. (5):

$$RSSI = A - 10n\log_{10}(d) \quad (5)$$

Where A is received signal strength at 1m. BLE beacons were cheap, power efficient and had simple smartphone capability where it reached 0.5m - 2m of accuracy in ideal conditions [25, 27]. However, BLE signals are characterized by large short-term variations caused by antenna design, absorption by people, as well as multipath reflections [28]. Indoor localization was democratized during the Wireless Era. WiFi utilized the already available infrastructure, RFID allowed an accurate positioning of objects, and BLE created mobility and affordability. Nonetheless, none of the three technologies had solved the problem of RSSI instability, multipath, and device heterogeneity, encouraging sensor fusion and machine-learning-based hybrid localization methods to be developed in the next decade. Table 2 outline the observation from literature that delineates the evolution of indoor localization technologies from the 1990 to 2010.

Table 2. Comparative Summary of Indoor Localization Systems from 1995-2010

Ref	Technology	Approach/ Focus	Accuracy	Application	Advantages	Limitation
[21]	WiFi	RSSI-based fingerprinting with GMM and multivariate analysis	1-3m	Smart-building indoor localization	Utilizes the installed WiFi structure; low cost	Performance differs with environment; requires calibration
[24]	BLE	RSSI based trilateration with k-NN smoothing	0.5-2m	Mobile indoor positioning	Low power; smartphone compatible	RSSI instability; lower accuracy than UWB
[25]	BLE	Beacon-based RSSI positioning	0.7-2m	IoT smart environments	Simple deployment; cost-effective	Multipath and signal fading
[27]	BLE and AI	AI-enhanced BLE localization using CNN models	0.4-1.0m	Intelligent building navigation	Improved robustness via ML models	Requires training data; high computational demand

3.3 High Precision Systems (2010-2015): Ultra-Wideband and Visible Light Communication

As demand increased on sub-meter and even centimetre level indoor localization but more requirements, the era between 2010 and 2015 saw the development of high-precision localization technologies. Ultra-Wideband (UWB) and Visible Light Communication (VLC) are two major methods of positioning during this period.

3.3.1 Ultra-Wideband

UWB systems make use of extremely short radio pulse time periods of very broad bandwidth (typically of more than 500 MHz) to obtain fine time resolution. The giant resolution facilitates accurate distance (or time) determination with the use of Time of Arrival (ToA) or Time Difference of Arrival (TDoA), and position accuracy of the order of centimetres is achievable in favourable circumstances [29, 30]. A basic ToA-based formula are represented in Eqs. (6) and (7):

$$d = c \times t_{ToA} \tag{6}$$

where c delineates the speed of light and t_{ToA} signifies the travel time of the signal. For multi-anchor TDoA, the fundamental relation is:

$$\Delta t_{ij} = t_i - t_j \Rightarrow d_i - d_j = c\Delta t_{ij} \tag{7}$$

Eq. (7) generates hyperbolic curves whose intersections estimate tag position [31].

3.3.2 Visible Light Communication

VLC localization utilizes lighting infrastructure of LEDs as a medium of positioning. LEDs switch intensity at high frequencies that cannot be detected by the human eye whilst carrying identification codes or structured optical waveforms. Receivers Photodiodes or smartphone cameras determine position based on Received Optical Signal Strength (ROSS), AoA, or time-based optical ranging [32, 33]. A common ROSS model for VLC is [34] mathematically represented as in Eq. (8):

$$P_r(d) = \frac{(m+1)A_r P_t}{2\pi d^2} cos^m(\phi) cos(\psi) T_s(\psi) g(\psi) + N \tag{8}$$

The technologies of this era extended the limits of the accuracy of indoor localization by utilizing time-based ranging (UWB) and optical signalling (VLC). They replaced metre- and decimetre-scale resolution with centimetre, allowing extremely precise use in industrial automation, robotics and intelligent environments. Although infrastructure and the line-of-sight limitations still existed, the methods have formed the basis of the hybrid and AI-based localisation systems that emerged later. Table 3 outline the observation from literature that delineates the evolution of indoor localization technologies from the 2010 to 2015.

Table 3. Comparative Summary of Indoor Localization Systems from 2010-2015.

Ref	Technology	Approach/ Focus	Accuracy	Application	Advantages	Limitation
[30]	UWB	ToA/TDoA ranging via UWB pulses	~10cm	Industrial RTLS, robotics	High accuracy, strong NLoS resilience	Requires synchronized anchors; cost and infrastructure overhead
[35]	UWB	Two-way ranging and least-squares or Gauss-Newton methods	<10cm in experiments	Precision tracking	Good multipath reduction; high accuracy	Requires accurate clocks; hardware complexity
[36]	VLC	RSS/ToA with LED anchors and OFDM modulation	~10cm	Smart indoor positioning	Utilizes lighting infrastructure; RF interference free	Strong LoS dependency; Light coverage needed
[37]	VLC	RSS and Jaya optimization algorithm	~1cm (Simulation); <3cm in practice	High precision indoor positioning	Very high accuracy	Highly controlled setup; complex algorithm

3.4 Hybrid Architectures and Edge Intelligence (2015-2020)

As the technologies around indoor localization systems matured and utilized on a larger scale, and in more complex locations, a new paradigm appeared; these known technologies were hybridized to combine many sensors and technologies, edge intelligence to address latency, scalability and privacy needs.

3.4.1 Hybrid Sensor-Fusion Architectures

These hybrid architectures that formed this period of localization systems concatenated the outputs of several sensors on which the localization technology was built atop and utilized complex methods of probability or complex filtering approaches to generate better performing localization systems. Popular models adopted to improve the positioning estimates applied Kalman Filter (KF), Particle Filter (PF) or graph-based localization. Eqs. (9) and (10) delineates a standard KF model [38, 39]:

$$\boldsymbol{x}_k = \boldsymbol{F}\boldsymbol{x}_{k-1} + \boldsymbol{B}\boldsymbol{U}_{k-1} + \boldsymbol{W}_{k-1}\ (State\ prediction) \tag{9}$$

$$\boldsymbol{z}_k = \boldsymbol{H}\boldsymbol{x}_k + \boldsymbol{v}_k\ (Measurement\ update) \tag{10}$$

where $\boldsymbol{x}_k$ delineates the state vector, $\boldsymbol{U}_{k-1}$ signifies the input control, $\boldsymbol{F}, \boldsymbol{B}, \boldsymbol{H}$ outlines the system metrics, $\boldsymbol{W}_{k-1}$ denotes the process noise, $\boldsymbol{z}_k$ represents the measurement vector, $\boldsymbol{v}_k$ is the measurement vector. The estimate in particle filters is a collection of weighted particles. $\{x^{(i)}, \omega^{(i)}\}$, the update process consists of sampling, importance weighting and resampling [40]. Hybrid systems have proven to be more accurate than the single-technology systems. Indicatively, a combination of WiFi RSSI with IMU dead-reckoning driven by a KF resulted in error of lineal pedestrian movement of about 0.44 m [39].

3.4.2 Edge Computing and Federated Learning

Along with the convergence of sensors was the decentralization of computations to the edge: from centralized servers to devices, gateways or local servers. This design minimizes the latency, bandwidth consumption, and enhances privacy by storing raw data locally. A central enabling method is federated learning (FL): edge devices learn to work on local data, and send only model updates (not raw data) to a server or aggregator, which sends back aggregated global models. The ubiquitous representation of the Federated Averaging (FedAvg) is mathematically represented using Eq. (11) [41]:

$$w_{t+1} = \sum_{k=1}^{k} \frac{n_k}{n} w_{t+1}^{k} \tag{11}$$

In indoor localization, it implies that user devices or beacons can learn positioning models (fingerprint mapping or sensor-fusion parameters) by cooperatively exchanging sensitive location traces. Between around 2015 and 2020, the research focused on robust, scalable and privacy-conscious indoor positioning which utilizes a combination of several sensors (wireless and inertial and magnetic) and edge and federated intelligence. The systems mitigate the calibration overhead, are dynamic, and encourage lifelong learning. They are however complex (computational cost, synchronisation, heterogeneous sensors) and encounter deployment issues (device drift, sensor failure, different user behaviour). Table 4 outline the observation from literature that delineates the evolution of indoor localization technologies from the 2015 to 2020.

Table 4. Comparative Summary of Indoor Localization Systems from 2015-2020

Ref	Technology	Approach/ Focus	Accuracy	Application	Advantages	Limitation
[42]	Wireless inertial fusion: WiFi (RSSI) and IMU (PDR) and neural network correction	Fusion of IMU and RSSI through deep learning and dead reckoning	0.36m RMSE (Static); ~0.17m (controlled)	Pedestrian indoor localization (smartphone)	Joins WiFi availability with IMU robustness; adapts to multipath and dynamic conditions	Requires CSI or fine grained, neural network training, may overfit to environment
[43]	Multi-sensor fusion (LiDAR and IMU and WiFi RSSI) for indoor navigation	Extended Kalman Filter (EKF) combining LiDAR SLAM, IMU odometry, WiFi fingerprinting for coarse update and drift correction	0.24m – 0.38m	Mobile robots or service robots' indoor environments	Robust across different sensor modalities; maintains accuracy when WiFi noisy or IMU drifts	Increased Complexity; requires LiDAR and IMU hardware and map building; computational load
[44]	UWB and IMU or INS fusion for 3D indoor positioning (anchor-auto calibration and barometer for altitude)	UWB ToA or TDoA ranging and barometric altitude and INS fusion through filter and ML for error correction	Improved 3D localization error over baseline in drone or indoor UAV scenarios	Indoor drone navigation, 3D asset tracking	High accuracy in 3D; mitigates altitudes ambiguity; robust motion tracking	Requires UWB anchors and barometer and IMU; complexity and calibration needed; NLoS still challenging
[45]	Federated meta-learning for adaptive wireless indoor localization (edge IoT)	Federated meta-learning: global meta-model pretrained across device and rapid fine tuning on local data	Reported large accuracy improvement against baseline NN; faster adaptation (fewer calibration samples)	IoT networks, smart building localization, privacy sensitive deployment	Privacy preserving scalable, adapts rapidly to new environments without centralized data collection	Requires coordination across many devices, consistent model update or aggregation network overhead

3.5 Intelligent and Quantum-Enhanced Localization (2020-Beyond)

Indoor localization of the post-2020 is characterized by two significant converging trends: integrating Artificial Intelligence (AI) and Machine Learning (ML) into positioning systems, and the introduction of next-generation wireless and quantum sensing. The advances will enable provision of ultra-high accuracy, pervasive coverage, higher context-awareness and application domains.

3.5.1 AI/ML Localization

Indoor positioning is now associated with AI and ML. It makes use of rich sources of data, including channel state information (CSI), received signal strength (RSSI) patterns, inertial sensor streams, magnetic anomalies, visual/light cues, and feeds them into deep neural networks (DNNs), like convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The WiFi CSI fingerprint maps fed to a hybrid CNN-LSTM model yielded ~0.17 m in the cases of stationary scenario and ~0.36 m in the case of a dynamic one [46]. The model that is typical to be formulated using AI may be expressed as Eq. (12):

$$\widehat{\boldsymbol{P}} = f_{\theta}(\boldsymbol{x}) \tag{12}$$

where $\boldsymbol{x}$ CSI matrices, RSSI vectors, or IMU data, this is the raw input vector f_{θ} a parameter of a deep network, represented by weights (θ). where, the estimated 2D/3D location is denoted by $\boldsymbol{P}$. Other architectures include attention mechanisms (Self-Attention (SA) or Channel-Attention (CA)) to enhance localization robustness. In 6G indoor positioning research, CNN and SA in the study had significantly lower RMSE error than a simple CNN [46]. It can be used in real-time pedestrian monitoring, AR and VR navigation, locating occupants in a smart building, and industrial robots in dynamic indoor environments. **Strengths**: can adjust to changes in the environment; can model non-linear relationships; can bypass explicit ranging modelling. Restrictions: must have big training datasets, the problem of device heterogeneity, and the probability of overfitting or model drift.

3.5.2 5G/6G, Quantum-Sensing Capabilities, RIS

Outside the domain of AI, the next generation wireless networks (6G) and sensing platforms are changing indoor localization. The tool of ultra-massive MIMO, beamforming, terahertz (THz) bands, and reconfigurable intelligent surfaces (RIS) will be incorporated in 6G, according to the standardisation and research, and 6G will combine communication, sensing and localisation such as Joint Communication and Sensing (JCAS) [47]. The base equation of ranging (Time of Flight) or angle of arrival used in such systems is more accurate since the bandwidth (B) is wider and the beam (σ) is narrower. As in Eq. (13):

$$\sigma_d \approx \frac{c}{2B} \tag{13}$$

where σ_d is the range resolution, c is the speed of light, and B is signal bandwidth. A higher B (for example, tera-hertz hundreds of GHz) therefore allows centimetre-level or even millimetre-level resolution. The simplified concept of RIS-assisted systems is that effective anchor geometry is enhanced through virtual anchors; experimentally, significant accuracy (typically at millimetre levels) can be attained. They are used in autonomous vehicles within the indoor warehouse, robotics in the smart factory, AR/VR with precise user positioning, and smart logistics. Strengths: extreme precision, localisation network native, network coverage. Limitations: cost, complexity of infrastructure, synchronization and calibration, privacy concerns and still in its early research stage. Indoor localization will be shifting towards ubiquity, intelligence and ultra-precision in Intelligent and Quantum-Enhanced era. The AI/ML methods allow systems to learn high-level features and change to dynamic indoor conditions; at the same time, 6G, RIS and quantum-sensing technologies will provide centimetre- or even millimetre-accurate features integrated into the network infrastructure. The net implication is that localisation has been moved beyond being an appendage to location as a network service. Nevertheless, realisation at scale continues to have significant problems in infrastructural deployment, data demands, standardisation and privacy. Table 5 outline the observation from literature that delineates the evolution of indoor localization technologies beyond 2020.

Table 5. Comparative Summary of Indoor Localization Systems Beyond 2020.

Ref	Technology	Approach/ Focus	Accuracy	Application	Advantages	Limitation
[48]	AI (ANN or RNN or CNN) on RSSI and IMU data for mobile tracking	Deep learning regression on combined RSSI and IMU sensor data; model trained end-to-end mapping sensor inputs to position	~0.247m	Mobile user pedestrian tracking (smartphones)	High accuracy; real-time interference; leverages common sensors	Requires large labelled dataset; sensitive to device-specific variation; generalization across devices or environments may be limited
[42]	WiFi CSI based deep learning with hybrid CNN and LSTM and fingerprint maps	Hybrid CNN and LSTM on CSI fingerprint maps, sometime followed by a particle filter post processing for trajectory smoothing	0.36m (RMSE) dynamic; 0.17m RMSE (static) in indoor pedestrian experiments	Dynamic indoor pedestrian tracking	High spatial resolution; accounts for temporal dynamics; moderate infrastructure (WiFi only)	Requires CSI-capable NICs or access points; training overhead; environment dependency
[49]	6G (THz high and bandwidth) and deep learning (CNN and attention) for indoor localization	CNN augmented with channel and spatial attention blocks and trained on simulated or measured 6G or THz channel data	~7m	Future IoT or smart building localization, 6G capable indoor positioning systems	Very high precision potential; benefits from high bandwidth and advanced ML feature extraction; good noise robustness under interference in simulation	Experimental or simulation only, real world 6GHz or THz infrastructure not yet widely deployed; results may degrade in practical deployment; hardware cost and regulatory issues
[50]	RIS assisted mmWave or 6G localization (with ML optimizations)	Use of reconfigurable intelligent surfaces and beamforming and optimization or ML for improved path control and NLoS compensation	Sub-centimetre to millimetre level erro claimed in simulated 3.5 GHz	Smart factories, warehouses, future 6G indoor deployment	Potential ultra-high precision; improved multipath and NLoS resilence; leverages reconfigurable environment rather than many anchors	Highly experimental; needs RIS hardware installation; real-world validation scarce; complexity of phase control, calibration and robustness under dynamic changes yet to be proven

Figure 2 delineates the timeline that captures the aforementioned indoor localization systems.

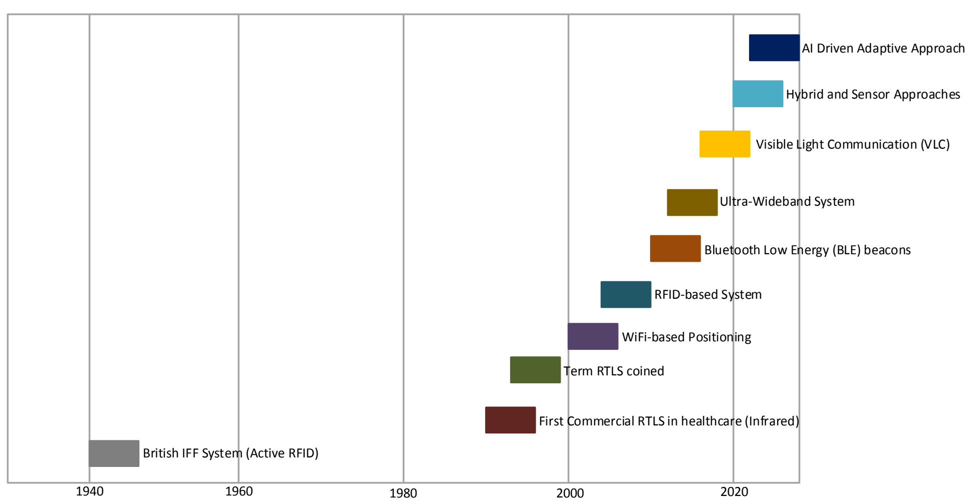

Figure 2. Technology Timeline of Indoor Localization Systems

4 ARCHITECTURES AND TECHNIQUES

A common structure of the indoor localization system is of a multi-layered design, which incorporates data collection, signal processing, localization algorithm, and application interfaces. Its general architecture comprises of a number of important elements: There are system hardware at the physical layer: wireless access points, ultra-wideband (UWB) anchors, Bluetooth Low Energy (BLE) beacons, visible light communication (VLC) LEDs, and receivers determine basic performance limits such as coverage range, transmission strength, environmental robustness, and geometric positioning of reference nodes [2, 8, 12]. The data acquisition layer gathers the raw measurements of sensors and wireless receivers, which may include analog-to-digital conversion and preliminary filtering to decrease noise [2]. Signal processing layer implements low- pass filtering, multipath mitigation, and feature extraction to generate more quality data to be used by the localization algorithms [8]. The localization algorithm layer applies either the geometrical, fingerprinting, or machine learning to approximate position. Application layer provides end-user services--navigational, tracking of assets or contextual automation, commonly found in IoT systems [1, 2].

4.1 Geometric Approach

Geometric methods determine the position of a target device by using geometric relationships that can be determined between the target device and anchor nodes. These are based on physical propagation models, and form the basis of a large number of radio-frequency and optical localization systems.

4.1.1 Time of Arrival

Time of Arrival (ToA) quantifies the direct travel time of a signal between transmitter and receiver as shown in Eq. (14):

$$d = c \times (t_2 - t_1) \tag{14}$$

In which d is the estimated distance, c is the speed of propagation (speed of light with RF signals, speed of sound with acoustic signals), and t_1 and t_2 are the times of transmission and reception, respectively [3, 8]. The accuracy of ToA is greatly affected by the accurate clock synchronization- 1ns error is equivalent to approximately 30 cm of the range error. Recent implementations of ToA tend to use advanced technology so as to overcome these issues. Two-way ranging protocols do not require perfect clock synchronization, as they use round trip times. The special signal processing methods, including super-resolution algorithms, can be used to separate the direct path and the multipath components.

4.1.2 Angle of Arrival

Angle-of-Arrival (AoA) localization is an error minimization scheme that localizes the direction of arrival of a signal by taking advantage of spatial variations between the phases (or time) of several antenna elements (an array) or explicitly directional antennas. When a narrow band plane wave incident is struck against a Uniform Linear Array (ULA) with element inter-separation d, the difference in phase between neighbouring elements is represented using Eqs. (15) to (17):

$$\Delta\emptyset = \frac{2\pi d}{\lambda} \sin\theta \tag{15}$$

where λ signifies the carrier wavelength and θ delineates the azimuth angle. Calculating for θ from an estimated $\Delta\phi$ gives:

$$\theta = arcsin\left(\frac{\lambda\Delta\phi}{2\pi d}\right) \tag{16}$$

Assuming that the position p_0 of an anchor is known, an AoA measurement θ contains the target a ray.

$$p = p_0 + \lambda_r \begin{bmatrix} \cos\hat{\theta} \\ \sin\hat{\theta} \end{bmatrix} \tag{17}$$

And a 2-D position estimate is obtained by the coincidence of two (or more) such rays (at different anchors). These are the geometric relations which provide the analytical foundation of array based AoA processing and encourage tradeoffs concerning the aperture, element spacing and unambiguous range of angle. Experimental reviews of UWB and mmWave arrays have confirmed that with very small l and/or large bandwidth, arrays can be used to achieve fine angular (and in many cases simultaneous range) resolution in controlled LoS systems [51].

- **Classical High-Resolution Estimators**

Practical AoA estimation typically is based on array signal-processing algorithms that derive the angular information by means of sample covariance of received array snapshots [52, 53].

Let $x(t) \in \mathbb{C}^M$ define the spatial covariance matrix and be the array snapshot of M-elements as in Eq. (18).

$$\boldsymbol{R} = E[x(t)x^H(t)] \tag{18}$$

Eq. (19) delineates the Eigen-decomposition of **R** which yields:

$$\boldsymbol{R} = \boldsymbol{E}_s \boldsymbol{\Lambda}_s \boldsymbol{E}_s^H + \boldsymbol{E}_n \boldsymbol{\Lambda}_n \boldsymbol{E}_n^H \quad (19)$$

and $\boldsymbol{E}_s$ is the signal eigenvector matrix and $\boldsymbol{E}_n$ is the noise eigenvector matrix. The AoA estimation is carried out by determining the orthogonality between noise sub space and steering vector. In the case of ULA, the steering vector of angle θ is represented using Eq. (20).

$$a(\theta) = \left[1, e^{-j\frac{2\pi d}{\lambda}\sin\theta}, \dots, e^{-j\frac{2\pi d}{\lambda}(M-1)\sin\theta}\right]^T \quad (20)$$

- **Multiple Signal Classification**

MUSIC takes advantage of the orthogonality of noise and steering vectors. The MUSIC pseudo-spectrum is mathematically represented using Eq. (21) [52]:

$$P_{MUSIC}(\theta) = \frac{1}{a^H(\theta)\boldsymbol{E}_n\boldsymbol{E}_n^H a(\theta)} \quad (21)$$

Indicate sources of incident AoAs. MUSIC gives super-resolution in case of the number of sources to be lower than the elements in the array and the covariance is estimated. Recent literature integrates CSI improvement and ML pre-processing to reduce the phase offsets and low-snapshot effects to enhance the applicability of MUSIC to commodity WiFi equipment [54, 55].

- **Estimation of Signal Parameters through Rotational Invariance Techniques**

ESPRIT provides a computationally efficient version of MUSIC, which does not require spectral search. The algorithm is based on the property of rotational invariance between two fully overlapping subarrays of the antenna. $\boldsymbol{J}_1$ and $\boldsymbol{J}_2$ denote selection matrices extracting the two sub arrays of the entire antenna array [52, 53]. ESPs are used to model the rotating relationship as using signal subspace $\boldsymbol{E}_s$. This core relationship is represented using Eqs. (22) to (24):

$$\boldsymbol{J}_2\boldsymbol{E}_s = \boldsymbol{J}_1\boldsymbol{E}_s\boldsymbol{\Phi} \quad (22)$$

Where

$$\boldsymbol{\Phi} = diag\left(e^{j\frac{2\pi d}{\lambda}\sin\theta_1}, \dots\right) \quad (23)$$

The eigenvalues ϕ_k of $\boldsymbol{\Phi}$ give direct AoA estimates:

$$\hat{\theta}_k = arcsin\left(\frac{\lambda}{2\pi d} arg(\phi_k)\right) \quad (24)$$

ESPRIT is highly adaptable to real-time mobile and IoT applications because the algorithm does not need a grid search. It is, however, imperative that the method necessitates highly organized array geometry, and can therefore only be utilised with compact or irregular antenna patterns. Recent literature has enhanced ESPRIT robustness by including mutual coupling compensation and near field propagation in large 6G arrays [56].

- **Compressive Methods and Deep Learning**

Classical subspace techniques presuppose dominant straight line and adequate snapshots- assumptions which are frequently broken in the indoors. In order to mitigate dense multipath, limited snapshots, and limited apertures, recent literature focuses on two complementary directions: compressive recovery and data-driven deep models [57] are shown as in Eqs. (25) and (26).

$$x = A(\Theta)s + n \quad (25)$$

Sparse recovery solves:

$$\hat{s} = arg\min_{s} \|x - A(\Theta)s\|_2^2 + \lambda\|s\|_1 \quad (26)$$

and support of $\hat{s}$ implies AoAs. Recently, off-grid Bayesian sparse learning, low-snapshot compressive estimators, RIS-aware sparse recovery variants have been suggested to overcome the closely spaced multipath components as well as to leverage the controllable reflections offered by RIS deployments [58, 59].

- **Deep-Learning AoA Estimation**

Deep models are trained on a direct mapping $\hat{\theta} = f_{NN}(X)$ between raw CSI, beamspace samples, or covariance features towards angle estimates. Transformer and CNN architectures (and hybrid DL+classical pipelines) are able to compensate hardware phase errors, sampling offsets and irregular arrays as well as allow AoA prediction with commodity WiFi NICs with small aperture by learning environment-specific signatures. Recent literature can be seen as the strong AoA estimation on the inputs of CSI and better resilience in the multipath and low-SNR regime [3, 7]. Neural approaches to positioning have also started to adopt Bayesian and uncertainty-aware approaches to 6G positioning to give confidence in the angle estimate [3]. Table 6 summarizes the findings in literature that compare the legacy and modern AOA estimation algorithms.

Table 6. Comparison of Legacy and Modern Angle of Arrival Estimation Algorithms.

Algorithm	Methodology	Key Equation	Strength	Limitation
MUSIC	Signal to noise subspace orthogonality	$P_{MUSIC}(\theta) = \frac{1}{a^H(\theta)\boldsymbol{E}_n\boldsymbol{E}_n^H a(\theta)}$	Super-resolution robust for moderate multipath	Requires scanning; sensitive to calibration; high computational load
ESPRIT	Rotational invariance between subarrays	$\boldsymbol{J}_2\boldsymbol{E}_s = \boldsymbol{J}_1\boldsymbol{E}_s\boldsymbol{\Phi}$ $\hat{\theta}_k = arcsin\left(\frac{\lambda}{2\pi d} arg(\phi_k)\right)$	Fast; no spectral scan; real-time capable	Requires structure array; lower resolution than MUSIC
Spare CS AoA	Sparse reconstruction on angle grid	$\hat{s} = arg \min_s \|x - A(\Theta)s\|_2^2 + \lambda\|s\|_1$	Handles rich multipath; resolves close components	High complexity; grid mismatch issues
Deep Learning AoA	Neural mapping of CSI/covariance	$\hat{\theta} = f_{NN}(X)$	Compensates for hardware distortion; fast interference once trained	Requires large datasets; limited cross-environment generalization

4.1.3 Time Difference of Arrival

Time Difference of Arrival (TDoA) localization finds the position of a target by calculating the differences between the arrival time of signals at a large number of synchronized anchors. The difference in the propagation distance of two anchors *i* and *j* is proportional to the difference in the arrival time [53, 60] as shown in Eq. (27):

$$d_i - d_j = c(t_i - t_j) \tag{27}$$

where d_i and d_j delineates the distances from the target to the anchors, *i* and j, $t_i - t_j$ signifies the differential arrival time, and c represents the propagation speed.

The equation defines a branch of a hyperbola with anchors at its foci as shown in Eq. (28):

$$\sqrt{(x - x_i)^2 - (y - y_i)^2} - \sqrt{(x - x_j)^2 - (y - y_j)^2} = c\Delta t_{ij} \tag{28}$$

In 2-D (or 3-D) with at least three anchors, crossing several hyperbolas, the target position is obtained. The algorithm does not require tag-side synchronization and thus TDoA is appealing to small embedded computers [61].

TDoA differences in the order of nanoseconds can be used in real time with modern UWB radios (offering nanosecond temporal resolution), whereas sub-centimeter differences in TDoA can be measured with modern acoustic microphones because sound propagates very slowly. Nevertheless, both RF and acoustic versions are very susceptible to multipath and anchor synchronization error.

- **Nonlinear Estimation and Modern Optimization**

Since inherently nonlinear hyperbolic equations are used to control TDoA localization, numerical optimization is an important aspect, as opposed to closed-form analytical solutions. First methods start with hyperbolic multilateration, in which linearized models give an initial estimate, but tend to deteriorate in the presence of noise or NLoS. More precise approaches then use iterative nonlinear least-squares algorithms like Gauss-Newton or Levenberg-Marquardt which optimize the position estimate by the amount of residual between measured and predicted time differences [28, 62] as shown in Eq. (29).

$$\hat{p} = arg \min_p \sum_{i,j} \left((d_i - d_j) - c\Delta t_{ij}\right)^2 \tag{29}$$

State-space formulations are desirable in the case of mobile targets, where Extended and Unscented Kalman Filters (EKF/UKF) offer recursive estimation, including dynamics of motion and sensor uncertainty. In order to make the methods more robust when operating in settings with strong multipath or poor initializations, convex relaxation techniques have been proposed, including semidefinite relaxation (SDR), which can be made to converge more robustly when subjected to non-ideal measurement conditions. The factor-graph optimization is also the most important recent development as it allows globally joint inference of all the TDoA constraints of multi-anchor networks, and also tightly couples with other modalities like IMU or AoA. Experiments always reveal that factor-graph and EKF/UKF combination schemes work better than the conventional multi-lateration in complicated indoor settings, especially to counteract the multipath and clock-drift influences [28, 62].

- **State-of-the-Art TDoA Performance**

In recent literature, Time Difference of Arrival (TDoA) systems have shown high performance gains in both RF-based modalities and acoustic modalities. UWB TDoA is the most precise radio-frequency implementation with practical 10-30 cm accuracy in indoor deployments and less than 15 cm RMSE in LoS testbeds with the current Qorvo/Decawave DW3000 anchors [63]. Individual cluttered industrial NLoS Performance is in the 20-40 cm range, but with the addition of AoA or IMU through EKF/ESKF, performance can be reduced to a range of 10 cm or below. These advantages are made possible by better synchronization of the anchor (through PTP or IEEE 802.15.4z), distributed Kalman-based clock drift correction, UWB CIR-based multipath rejection, and deep-learning TDoA bias-correction models. By comparison, Acoustic TDoA, which is made possible by microphone arrays and enjoys the advantage of the low velocity of sound, are only 1-2 cm accurate in small controlled rooms, but have a degradation rate that is much higher than HVAC noise, human motion, and occlusions, and has a limited range generally of 8-10 m [11]. Therefore, the contemporary acoustic TDoA can be used primarily in VR/AR room-scale tracking, robot docking, and laboratory purposes. In general, TDoA has significant advantages including no tag synchronization, scalability, and excellent fusion capabilities but has the drawbacks of strict anchor synchronization, multipath sensitivity, geometric conditioning, and complexity of deployment in large anchor networks.

4.1.4 Triangulation

Triangulation is a localization method based on angles-of-arrivals (AoA) that is used to estimate the position of a target when measured by two or more spatially separated anchors. Every AoA estimate θ_i is a method of defining a geometric ray whose origin is the position of an anchor $p_i = (x_i, y_i)$ and is directed outwards along a direction that is set by the measured angle. This is mathematically representation of the ray is outlined as in Eq. (30):

$$L(\theta_i) = \left\{p_i + \rho \begin{bmatrix}\cos\theta_i \\ \sin\theta_i\end{bmatrix} :\ \rho > 0\right\} \tag{30}$$

The goal of triangulation is to determine the intersection of all rays [64, 65] as shown in Eq. (31):

$$(x, y) = \bigcap_{i=1}^{N} L(\theta_i) \tag{31}$$

In theory, the position of the target is the intersection of these rays but due to the noise, reflections, and errors of calibration the rays will hardly converge at a point. This has led to the practical triangulation systems being based on least-squares formulations to minimise the perpendicular distance to all rays at once. The ensuing solution balances the measurement of angular differences in order to estimate the position that most competently fits the geometry that is observed. This is presented in Eq. (32).

$$p^* = arg\min_{p} \sum_{i=1}^{N} \|p - L(\theta_i)\|^2 \tag{32}$$

Triangulation has relative accuracy based on a number of interacting factors. First, the angular precision is determined by AoA variance, which is determined by the antenna aperture, SNR, bandwidth, as well as algorithmic processing itself, meaning it is directly proportional to the angular precision. Second, the geometry of anchors is also very important: spaced-out anchors with excellent angular diversity will provide low geometric dilution of precision (GDOP), and collinear or clumped anchors will cause unstable solutions. Third, the quality of array calibration influences systematic phase or timing errors in the receiving array, which are usually the leading source of random noise in commodity systems. Lastly, propagation environment, specifically, whether or not LoS paths exist, also affects angular estimation in that multipath and NLoS distort steering vectors and bias AoA estimates. Narrow beam, large aperture antennas, and broadband CIR make triangulation more and more practical even in difficult indoor applications with modern RF systems, including UWB, mmWave and early 6G arrays, where angular resolution can be finer than 1 degree.

- **Algorithms of estimation and implementations**.

The basic triangulation in practice is determined by the manner of the underlying AoA estimates generation and various AoA pipelines have various accuracy and computational properties. MUSIC and ESPRIT algorithms can be used to extract AoA using spatial covariance matrices, which are the algorithms used in classical array-processing systems. WiFi CSI systems, commodity access points using small linear arrays and various research prototypes use these algorithms. As soon as the AoA values have been obtained, they are directly fed into geometric triangulation solvers or pose estimators. The method is easy and readable yet very vulnerable to the array calibration and snapshot presence. A second category of implementations comes up in 5G/6G and UWB triangulation that uses beamspace, especially in 5G/6G hardware. Rather than using subspace algorithms, these systems use beam sweeping, cross-correlation of the antenna pairs, or CIR estimation of leading-edge angle. These hardware-based AoA methods are capable of making angle measurements at low computational expense, and the design is designed with a close relationship with filtering-based position trackers. Triangulation is commonly incorporated in extended Kalman filters (EKF) or factor-graph-based localization engines in these systems, enhancing noise and motion resilience [43]. Lastly, triangulation through learning developed in recent literature, has learned a direct mapping of one or more AoAs to position, bypassing explicit geometric inversion, and is learned using neural networks instead. Transformers, GNNs, or systems with hybrid physics-informed networks can be trained to correct systematic calibration errors, phase offsets of specific devices, or multipath bias. They retain this geometric understanding of triangulation but provide corrections based on data, allowing them to achieve stronger robustness, particularly with NLoS or irregular array geometries [43].

4.1.5 Trilateration

The trilateration is a basic geometric localization algorithm which approximates the position of a target through distance measurements to anchors with known locations. Assuming the location of an anchor is at $p_i = (x_i, y_i)$ and the measured distance to the target is d_i, then the target location (x, y) must obey the circle equation [34] as represented in Eq. (33):

$$(x - x_i)^2 + (y - y_i)^2 = d_i^2 \tag{33}$$

The location of the target is determined by the point of intersection of two circles or four in a 2-D and 3-D system respectively where there is an anchor. Nonetheless, measurements in the real world rarely coincide or overlap with ideal values because noise, multipath, or synchronization errors occur. On this premise, trilateration is normally formulated as a least-squares optimization problem [66],

$$p^* = arg \min_{p} \sum_{i=1}^{N} (\|p - p_i\| - d_i)^2 \tag{34}$$

That supports noisy or discrepant distance estimates. Distances that are used to perform trilateration typically have their source in Time-of-Arrival (ToA), Two-Way Ranging (TWR), or Time-Difference of Arrival (TDoA). In the case of ToA-based systems the distance measured is calculated as:

$$d_i = ct_i \tag{35}$$

where t_i is the propagation time measured and c is the speed of light. TDoA systems are based on inferring variations in distance between anchors and do not need tag-side synchronization, but demand high inter-anchor synchronization. Whereas both ToA and TDoA are capable of giving accurate range, both methods depend on proper synchronization, such as among anchors (TDoA) or between anchors and tags (ToA), which complicates their deployment in an indoor environment [1, 2, 34]. The accuracy of trilateration is highly affected by the accuracy of the underlying range measurements, as the UWB and BLE RSS technologies have considerably different ranges: on geometry, because poor spatial separation leads to high geometric dilution of the accuracy (GDOP); and on propagation, especially NLoS existence, which causes positive bias in all time-dependent measurements. The trilateration method is one of the strongest and most common geometric localization methods due to highly reliable estimates of distances offered by modern indoor positioning architectures, in particular, UWB systems.

- **Estimation Algorithms and Real Implementations.**

Two-Way Ranging (TWR) and UWB ToA Trilateration.

Ultra-Wideband (UWB) systems include sub-nanosecond timing of signal propagation which allows ranging of centimetres. The chipsets of today (e.g., Qorvo DW3000, NXP SR150/SR040) operate on the broad band to filter the first path in the channel impulse response (CIR), reducing multipath bias. These measured ranges are then fed into least-squares or nonlinear solvers giving them very robust trilateration performance even in cluttered indoor scenes [1, 3].

BLE and WiFi RSS-Based Trilateration.

BLE and WiFi trilateration normally extract distances based on RSS values on the basis of a log-distance path-loss model as shown in Eq. (36) [4, 5]:

$$d_i = d_0 \frac{P_0 - P_i}{10n} \tag{36}$$

where n is the path-loss exponent. Because of extreme changes in RSS caused by shadowing, human motion, and fading and variations in device behavior, these distance estimates are volatile, which frequently causes positioning errors in the meters. More recent applications use machine learning to estimate path-loss parameters, or to estimate RSS-distance mapping, but RSS trilateration is a much less precise method than UWB [4, 5].

4.1.6 Fingerprinting

Localization based on fingerprint is a total paradigm shift as compared to geometric methods like trilateration and triangulation. Fingerprinting takes advantage of the spatial variation of wireless signal properties to acquire an approximation to a mapping between signal characteristics and physical location; instead of using explicit physical measurements, such as distance, propagation time or angle. Locations in this framework are regarded as distinctive signatures (or fingerprints) of the radio environment, and position estimation in this framework can be carried out by matching patterns instead of geometric computation [4, 67, 68]. This eliminates reliance on anchor synchronization, array of antennas, or a model of ideal propagation, providing fingerprinting with increased flexibility and resilience in highly mobile indoor environments, in contrast to the situation with conventional ranging methods. Fingerprinting often takes place in two phases of operation like an offline (training) stage, and an online (inference) stage. Under the offline phase, the target environment is then discretized into pre-determined sampling points and wireless fingerprints, which can be RSSI but increasingly are Channel State Information (CSI), CIR features, or multi-modal sensor data, are measured at a number of access points or beacons. The multidimensional measurements are stored in the creation of a fingerprint database by site-survey process. During the online stage, real-time fingerprints are collected with a user device and compared with the database to make an implication of the most likely whereabouts. Classical algorithms are k-Nearest Neighbours (KNN), probabilistic algorithms and kernel-based regression and modern systems are machine learning models (SVM, RF) or deep networks (CNNs, RNNs, transformers) classifying or regressing the fingerprint space. The major benefit of fingerprinting is that it has inherent resistance to multipath and non-line-of-sight (NLoS) effects. As opposed to the trilateration method with its biased range measurements and triangulation method with its high-quality AoA estimation, fingerprinting accepts environmental distortions as a component of the signature. This is especially useful in the very crowded indoor environments (offices, malls, hospitals, and factories). Nevertheless, the approach has its own issues: the creation of the fingerprint database is time-consuming, and the dynamics of the environment, including the movement of furniture, the crowd, or alterations in APs may lead to the drift in the database. Consequently, some recent studies have emphasized adaptive and self-updating fingerprinting models, including crowdsourced-driven data collection, semi-supervised incremental generation, domain adaptation, and generative augmentation, which keep databases relevant with a lesser amount of manual labour [34]. On the whole, fingerprinting has emerged a widespread technique of indoor positioning thanks to its low cost of deployment, high adaptability, and ability to work with commodity hardware, including WiFi, BLE, and UWB. Fingerprinting is more robust in multipath-rich conditions than trilateration and triangulation and has a need to carefully maintained databases, and in many cases is enhanced with machine learning or sensor fusion modules to attain more stable long-term behaviour.

4.1.7 Hybrid and Fusion Approaches

Hybrid trilateration has been adopted as the new strategy of enhancing indoor localization robustness, especially in the setting where pure range-based estimation is prone to noise, multipath, or bad anchor geometry. One of the developments has been the integration of UWB trilateration and inertial sensing on top of the Extended Kalman Filters (EKF) or the Error-State Kalman Filters (ESKF). IMU fusion stabilizes the trajectories during motion of the user or robot, corrects short-term range errors, and offers short-term dead reckoning free of drift, which greatly increases continuity in positioning measurements in cluttered environments [28, 69]. Correspondingly, AoA-assisted trilateration has become popular due to the angular constraints that assist in disambiguation of nonlinear distance solutions particularly when there is no ideal distribution of anchors. Using AoA plus UWB or BLE ranges, such systems enhance the divergence of iterative solvers due to multi-paths and the LoS and NLoS localization precision [70]. Fingerprint-based trilateration is a third notable solution: using RSS, CSI/CIR fingerprint maps combined with geometric range equations, system is able to overcome consistent bias in BLE/WiFi RSS-based ranging or ToA measurements. It has been demonstrated that fingerprinting with machine-learning improvement can strongly stabilize RSS distance estimates so that BLE trilateration can deliver better performance in spite of underlying RSS instability [11, 48, 71]. These hybrid systems (UWB and IMU, AoAs enhanced trilateration, BLE and Fingerprinting) have become commonplace in robotics, autonomous drones, warehouse navigation, and industrial cyber-physical systems, and here it is necessary to have high reliability and be able to survive the multipath.

5 CHALLENGES AND POTENTIAL RECOMMENDATIONS

Indoor localization is fast developing with the improvement of wireless technology, sensory equipment, and AI-based inference. Nonetheless, the way to extremely precise, scalable and privacy-sensitive systems is informed by a number of longstanding challenges. This section summarizes important technical barriers and give future recommendations with regard to the current research trends.

5.1 Integration with 6G and Beyond

Indoor localization in the future will be closely interconnected with the 6G and terahertz-band communication systems, which will offer an unprecedented level of sensing granularity but pose serious deployment challenges. Although increased carrier frequencies and very wide bandwidths can provide millimetre-scale ToA resolution and sub-degree AoA accuracy, blockage, hardware noise, and environmental attenuation are very sensitive to THz propagation. Additionally, there is a need to employ Reconfigurable Intelligible Surfaces (RIS) at scale that need calibration, signalling control, and standard interfaces. The implementation of the localization as a native 6G network service also requires the ability to work with reliable synchronization, uplink/downlink measurement reporting, and support of new protocols. The work should create hybrid sensing-communication systems, which combine THz/6G ranging with strong fallbacks to UWB or WiFi CSI, and design RIS-enabled testbeds to test localization and communication performance together. The focus of the research should be on synchronization schemes, RIS calibration schemes, and standard APIs of network-assisted positioning.

5.2 AI based Localization and Real Time Adaptation

The latest indoor localization in modern world depends more on machine learning- CNNs to identify the spatial fingerprints, RNNs/transformers to model the trajectory, and Reinforcement Learning (RL) to develop the adaptive sensing. Implementation of these systems on a large scale, however, brings about issues of data labelling, resistance to non-IID data, computational efficiency, and environmental drift. Deep neural networks need a lot of site surveys and when the layouts or user behaviour varies their performance is likely to drop. Sample efficient and environment adaptive learning algorithms like contrastive pretraining, online domain adaptation and anchor/beam selection via RL. Inference of movement and training to the edge to reduce latency and avoid privacy loss, and adopt federated learning with secure aggregation to provide room to make constant improvements without raw location traces.

5.3 Context-Sensitive and Individualized Localization

The next-generation localization systems will not just focus on determining the location of the users but also determine what they are doing and where they are about to go next. Nevertheless, to do so, the data fusion on the multimodal scale, including calendar, environmental IoT sensors, and user preferences, is necessary, and it creates tremendous privacy and semantic-mapping issues. The semantic map of an indoor environment is dynamic, and updating to new semantic maps is costly. Create lightweight semantic-mapping systems with the help of crowdsourcing, robot-assisted mapping, and on-device reasoning. Apply privacy-conscious personalization with local models, user-managed preference profiles and context sensitive routing algorithms, which respond to accessibility limits and user intent. Studies are needed in areas where multimodal fusion is to be done with limited devices and strong inference on evolving building configurations.

5.4 Smooth Indoor outdoor (I/O) Navigation

There is a fundamental challenge of achieving continuous localization in both GNSS-supported outdoor environment and GNSS-denied indoor environment. There is poor signal performance around building entrances which causes sudden reduction in accuracy. It is not an easy task to maintain the same coordinate frames, deal with sensors that are asynchronous, and initialize indoor trackers quickly. Embrace closely-knit GNSS-INS/UWB/WiFi fusion designs based on EKF/UKF or particle filters, where learned models are used to forecast I/O transitions and initiate adaptive handover policies. Create lightweight re-initiating algorithms of indoor trackers and other resilient time-synchronisation systems to maintain continuity environments.

5.5 Localization Data security and privacy

The privacy and security of the indoor localization is of primary importance as it detects the delicate behavioral and movement patterns. Storing fingerprints, CSI measurements, or user trails in a central place puts the system at risk of re-identification attacks, model inversion attacks, and data poisoning attacks. The distributed ledgers or blockchain can provide transparency, yet not privacy or scalability. Add homomorphic encryption, secure aggregation, secure multiparty computation, and differential privacy to localization pipelines. Use federated learning to prevent the transfer of raw sensor data. Maintain audit trails by use of decentralized trust frameworks (e.g., lightweight permissioned ledgers) to prevent poisoning in collaborative indoor localisation settings. The studies should measure the accuracy-privacy-latency tradeoff in practical implementations.

6 CONCLUSIONS

The paper introduced a thorough and technically demanding survey of the emerging indoor localization research, including both the classic geometric algorithms, covering ToA, TDoA and trilateration, and more recent fingerprinting, CSI-based sensing and multi-modal fusion algorithms. In the quickly changing field of indoor positioning, the recent trends always show that regardless of the maturity of separate modalities, the strongest and most precise results occur when combined, heterogeneous systems are used instead of an individual technique. Geometric techniques are vital because of their physical models which are clearly understood and can be implemented in real time. In specific cases, UWB ToA and TDoA systems, in particular, are now routinely capable of decimetre-level performance, and hybrid ToA-AoA, TDoA-IMU, and machine-learning-assisted bias compensation takes the accuracy down to below 10 cm even in hostile NLoS conditions. Approaches to fingerprinting have both advanced to deep CSI-based models and recurrent neural networks that take advantage of temporal structure with sub-meter accuracy in most WiFi or BLE applications. In the meantime, high-fidelity sensor-fusion models, that is, Kalman filters, particle filters, factor graphs, and edge-assisted AI, facilitate smooth drift-free tracking in dynamic and cluttered indoor environment. In spite of these improvements, the review observes that there remain various system-wide issues, such as multipath and NLoS sensitivity, the cost and complexity of large-scale anchor coverage, privacy and security impacts with fine-grained location traces, and absence of seamless indoor-outdoor handover. Emerging 6G/THz communication, environment shaping with RIS, and adaptive localization architecture based on AI provide the hopeful solutions to these drawbacks. Nevertheless, they create new problems connected with synchronization, calibration, robustness, hardware limits, and standardization. In the future, some of the features that the next generation of indoor localization systems will have will be (i) sensing-communication infrastructures that are tightly integrated, (ii) edge-intelligent and federated learning models that do not violate privacy, (iii) context-aware and personalized positioning services, and (iv) a multi-technology fusion framework that can be self-optimizing under environmental dynamics. These objectives will presuppose a concerted advancement of RF hardware and signal processing, AI or ML and privacy-preserving computation, and systems engineering. Additionally, indoor localization is shifting towards individual algorithmic fixes and comprehensive, intelligent, and safe positioning systems. Already with further developments made in UWB, WiFi CSI, RIS-assisted propagation, deep learning, and 6G sensing, the aforementioned space is currently set to provide ubiquitous, centimetre level, privacy-conscious indoor positioning that can support the next generation of smart buildings, robotics, AR/VR environments, and context-aware services.

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