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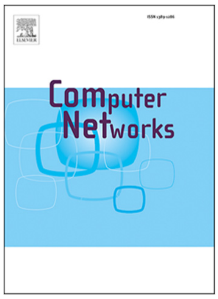

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A Survey of Indoor Positioning Systems Based on a Six-Layer Model

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ABSTRACT

Indoor positioning has attracted considerable interest in both the industry and academic communities because of its wide range of applications, such as asset tracking, healthcare and context-aware services like targeted advertisements. While there are many indoor localisation methods, each has its advantages and disadvantages, taking into consideration various factors such as the effect of the indoor environment, ease of implementation, computational cost, positioning accuracy, etc. In other words, no single solution can cater for all different situations. Although many survey papers have been published on indoor positioning, new techniques and methods are proposed every year, so it is important to stay abreast of its latest developments. In addition, each survey has its own classification for indoor positioning systems without a common scheme. Inspired by the well-known OSI model and TCP/IP model, it would be desirable to develop a systematic framework for studying indoor positioning systems. In this paper, we make this new contribution by introducing a systemic survey framework based on a six-layer model to give a comprehensive survey of indoor positioning systems, namely: device layer, communication layer, network layer, data layer, method layer and application layer. Complementing the previous survey papers, this paper provides a survey of the latest research works on indoor positioning based on the six-layer model. Our emphasis is on systematic categorisation, machine learning-based enhancements, collaborative localisation and COVID-19-related applications. The six-layer model should provide a useful framework and new insights for the research community.

1. Introduction

In the last few decades, indoor positioning has risen in popularity in the scholarly community because of the growing availability of smartphones and their support for indoor localisation technologies such as WiFi and Bluetooth. Indoor positioning refers to the process of determining a target's location indoors and has a wide range of applications, including targeted location-based advertising [1], tracking the elderly [2] and the handicapped [3] and navigation in low-visibility environments [4]. While GPS (Global Positioning System) is one of the most widely used positioning systems, it performs poorly in indoor environments because of the high number of obstructions and low signal penetration [5]. Therefore, other indoor positioning technologies are required, the most common ones being Bluetooth, WiFi, UWB (Ultra-Wideband), VLC (Visible Light Communication), acoustic sound and ultrasound, but sub-metre accuracy with minimal installation and maintenance costs is still hard to achieve. The general trends in recent years have been the adoption of machine learning in indoor positioning [6] as well as the fusion of multiple technologies [7] to strike a balance between the advantages and disadvantages of each. Overall, researchers are seeking to address the following problems when designing an IPS (Indoor Positioning System): (1) infrastructure installation cost, (2) infrastructure maintenance cost, (3) computational complexity/positioning latency, (4) accuracy, (5) device battery life (if any). Note that localisation is different from tracking as localisation aims to acquire an object's position just once, whereas in tracking, the object's location is updated in real time as it is moving. Both involve position estimation, but tracking is more long-term. This paper will focus more on localisation, but some popular technologies are being extensively used for tracking as well, so the paper will cover these use cases as well.

Indoor positioning is an ever-changing field with new techniques and methods proposed each year, so it is important to keep surveying the recent trends. To facilitate this, it would be helpful to have a single standardised framework for IPSs, which, to the best of our knowledge, has not been devised yet. This paper presents a new framework for this purpose, and a survey of the latest indoor positioning works is conducted based on the framework, with emphasis on collaborative localisation and COVID-19 applications in view of the recent pandemic situation worldwide. Because of GPS's poor performance in indoor environments, indoor positioning technologies have been used in enforcing social distancing in indoor spaces to prevent the spread of COVID-19 by tracing people who have been in proximity to infected individuals and placing them in quarantine to lower the risk of further infection. The authors of [8] ran simulations to study the effectiveness of contact tracing with different communication technologies and found that a minimum of 60% adoption of contact tracing systems was required to flatten the curve, and the best effect would be achieved with 2 m proximity detection range systems, e.g., those based on BLE (Bluetooth Low Energy). They also looked at less

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popular technologies for contact tracing, e.g., RFID (Radio-Frequency Identification) and GPS. Contact tracing systems are not designed to localise people but rather to detect distances between them. Nevertheless, they are still going to be considered in this paper as IPSs can be extended to be used for proximity detection as well.

1.1. Recent IPS Survey Analysis

Many survey papers on indoor positioning have been written in recent years. Zafari et al. [9] wrote one of the most popular indoor positioning surveys that gives a detailed overview of indoor positioning techniques and compares different IPSs against criteria like energy efficiency, cost, etc. [10] gave a more recent account of the state of the art of indoor positioning research, comparing different positioning methods. [11, 12] also reviewed indoor positioning techniques, methods and technologies but with a special emphasis on IoT applications. [13] reviewed real indoor positioning systems and described their applications in the industry in more detail, while also providing use cases for different communication technologies along with their strengths and limitations. [14] is one of the most comprehensive indoor positioning surveys with descriptions of more advanced techniques and methods.

Many surveys focused on a specific theme instead of providing a general overview of recent works on indoor positioning. A large cluster of surveys focused on machine-learning-based indoor positioning methods [15, 6, 16, 17, 18], which can be explained by the ability of machine learning to handle complex noise patterns in indoor settings as opposed to traditional methods. [18] gave a comprehensive overview of deep learning methods for WiFi-based fingerprinting (see section 8.3.3), where the authors show that despite the emergence of more advanced WiFi signal measurements like CSI (Channel State Information) (see section 7.1.3), RSS (Received Signal Strength) (see section 7.1.1), which is known to be unstable, can still yield competitive results for indoor positioning with the help of deep learning. [18] reviewed works specifically on WiFi RSS-based fingerprinting with the help of machine learning and discussed dataset collection and open-source datasets. Another significant cluster of surveys concentrated on indoor positioning for smartphones [19, 20, 21, 22], which can be explained by the fact that smartphone use is rising, meaning that they can be used to localise people indoors. [19, 22] outlined smartphone sensors that can be used for positioning such as barometer, camera, accelerometer, gyroscope, Bluetooth, etc., along with positioning methods that can be used with them. [20] complemented this survey by discussing the challenges and possible solutions for implementing ubiquitous IPSs for smartphones based on WiFi without additional hardware to account for the problem of device heterogeneity. Advances in UWB technology for indoor positioning prompted surveys on the topic to also gain traction. [23] discussed developments in UWB positioning systems since 2017 and their use for smart logistics. The survey also went over the use of multi-sensor fusion and machine learning for addressing the NLOS (Non-Line-of-Sight) problem in UWB signal propagation. [24] surveyed collaborative UWB-based systems. According to the authors, UWB system infrastructure is expensive to deploy because of the anchor nodes required, but collaborative methods can turn mobile nodes into anchors, reducing deployment costs. Other surveys that focused on specific communication technologies for indoor positioning are [25] (magnetic-field-based), [26] (BLE), [27] (VLC). There are also surveys on emerging trends in indoor positioning. For example, [28] described multi-sensor fusion positioning methods, which fuse measurements from different positioning technologies to achieve better performance, and [29, 30, 31] surveyed device-free indoor positioning, where no device is attached to the localisation target.

Many indoor positioning surveys provide a classification system for indoor positioning methods, techniques and/or technologies but, according to a meta-review of indoor positioning surveys [32], there is no consensus on a general IPS taxonomy. Note that in this paper, we define "methods" as the positioning algorithms used, e.g., kNN (k-Nearest Neighbours), trilateration, etc. It is necessary to review classifications in recent surveys and distil them into a single unambiguous framework because some authors do not use the same terms. [9] provided an architecture-based classification with three classes: device-based (DBL), monitor-based (MBL) and proximity-based (PBL) localisation systems. In DBL, the target (usually a smartphone) makes use of reference points, whose positions are usually known, to calculate its position. In MBL, the network is responsible for localising the target, and in PBL, the task is to determine how far the target is from a point of interest. The authors of the survey also highlighted the importance of distinguishing between localisation technologies (BLE, WiFi, etc.) and techniques (RSSI (Received Signal Strength Indicator), AoA (Angle of Arrival), etc.). [12] offered a similar categorisation for localisation topologies: mobile-node-based (similar to DBL), reference-node-based (similar to MBL), IMU-based (Inertial Measurement Unit) and proximity-based (similar to PBL). Similar to [9], both [17] and [12] distinguished between techniques and methods but [12] used algorithms and techniques interchangeably. Kunhoth et al. [5] divided IPSs into three groups: computer vision, communication and PDR-based (Pedestrian Dead Reckoning) systems, i.e., they classified IPSs based on the technology and method used. Similarly, Ridolfi et al. [24] categorised IPSs based on their algorithms (e.g., triangulation, fingerprinting, etc.) and architectures (collaborative vs. non-collaborative). [20] categorised IPSs based on infrastructure availability (infrastructure-based vs infrastructure-free) and further classified them by "mode" (single vs hybrid), which specifies whether a single technology or multiple technologies are used for localisation. [13, 11, 10] described IPSs in terms of their underlying communication technologies and techniques used, and [14] gave a custom classification for positioning methods (distance-based, direction-based, connectivity-based, signal-based), technologies (RF (Radio Frequency) vs non-RF) and "parameters" (distance-based,

Table 1
Abbreviations used in the paper

AAL	Ambient Assisted Living	MDS	Multidimensional Scaling
AE	Autoencoder	ML	Machine Learning
AoA	Angle of Arrival	MLE	Maximum Likelihood Estimator
AoD	Angle of Departure	MMSE	Minimum Mean Square Estimator
AP	Access Point	NLOS	Non-Line-of-Sight
APIT	Approximate Point in Triangle	OSI	Open Systems Interconnection
BLE	Bluetooth Low Energy	PDoA	Phase Difference of Arrival
BP	Belief Propagation	PDR	Pedestrian Dead Reckoning
CAB	Concentric Anchor Beacon	POCS	Projection Onto Convex Sets
CFR	Channel Frequency Response	PPM	Parallel Projection Method
CIR	Channel Impulse Response	RBM	Restricted Boltzmann Machine
CL	Centroid Localisation	RF	Radio Frequency
CNN	Convolutional Neural Network	RFID	Radio-Frequency Identification
CSI	Channel State Information	RNN	Recurrent Neural Network
DBN	Deep Belief Network	RSS	Received Signal Strength
DV-Hop	Distance-vector hop	RSSI	Received Signal Strength Indicator
EKF	Extended Kalman Filter	RTI	Radio Tomography Imaging
GAN	Generative Adversarial Network	RToF	Return Time of Flight
GPS	Global Positioning System	RTT	Round Trip Time
HF	High Frequency	SDP	Semi-Definite Programming
IMMA	Interacting Multiple Model Algorithm	SVM	Support Vector Machine
IMU	Inertial Meaurement Unit	TDoA	Time Difference of Arrival
IPS	Indoor Positioning System	ToA	Time of Arrival
IR	Infrared	ToD	Time of Departure
IRS	Intelligent Reflecting Surface	ToF	Time of Flight
ISM	Industrial, Scientific and Medical	TWR	Two-Way Ranging
KF	Kalman Filter	UCA	Uniform Circular Array
kNN	k-Nearest Neighbours	UHF	Ultra-High Frequency
LDA	Linear Discriminant Analysis	UKF	Unscented Kalman Filter
LED	Light Emitting Diode	ULA	Uniform Linear Array
LF	Low Frequency	URA	Uniform Rectangular Array
LoRa	Long Range	UWB	Ultra-Wideband
LoRaWAN	Long Range Wide Area Network	VLC	Visible Light Communication
LOS	Line-of-Sight	WCL	Weighted Centroid Localisation
LPWAN	Low Power Wide Area Network	WCWCL	Weight Compensated Weighted Centroid Localisation
LSTM	Long Short-Term Memory	WKNN	Weighted kNN
MAP	Maximum a Posteriori	WLAN	Wireless Local Area Network

time-based, direction-based). [17] classified IPSs by technologies, techniques and methods used. It is evident that some surveys distinguish between techniques and methods, while others describe them jointly, which can be confusing.

In general, a layered model can provide a more systematic classification approach, which can then be translated into a clear survey structure. However, none of the previous survey papers have studied this layered model approach. The aim of this paper is to provide this new contribution to complement the previous survey papers. All abbreviations used in the paper are listed in Table 1.

1.2. Key Contributions

Based on a six-layer model, this survey paper covers major papers published in the last five years. While we shall cover indoor positioning systems/applications in general, our focus is on machine learning-based enhancements, collaborative positioning methods and COVID-19-related applications in particular. Compared to other survey papers, the main contributions of this paper are summarised as follows:

- *A Systemic Survey Framework based on a Six-Layer Model*: Inspired by the OSI (Open Systems Interconnection) model and TCP/IP model and complementing the previous work, this paper presents a systemic framework based on a six-layer model for organising indoor positioning surveys. Note that for computer networks, it is common to define layered models for various purposes such as the well-known OSI and TCP/IP models and other models e.g., for cloud computing. There is yet a layered model for indoor positioning systems/methods. One major difference between our model and frameworks used in other survey papers is that we consider a more holistic approach, covering different layers: device layer, communication layer, network layer, data layer, method layer and application layer. To the best of our knowledge, little work has been done to construct a similar layered model. Therefore, our work should provide new contributions to the research community. It can provide a more standardised structure for surveys in the field, making them easier for readers to navigate. Indoor positioning surveys use different frameworks, which may be hard for the reader to put together, especially because of overlaps. In addition, a survey framework can facilitate IPS analysis by providing structure and thus help compare different systems against each other.

- *Systematic Review of Recent Papers on Indoor Positioning*: Based on the six-layer model, we study recent papers on indoor positioning. The majority of our studies are from 2017 to 2022. Note that due to COVID-19 in the last two years, there have been big changes around the world. Hence, there is a need to conduct a new survey to complement the previous surveys.
- *A Holistic Categorisation Framework at Various Layers*: At each layer of the six-layer model, whenever appropriate, we provide a holistic categorisation framework such as categorising devices as transmitter, receiver, localiser, tag, anchor and processor at the device layer; providing network classification based on infrastructure availability, passivity, centralisation and collaboration at the network layer; and dividing methods into two general types: collaborative and non-collaborative methods at the method layer. In summary, compared to other surveys, the presented six-layer model with the categorisation framework should provide more insights.
- *A Comprehensive Overview of Indoor Positioning Methods*: Most surveys cover a subset of indoor positioning methods, usually traditional methods like trilateration and fingerprinting. This paper discusses both collaborative and non-collaborative methods, with more emphasis on the former because they are less dependent on the availability of infrastructure. In addition, we provide examples of machine-learning-based enhancements that address the shortcomings of non-collaborative methods and give an overview of machine learning algorithms in the appendix for reference purposes.
- *A Wide Range of Examples of Indoor Positioning Applications*: Unlike other surveys, we classify indoor positioning applications based on the function(s) a system is designed for, e.g., proximity detection, navigation, tracking, as opposed to the domain the system operates in. We give real-life examples of each application type and domains/industries it is applicable in, with more emphasis on examples related to COVID-19.

To summarise, this paper serves as a proposal for an indoor positioning system framework accompanied by a literature review of the latest works to demonstrate the framework.

1.3. Roadmap

The next section will provide an overview of the indoor positioning survey framework, and the rest of the paper will delve into each layer in detail while also covering the most common types of data, technologies and methods as well as general trends in indoor positioning simultaneously. This paper will only focus on recent works on indoor positioning, i.e., it does not aim at providing a historical overview of the field. In addition, acknowledging that other surveys used extensive evaluation frameworks for indoor positioning systems, e.g., based on accuracy, computational complexity, etc., in this paper, whenever examples of systems are presented from the literature, they are mainly evaluated in terms of positioning accuracy.

2. Methodology

In this section, we give an overview of the methodology adopted for finding related works, which consists of two parts: a general search and a specific search. For general search, we followed the guidelines of [33] to perform a systematic literature review on indoor localisation surveys and distil a general model for indoor positioning. Our methodology for general search consists of the following stages, inspired by a survey written by [34]:

1. Planning
2. Formulating research questions
3. Outlining inclusion criteria
4. Finding papers
5. Data collection and extraction
6. Quality assessment

The rest of this section will describe each stage in more detail.

2.1. Planning

In the planning stage, the scope of the survey was defined based on a preliminary literature review, and the significance of the topic was assessed. Based on this, it was discovered that there is a lack of consensus on a general indoor positioning system taxonomy in the literature. It would be useful to define a model for indoor positioning similar to the OSI model for the Internet to assist standardisation, avoid inconsistencies in terms used in the literature, guide readers unfamiliar with the topic, etc.

2.2. Formulating Research Questions

Research questions were formulated to define the scope of the survey for general search in particular. In general, there are four research questions as discussed below.

RQ1. How can indoor positioning systems be divided into layers similar to other models like the OSI model for the Internet? This question can help identify general patterns among indoor positioning systems and facilitate their comparison.

RQ2. What technologies are typically used for indoor localisation? How can they be classified? We need to study indoor positioning technologies currently in use and their strengths and limitations. This question is necessary to ascertain how to further categorise each layer.

RQ3. What methods are most commonly employed in indoor localisation? What classification system can be designed for them? It is necessary to examine what indoor positioning methods recent papers employ and how they are classified in other surveys/frameworks.

RQ4. What are the applications of indoor positioning? Similar to the OSI model, the new indoor positioning model should have an application layer at its highest level to help people understand the uses of indoor positioning systems.

2.3. Outlining Inclusion Criteria

Based on the research questions defined in the previous section, the following list of inclusion criteria was curated. In order to be included in this survey, a paper must

1. be related to indoor localisation
2. be a journal article or a conference paper
3. be published between 2018 and 2023
4. be in English
5. specific search: be an empirical study with experimental results (simulated conditions are accepted); general search: be a survey paper

Preference was given to papers from peer-reviewed journals.

2.4. Finding Papers

For both general and specific search, paper search was conducted over four databases:

1. Scopus (https://scopus.com/)
2. Google Scholar (https://scholar.google.com/)
3. IEEE Xplore Library (https://ieeexplore.ieee.org/)
4. Web of Science (https://webofscience.com/)

For general search, the following search string was used: "indoor AND (posit* OR locali*) AND (survey OR review OR overview)". Search results from the databases were exported and combined into a single spreadsheet.

2.5. Data Collection and Extraction

The data collection stage was divided into two phases: the general search phase and the specific search phase. In the former, search results from the four databases in section 2.4 were collated and analysed to define the structure of the survey, including outlining relevant security and privacy issues. Specific search was needed to obtain more details for insights derived from the first phase.

2.5.1. General Search

After compiling search results, duplicates were discarded. Specifically, articles with the same DOI and/or title were dropped. The following pieces of information were extracted for each paper:

1. abstract
2. title
3. keywords
4. year of publication
5. citation count
6. document type
7. journal/conference title
8. DOI

The PRISMA framework by [35] was used to systematically search for relevant papers, and the PRISMA diagram for this survey is presented in Figure 1. Overall, out of 1869 search results, 134 surveys were analysed.

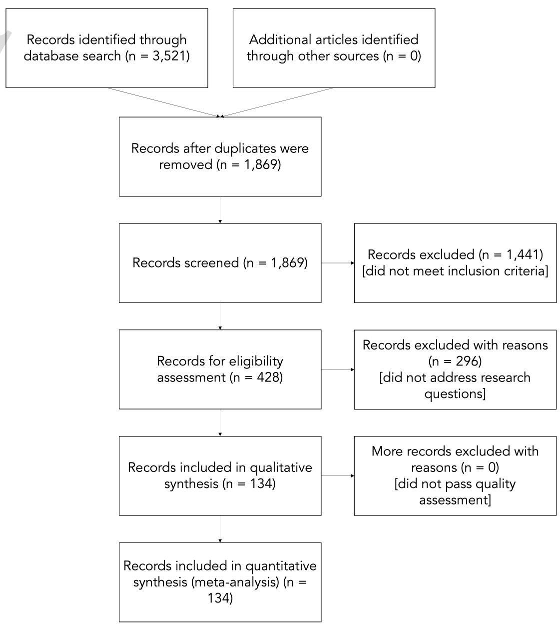

Figure 1: PRISMA diagram for this survey.

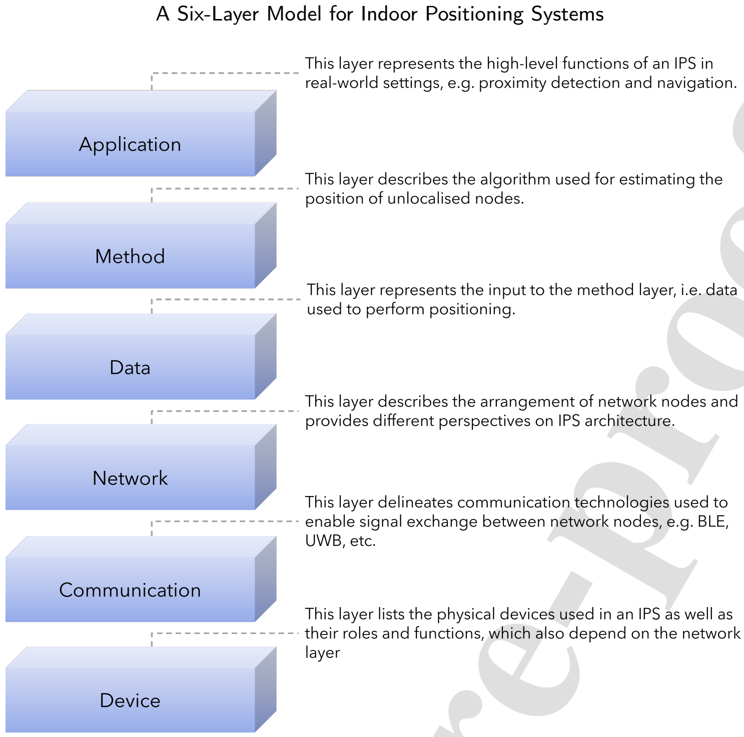

Figure 2: A six-layer model used for indoor positioning systems survey

2.5.2. *Specific Search*

The aim of specific search was to find more details for each layer in the proposed framework and refine its structure. The same databases as in section 2.4 were in this stage, and roughly 150 papers were included in this survey.

2.6. Quality Assessment

[34] used the DARE criteria from the York University Center for Reviews and Dissemination CDR Database of Abstracts of Reviews of Effect to perform quality assessment, but these criteria are for review papers. Since this survey is not restricted to reviews, a custom set of quality assessment criteria were employed, as listed below:

- QA_1: Does the paper meet the inclusion criteria?
- QA_2: Does the paper evaluate its proposed method? Is evidence provided?
- QA_3: Was related work covered and the strengths and contributions of the work compared to others described?

3. A Systematic Survey Framework - Six-Layer Model

Based on extensive review of recent papers on indoor positioning, this section presents a novel six-layer model for IPSs in general and the survey framework in particular, which is illustrated in Figure 2. The model/framework consists of six layers (starting from the bottom layer): device, communication, network, data, method and application. As one goes up the hierarchy, the more abstract and high-level each layer becomes. Table 2 describes interrelationships between different layers, which are directed and are defined as “row item determines column item”. The table demonstrates that even though the layers are distinct, they are interconnected and influence each other. For example, the positioning method used determines the types of data and communication technologies required. Similar to the classification of [17], we separate algorithms, technologies and types of data into distinct categories.

The device layer serves as the physical backbone of an IPS, describing the types of devices employed as well as their roles and functions. Most IPSs rely on a model of inter-device signal exchange, so three device functions can be delineated: transmitter, receiver and localiser. One device does not have to be restricted to just one function, e.g., a transmitter can be a receiver and a localiser, i.e., be able to calculate its own position. Device functions are different from device roles in that functions are about what the device does, whereas roles are what the device is, i.e., it could be a tag (a device attached to the target), an anchor (part of the network with a known location), or a processor, i.e., positioning facilitator. Interactions between entities and functions are discussed in more detail in section 4.

Table 2
Interrelationships between the different layers of the proposed framework.

	Device	Communication	Network	Data	Method	Application
Device	-	Determines communication technologies supported	Determines architecture, passivity, collaboration ability and infrastructure dependence	Determines positioning data supported	Determines computational complexity supported	Determines the scope of applications
Communication	Determines devices required	-	Determines passivity, collaboration ability and infrastructure dependence	Determines positioning data supported	Determines method supported	Determines the scope of applications
Data	Determines devices required	Determines communication technologies allowed	Determines collaboration ability and architecture	-	Determines method supported	Determines the scope of applications
Method	Determines devices required	Determines communication technologies allowed	Determines architecture, passivity, collaboration ability, infrastructure dependence	Determines positioning data required	-	Determines the scope of applications
Application	Determines devices required	Determines communication technologies allowed	Determines the architecture, passivity, need for collaboration and infrastructure	Determines the type of data allowed for collection	Determines computational complexity, accuracy, latency, response time, scalability and other requirements	-

The next layer in the model is the communication layer, which describes the technologies used to enable communication between devices. A wide variety of technologies are used for indoor positioning, and they can be broadly classified into four categories: light-based, sound-based, radio-frequency-based and communication-free technologies. The reason for the wide variety of indoor positioning technologies is that each has its own strengths and weaknesses, meaning one is more suitable for a certain application than another. Light-based technologies, for example, tend to be more precise if used for distance estimation but can only operate at room level because light cannot penetrate walls, just like sound. Radio-frequency-based technologies vary in terms of ranging accuracy but in general are attractive because of low cost, invisibility and ease of use. One of their major limitations is that they perform poorly in obstructed environments. As for communication-free technologies, as the name suggests, these do not involve signal exchange between devices. IMU-based and magnetic-field-based positioning rely on navigation sensors embedded in smartphones, and computer vision relies on image processing for localisation.

The first two layers establish the devices used in an IPS as well as how they communicate, and the next layer, i.e., the network layer, describes their arrangement and mode of interaction. Network architectures can be classified in four ways. The first categorisation is based on the extent to which the system relies on specialised infrastructure, with infrastructure-free systems rising in popularity because they entail little to no installation and maintenance costs [36, 37]. IPS architectures can also be classified into passive and active systems, depending on the interplay between device functions and entities. If the tag is a transmitter, the infrastructure is said to be passive, and if the tag is a receiver, the network is expected to consume power for signal transmission, so the infrastructure is labelled as active. The next type of IPS architecture classification is based on the distribution of computational power. If positioning is delegated to a single device, then the system is said to be centralised, and centralised systems are generally easier to implement but might pose problems like privacy issues, communication bottlenecks and single point of failure. Finally, IPSs can be collaborative and non-collaborative, which is not the same as being distributed vs centralised. A collaborative

Table 3
Examples of IPSs from the literature described based on the proposed framework

Paper	[38]	[39]	[40]	[41]
Application	• Localisation • Navigation	• Localisation	• Localisation • Navigation	• Localisation • Navigation
Method	• Positioning: (1) fingerprinting (LSTM-based); (2) PDR • Fusion: loose • Distance estimation technique: N/A	• Positioning: recursive DV-Hop • Fusion: N/A • Distance estimation technique: RSSI-based	• Positioning: other (geometric) • Fusion: N/A • Distance estimation technique: light-based	• Positioning: fingerprinting (LSTM-based) • Fusion: none • Distance estimation technique: N/A
Data	• RSSI heatmap (signal-characteristics-based data) • Stride length and heading direction angle (motion-based data)	• RSSI	• Linear velocity, angular velocity, speed cycle (motion-based data) • Images of LEDs (image-based data)	• Magnetic field data
Network	• Infrastructure availability: infrastructure-based • Passivity: passive • Computing architecture: client-based (edge computing) • Collaboration: non-collaborative	• Infrastructure availability: infrastructure-free • Passivity: passive • Computing architecture: client-based (edge computing) • Collaboration: collaborative	• Infrastructure availability: infrastructure-based • Passivity: passive • Computing architecture: server-based (fog computing) • Collaboration: collaborative	• Infrastructure availability: infrastructure-free • Passivity: N/A • Computing architecture: client-side (edge computing) • Collaboration: non-collaborative
Communi-cation	• WiFi (RF-based) • IMU (communications-free)	• An RF technology that supports RSSI	• VLC (light-based) • Odometer (communications-free)	• Magnetometer (communications-free)
Devices	• Transmitters: WiFi access points; receiver: a smartphone; localiser: a smartphone • Tag: smartphone; anchor: WiFi access points; processor: none • Auxiliary devices: a PC to train the model	• Transmitter: wireless sensor node; receiver: wireless sensor node; localiser: wireless sensor node • Tag: wireless sensor node without access to GPS; anchor: GPS-equipped wireless sensor node; processor: none • Auxiliary devices: none	• Transmitters: LED lamps; receiver: rolling shutter camera on a robot; localiser: robot • Tag: robot; anchor: LED lamps; processor: a remote controller PC • Auxiliary devices: none	• Transmitter: N/A; receiver: N/A; localiser: a smartphone • Tag: a smartphone; anchor: N/A; processor: N/A • Auxiliary devices: a PC to train the model
Main findings	• WiFi data can be fused with IMU data • LSTMs can be used for WiFi and IMU data as a time series and yield a positioning error of around 1 m	• Recursive DV-hop improves localisation accuracy in WSNs	• Cooperative localisation of robots enabled with VLC and an odometer can achieve an average positioning error of 4.31 cm	• LSTMs can be used for magnetic field positioning data as a time series for localisation and yield a positioning error of around 1 m

system is one where devices exchange data and propagate new information to their neighbours. In non-collaborative systems, unlocalised nodes cannot act as anchors, and if they have an insufficient number of localised neighbours, their position cannot be obtained. In collaborative systems, on the other hand, once an unlocalised node obtains its position, it can become an anchor and assist in the localisation of other unlocalised nodes.

The data layer of the model focuses on the data used as input for positioning methods, which are represented by the next layer. Data such as ToA (Time of Arrival) and AoA are sometimes referred to in the literature as localisation algorithms, e.g., [12]. However, in our framework, they are regarded as data because ToA values on their own, for example, cannot be used to localise a node. Our framework separates these data from the method layer and considers distance estimation part of the method layer. Note that, in

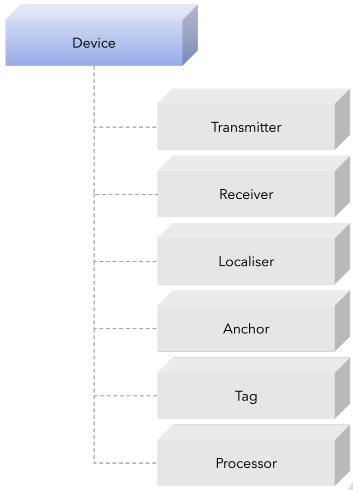

Figure 3: Device layer breakdown

other papers, e.g., [9], indoor positioning data such as ToA and AoA are referred to as techniques, so we use these terms interchangeably. Data that can be used for positioning largely relies on the communication technology used. For example, AoA has only just recently been integrated into the BLE standard [42]. Data for indoor positioning algorithms can be broadly classified into signal-characteristics-based, angle-based, time-based and sensor-based data. Most types of data are used for inter-node distance estimation, which is difficult in indoor environments because most distance estimation schemes assume that the signal travels in LOS (Line-of-Sight) conditions, which can easily be disrupted by moving objects.

The method layer represents the algorithm used in an IPS to calculate targets' positions. A wide variety of positioning methods exist, depending on the system architecture and technologies used. Similar to IPS architectures, there are many ways to classify indoor positioning methods, and many of these classifications overlap, so this paper provides a custom categorisation. In general, positioning methods can be classified into collaborative and non-collaborative methods, where the former rely on inter-node data exchange and the others do not. Most traditional positioning methods (e.g., multilateration) are non-collaborative. They can be further classified into proximity-based, geometric, self-processing, fingerprinting and other methods. Out of these methods, fingerprinting is the best in terms of positioning accuracy [15], but, like other traditional methods, usually requires the use of machine learning for best results. In recent years, collaborative methods have been rising in popularity [36] because of their shared merits with collaborative architectures. Collaborative methods can also be categorised in different ways. Some of them are probabilistic, e.g., belief propagation, and some are deterministic, e.g., MDS (Multi-dimensional Scaling). Some allow the use of virtual anchors, i.e., treating recently localised nodes as anchors, while others do not.

Finally, the topmost layer of the model, the application layer, provides a high-level overview of an IPS. It describes the real-life context in which the system is used, e.g., navigation for customers in a shopping mall, tracking assets in a warehouse, etc. Most studies do not cover the specific application aspect of their proposed systems. In this paper, IPS applications are classified based on the high-level functions they were designed for, and one system can be used for multiple applications. Four functions can be distinguished: proximity detection, localisation, tracking and navigation. Previous work generally discusses indoor positioning applications in the context of their use cases and/or industries, but this work argues that an application should not be domain-dependent. Of course, technologies and methods used may be different between domains, but the underlying application can be the same. In other words, this survey presents the application layer from a more abstract viewpoint, but it also gives examples of use cases for each abstract application. When it comes to industries and use cases where indoor positioning has been most commonly used, researchers generally list healthcare, robotics, asset tracking, disaster management, marketing and security and defence.

To demonstrate how the framework can be used, Table 3 breaks down some IPSs from the literature based on the proposed six-layer model.

4. Device Layer

The device layer is the foundation layer of the six-layer model that provides a high-level overview of the entities and functions of physical devices involved in the positioning process. Figure 3 presents the outline of this section to guide readers.

There is a wide variety of devices used in indoor positioning systems, and their choice depends on the type of communication technology they support. For example, an LED (Light Emitting Diode) lamp would not be able to transmit radio signals. Despite this, these devices can be generalised into entities depending on their role (tag, anchor, processor) and the function(s) they serve (transmission, reception, localisation). Note that this only applies to systems based on signal exchange, i.e., PDR-based systems are not covered and are considered a special case because they are utilised for target tracking rather than positioning. Figure 4 shows the different device types and whether one can be the other, e.g., a tag can be a transmitter, a receiver, a localiser and/or an anchor.

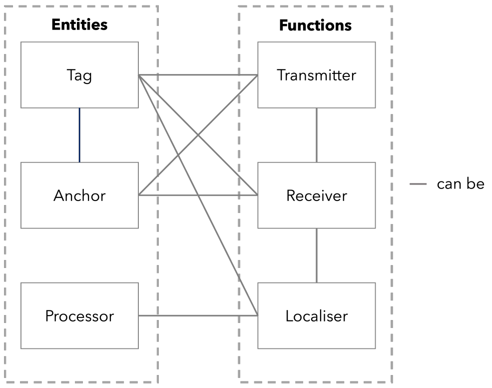

Figure 4: IPS device categories

These relationships are not necessarily mutually exclusive (e.g., a tag can be a transceiver) and are dictated by the variety of different IPS architectures, which will be covered in section 6. This section will describe each device type and provide examples from the literature. Please refer to Table 4 for examples of IPS entities and their functions based on the proposed framework.

4.1. Transmitter

A transmitter is a device that continuously sends signal pulses, be it radio waves, ultrasound or light, at a certain strength and time intervals. If a transmitter is wireless, battery life is a major consideration as frequent battery replacement might be impractical. Some devices can be configured to preserve energy by transmitting at sparser time intervals or not sending signals at all so that they can be "woken up" and broadcast signals as required whenever needed. Depending on the network architecture, a transmitter could be anything from a lightweight mobile device to a more complex equipment piece. One of the most popular examples of the former is a BLE beacon, which, according to [43], is a small radio device that transmits BLE signals periodically via channels 37-39 in the BLE 2.4 GHz ISM (Industrial, Scientific and Medical) band. It is connectionless, meaning that devices do not need to be paired to receive data advertised by a beacon, allowing multiple devices to read a single beacon's data (beacons can only act as transmitters). Beacons run on lithium-cell coin batteries, which can last for several years because of the fact that beacons save energy between advertisements. However, for some systems, battery replacement is not an option, and some work has been done to harvest energy for beacons from external sources, e.g., solar energy and human motion, but these attempts have not been able to provide sufficient energy to sustain beacons long-term, so more research is needed in this area. A WiFi AP would be an example of a heftier device that can be used for signal broadcasting. One of WiFi APs' attractive features is that existing APs can be used for localisation [44], meaning that it is possible to deploy WiFi-based IPSs with no additional infrastructure. The issue is that APs were designed for communication, not positioning, i.e., they do not have an in-built mechanism for noise elimination, making it very difficult to achieve sub-metre accuracy with WiFi alone in NLOS settings [45]. Another downside of access points is that they consume more power than beacons [46], and performance is poor in low-coverage areas. In a similar fashion, smart things with embedded BLE beacons could be used as anchors in home environments for monitoring the elderly or children, for example.

4.2. Receiver

A receiver is a device that detects signals broadcast by a transmitter using one or more antennas and converts it to machine-readable data. Figure 4 illustrates that a receiver can be a transmitter, and devices that support both functions are called transceivers. Examples of devices that only support signal reception include passive RFID tags, photodetectors, etc., but many IPSs use transceivers for reception, e.g., WiFi APs, smartphones, UWB transceivers, ultrasound transducers, etc. Position estimation can happen on the receiver's side, meaning that a receiver can act as a localiser, and this case will be described in more detail in subsequent sections. Different receivers come with their own caveats and may require special arrangements. For instance, wireless UWB transceivers need to be synchronised to a clock accuracy of less than 1 ns [23]. An example of how this can be achieved is provided in the system proposed by the authors of [47], where receivers were connected to a synchronous controller through fiber lines to record the arrival times of signals coming from all receivers and correct for transmission delay before positioning took place. However, there are other methods that do not require synchronisation, e.g., in [48], two-way ranging is used to remove UWB clock asynchronisation error.

4.3. Localiser

A localiser is a device that is responsible for calculating the position of a target. This is where the most computationally expensive part of the positioning process takes place, so a localiser is expected to have a framework for carrying out computational operations. Thus, a localiser is usually some sort of computer, but this is not to say positioning itself is too expensive to be handled by, say, a smartphone. Examples of localisers include servers, Raspberry Pis, PCs,

Table 4
Examples of the types of devices used for indoor positioning and their functions

-	Transmitter	Receiver	Localiser	Tag	Anchor	Processor
WiFi AP (access point)	✓	✓			✓	
UWB transceiver	✓	✓		✓	✓	
Ultrasound transducer	✓	✓		✓	✓	
Server			✓			✓
BLE beacon	✓			✓	✓	
LED lamp	✓				✓	
Photodetector		✓		✓		
Active RFID tag	✓			✓		
Passive RFID tag		✓		✓		
RFID reader		✓			✓	
Smartwatch	✓	✓	✓	✓	✓	
Smartphone	✓	✓	✓	✓	✓	
ZigBee transceiver	✓	✓		✓	✓	
Infrared LED lamp	✓				✓	

etc., which are processors, but tags can also be localisers. A smartphone that acts as a tag carried by the target can also be a localiser by employing self-positioning technologies and methods. However, in recent years, to improve positioning accuracy and capture the complexity of signal propagation, researchers have been proposing more sophisticated positioning algorithms, making them more computationally expensive, e.g., as was mentioned previously, there is a pronounced upward trend in the use of machine learning in IPSs. The more computationally expensive an algorithm is, the more likely it is to be delegated to a more powerful third-party device such as a server, which may not be possible or desirable. Thus, a trade-off between computational complexity and accuracy must be made, and the right architecture should be chosen accordingly. This trade-off is discussed in section 6.3 in the network layer.

4.4. Anchor

An anchor is a general term for any network node that facilitates the positioning process of the target by either transmitting or receiving signals. Typical examples of anchors include WiFi access points, RFID receivers, ultrasound receivers, etc. Anchors can be thought of as the constituents of the indoor positioning infrastructure. Like tags, anchors can be exclusive in their functionalities, i.e., some can only act as receivers, e.g., photodetectors, or transmitters, e.g., LED lights. Transceivers are also a common choice for anchors, e.g., ultrasound transducers, UWB transceivers, etc. As was mentioned in the previous section, localisation occurs either on the server side or on the client side, and since anchors do not belong in either category, they do not support localisation, i.e., they simply act as hubs for signal exchange. One of the most popular networking scenarios is several anchors transmitting signals to a receiving tag, which uses this information to position itself, e.g., a BLE-based IPS with BLE beacons as anchors and a smartphone as a tag [49], a VLC-based IPS with LED lights as anchors and a photodetector attached to a smartphone as a tag [50] and more. Another common blueprint is a transmitting tag and receiving anchors connected to a central unit responsible for position determination, e.g., a UWB-based IPS with UWB transceivers both as anchors and a tag [51], an RFID-based IPS with active RFID tags as tags and RFID receivers as anchors [52] and more. Finally, Figure 4 shows that the tag and anchor nodes are connected, meaning that a tag can be an anchor and vice versa. This happens in collaborative systems where devices can act as both transmitters and receivers and exchange signals to position each other so that no additional infrastructure is required [36].

4.5. Tag

Before discussing the definition of a tag, a distinction between a target and a tag must be made. This survey defines a target as the object or person of interest that needs to be localised, whereas a tag is defined as a device or piece of hardware attached to the target that helps pinpoint the location of the real object of interest, which could be a person, a robot, an asset, etc. Localisation targets do not have to be digital devices; they can be people, objects, etc. However, we may use "target" and "tag" interchangeably throughout the survey. In many IPSs, a device is attached to the target to enable positioning, and this is known as device-based positioning. In device-free positioning, on the other hand, no device is attached to the target, so positioning is performed purely with the help of anchors broadcasting a signal [14]. For example, computer vision-based systems based on camera surveillance are device-free because objects of interest do not have to carry any device with them. Another example is given by [53], where a device-free localisation optimisation-based method was proposed for RF-based systems, where the indoor space is divided into grids, and a matrix of RSS values exchanged between anchors is collected and analysed to identify the target's location. In a similar study [54], infrared sensors were used to collect measurements for a person walking over labelled grids, and a deep learning model was trained on time series data for location inference. This discussion is necessary to highlight that tags do not have to be present in an IPS.

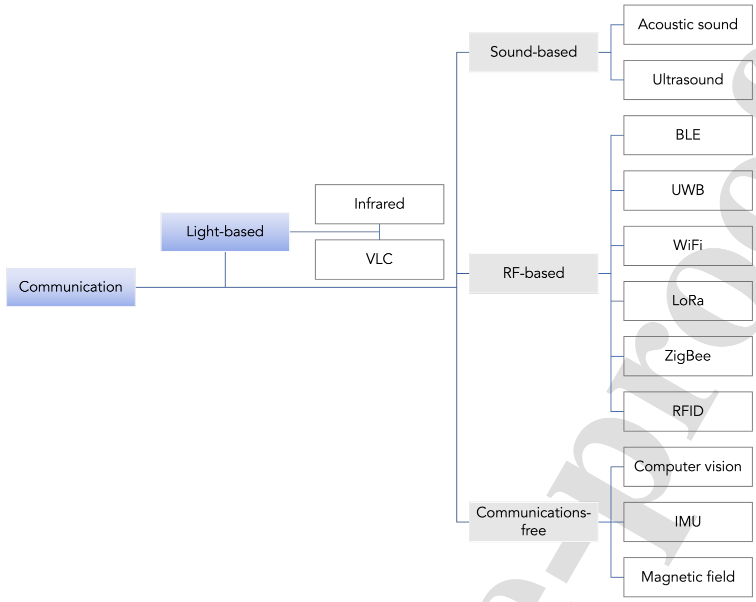

Figure 5: Communication layer breakdown

When it comes to device-based positioning, tags used in these systems are usually expected to be light and portable since the object of interest is mobile most of the time, and examples of such devices include RFID tags, BLE beacons, smartphones and wearable tech. Some devices can only act as transmitters, e.g., beacons [43], active RFID tags [55], some can only receive incoming signals, e.g., passive RFID tags [55], while others can do both, e.g., smartphones, smartwatches, transceivers, etc. When it comes to localisation, a tag can calculate its own position only when it acts as a receiver and if it has computational capability (e.g., the only functionality a passive RFID tag supports is signal reception, i.e., it was not designed to perform calculations required for indoor positioning). This is referred to as self-positioning in the literature. If the tag acts as a transmitter in a system, then positioning is either done by the receiver or is sent to a separate processor such as a server or a PC.

4.6. Processor

Processors and localisers may seem like they refer to the same thing, but their conceptualisations are different. A processor is a server or a PC where data is sent from receivers for position estimation, but, as was mentioned previously, it is not present in every IPS. In other words, a processor is an entity, whereas a localiser is defined by its function. It does not mean a processor cannot be a localiser. In case a processor is present in an IPS, it can only be responsible for localisation and is thus a localiser, but a localiser is not necessarily a processor. They do not have to be mutually exclusive, they are disparate concepts. The reason why processors are defined as separate entities is because they are not directly involved in communicating with tags, they simply process data they receive. This distinction can be useful for IPS security analysis because security and privacy considerations for third-party processing can be different.

Although servers can handle more computationally complex methods, server-side localisation has its own challenges. First, for privacy purposes [56], it would be better to compute location estimates on the client side, i.e., on the tag, which is described in the next section, but the tag's computational resources may be insufficient for the level of accuracy required. In general, for location privacy, it is better for the client to share as little information with third parties as possible. Although protocols have been proposed for location privacy, e.g., [57], they are still incomplete and do not ensure full privacy. Secondly, if machine-learning-based fingerprinting is used, for example, it is cumbersome for the client to download the model and keep it up-to-date. Another potential problem with server-based positioning is latency as it may be inefficient to keep exchanging data with the server. Smartphone-based indoor positioning is gaining more interest in the research community because more people have access to smartphones and smartphones are becoming more powerful, so client-side localisation is becoming more feasible. In general, researchers are striving to minimise the complexity of IPS infrastructure by using as few devices as possible, so the former issue is being addressed by new algorithms and techniques. Server-based systems are usually those where self-positioning is not viable, e.g., in UWB-based systems UWB transceivers do not support positioning, but after the integration of UWB chips in smartphones [58], serverless UWB positioning is likely to become an attractive option. Servers are usually not used for signal reception or transmission. Referring to the discussion

Figure 6: IPS communication technologies ordered by frequency (not to scale)

on computational paradigms in section 4.3, fog nodes and cloud servers would be considered processors, so an IPS can have more than one processor with different computational resources.

4.7. Auxiliary Devices

Some systems may require additional devices to assist in localisation and are part of the infrastructure but are not localisers and do not seek to be localised, e.g., routers for communicating with the server, database servers, etc. One notable example of an auxiliary device that has been gaining attention among researchers is the Intelligent Reflecting Surface (IRS). IRS is a two-dimensional surface that can redirect electromagnetic waves towards a desired location, thus acting as a relay [59]. As discussed in section 5.3, RF-based technologies suffer from environmental noise caused by obstacles, but studies show that IRS can significantly reduce noise by redirecting the signal in the desired direction, reducing multipath fading. [59] tested IRS in indoor and outdoor environments with a 30 cm concrete wall between the receiver and the transmitter and found that IRS was effective even in NLOS conditions, meaning the authors were able to significantly improve the signal's strength. Some studies have been done on employing IRS in IPSs. For example, the authors of [60] implemented a device-free WiFi-based IPS with an IRS and found that even in the presence of noise and multipath interference, the system could locate multiple people with sub-centimetre accuracy. This has far-reaching implications for indoor positioning as IRS could help address the problem of obstacles that undermine positioning performance. However, IRS also comes with its challenges. According to [61], one of the major problems is the high cost of channel estimation, which is performed either at the receiver or the transmitter, meaning that either one should have the computational capacity for channel estimation, and the large array of passive scattering elements may result in long estimation delay. Channel estimation can be performed by overhearing signals emitted by transceivers, but this requires a low-power information exchange protocol. Another issue is that, since IRS requires training, it needs to be retrained in dynamic, heterogeneous networks with multiple users. This requires additional infrastructure for coordinating multiple IRSs. In addition, phase reconfiguration of scattering elements is required for beam steering, but this is also a computationally expensive process.

5. Communication Layer

Serving the device layer, the communication layer determines how devices communicate with each other in an IPS. Figure 5 outlines the structure of this layer. There is a variety of different means of device communication, and they can be broadly classified into three categories: light-based, sound-based and radio-frequency (RF)-based technologies. Light-based and RF-based technologies are electromagnetic in nature but operate over different frequencies and thus have different characteristics (please see Figure 6 for how IPS communication technologies fit on the electromagnetic spectrum). Table 5 compares different indoor positioning technologies across different metrics like coverage and frequency, while Table 6 lists the advantages and disadvantages of the communication technologies covered. [12] categorised communication technologies that can be used for indoor positioning into four groups: light-based, radio-frequency-signal-based, sound-based and other technologies. A similar substructure for the communication layer is adopted in this paper, but since this layer only describes communications, other types of positioning technologies will be described in a separate subsection within the Communications section. Occasional references to positioning data may be made, but they will be explained in detail in the Data section.

5.1. Light-Based Technologies

As the name suggests, light-based technologies use light as a medium of inter-device communication. Light and radio are both on the electromagnetic spectrum but exhibit disparate characteristics. One of the major advantages of light-based technologies is high accuracy, but since light cannot travel through walls, they can only be used for room-level positioning. In addition, they require specialised hardware, meaning using them for infrastructure-free systems would be a challenge.

5.1.1. Infrared (IR)

IR light is an electromagnetic communication medium that operates on the 300 GHz-400 THz frequency band [79], meaning that it is between visible light and microwave radiation. This technology works similar to VLC in that there is an IR LED that emits bursts of IR light that is captured by a photodiode for further data processing. IR light's coverage can reach 4 m [80]. According to [87], an IR LED-based proximity sensor is embedded in most smartphones, making it convenient for end-users. The authors of the study used

Table 5
Comparison of different indoor positioning technologies

	Frequency	Coverage	Bit rate
WiFi	2.4 GHz or 5 GHz [62]	up to 75 m indoors and 250 m outdoors [63]	up to 600 MBps [63]
BLE	2.4 GHz [64]	up to 100 m [65]	up to 2 MBps [66]
UWB	3.1 – 10.6 GHz [67]	up to 50 m [68]	up to 27.24 MBps [69]
ZigBee	2.4 GHz [70]	up to 70 m [71]	250 kBps [71]
RFID [72]	125 – 134 kHz (LF ((Low Frequency)))	< 50 cm	< 1 kBps
	13.56 MHz (HF (High Frequency))	up to 1.5 m	25 kBps
	433 – 864 MHz (UHF (Ultra-High Frequency))	up to 100 m	100 kBps
	865 – 956 MHz (UHF)	0.5 – 5 m	100 kBps
	2.45 GHz (microwave)	10 m	100 kBps
LoRa (Long Range)	433, 868, 915 MHz [73]	up to 19 km [74]	0.3 – 37.5 kBps [75]
VLC	430 – 770 THz [76]	up to 1.4 km [77]	up to 1 TBps [78]
IR (Infrared)	300 GHz-400 THz [79]	up to 4 m [80]	up to 16 MBps [81]
Acoustic signal	< 20 kHz [82]	up to 1 m [83]	up to 1 kBps [84]
Ultrasound	> 20 kHz [82]	up to 8 m [85]	up to 30 MBps [86]

Table 6
Advantages and disadvantages of different communication technologies

Technology	**Advantages**	**Disadvantages**
WiFi	Existing access points can be used, so infrastructure costs can be cut	Operates poorly in NLOS conditions
BLE	Beacons are lightweight, portable and can last for several years	NLOS sensitivity
UWB	High accuracy	Special equipment needed for the target
ZigBee	Low cost and low power consumption	NLOS sensitivity
RFID	Low cost and low power consumption	NLOS sensitivity
LoRa	Highest coverage, low power consumption, can work indoors and outdoors	Cannot be used for real-time positioning; requires special equipment
VLC	High accuracy and low cost	Additional infrastructure is required; sensitivity to NLOS; smartphone-based positioning is not convenient for all methods
IR	High accuracy and low cost	Only operates on room level; sensitivity to sunlight
Acoustic signal	High accuracy and low cost	Only operates on room level; special arrangements needed to make sound inaudible
Ultrasound	High accuracy	Only operates on room level; high installation costs

smartphone IR LEDs as beacons and IR cameras as receivers in a $2.44 \times 2.23\,\mathrm{m}^2$ area and achieved an error of less than 10 cm on average. This goes in line with the high accuracy of VLC, meaning that light-based technologies would be preferred if positioning accuracy is critical. In addition, IR-based IPSs can be easier and cheaper to set up. For example, in [88], a device-free IR-based IPS was designed to count the number of people present in a room only using one sensor mounted on the ceiling. Despite the aforementioned benefits, IR-based positioning does not seem to be a viable option for wide-area positioning for a number of reasons. First, it is susceptible to sunlight and requires LOS conditions to perform well. Secondly, unlike other RF technologies, IR light cannot penetrate walls [89], so IR equipment would have to be deployed for each room in an indoor environment.

5.1.2. Visible Light Communication (VLC)

VLC is a communication technology that uses visible light as a medium of data transfer. There are other technologies that use light, but outside of the visible spectrum. According to [90], VLC operates on the 430–770 THz band, which is 10000 times the entire radio frequency spectrum. As a result, VLC consumes more power than radio technologies, but its bit rate (up to 1 TBps [91]) and range (1.4 km [77]) are also much higher. LEDs are used to emit light, which is detected by an optical sensor, e.g., a photodiode or a camera, and at least three LEDs are required for positioning. Recent improvements in illumination technologies made LEDs transmit data imperceptibly to the human eye, while also illuminating the environment, so they can serve multiple purposes [92]. In [93], VLC-based IPSs are classified into several categories depending on the devices used: camera-based (rolling shutter effect, double camera approach, camera and IMU), photodiode-based (one photodiode and many LEDs, one LED and many photodiodes, one photodiode and one LED), outdoor (traffic lights, vehicle lights, LED beacons) and hybrid systems (fusion with other technologies). VLC seems to be an attractive indoor positioning technology because of its high accuracy. For example, the authors of [94] achieved an accuracy of 8 cm with an SVM (Support Vector Machine) in a $5 \times 5\,\mathrm{m}^2$ area using four LEDs and a mobile node with a photodetector attached. In another study [95], the authors used a smartphone camera as the receiver and achieved 5 cm and 6.6 cm accuracy with four LEDs positioned at 50 cm and 80 cm heights respectively. Like other technologies, however, VLC also has its limitations. For example, it requires the target object to be in its line of sight, otherwise, its performance goes down. In addition, VLC positioning requires at least three LEDs in a single area of coverage, so special installation arrangements in buildings will need to be made. Moreover, photodiodes are not embedded in smartphones, so smartphone-based positioning with VLC is inconvenient.

5.2. Sound-based Technologies

Similar to light-based technologies, sound-based technologies typically are only applicable to room-level positioning because of their inability to penetrate walls. Two types of sound can be used for indoor positioning: acoustic (audible) sound and ultrasound (beyond human hearing range), and they will be briefly described next.

5.2.1. Acoustic Signal

Sound within the audible range (less than 20 kHz [82]) can be used as a means of data transfer and can thus be extended to be used for indoor positioning, but its range is limited to 1 m [83]. To make the sound inaudible, the transmission power from the speaker needs to be lowered, and special algorithms are needed to improve the ability of the receiver to detect the incoming signal [9]. In an acoustic-signal-based IPS, a speaker acts as a transmitter, and a microphone acts as a receiver, and since smartphones have both, they can be used to be an infrastructure-free positioning system. For example, in an acoustic-signal-based IPS described in [96], speakers were used as anchors to localise smartphones, which received the acoustic signal using their microphones and used TDoA for positioning, achieving an error of under 1.8 m 95% of the time. A system named EchoSpot [83] relied on inaudible sound sensing for device-free positioning, where a single speaker and a microphone available in household devices were used for human localisation based on ToF. The system achieved a 22.4 cm error at 5 m distance.

5.2.2. Ultrasound

Ultrasound is a communication technology that uses sound inaudible to the human ear (greater than 20 kHz) for data transmission [82], so its obvious advantage is that no extra measures need to be taken to suppress the sound volume. Ultrasound has a slower propagation speed compared to IR and RF technologies, making its clock synchronisation for time-based indoor positioning methods easier. Ultrasound indoor positioning is also based on the transmitter-receiver model and requires its own devices, i.e., ultrasound technologies are not embedded in smartphones. Usually, an ultrasound tag (microphone) is used as a receiver and a target, and ultrasound transmitters are attached to the ceiling to act as anchors. A common practice is to use RF technologies in ultrasound IPSs for clock synchronisation. For example, in their study, Carter et al. [82] combined RFID with ultrasound to determine the TDoA (Time Difference of Arrival) of the RF signal and the ultrasound signal to calculate the ToF (Time of Flight) of the latter. This helped them achieve a 5.5 cm error in LOS and a 35 cm error in NLOS conditions. The authors used ToF for positioning and reported that the majority of ultrasound-based IPSs use it as well, but some studies exploring RSS-based ultrasound positioning have been conducted as well. Another example of the fusion of ultrasound with another technology is a study by Paredes et al. [97], which combined optical and ultrasound signals. Specifically, the authors used a camera with IR LEDs to obtain depth information and used five ultrasonic transducers to locate a drone with an ultrasound receiver attached in 3D space. A maximum accuracy of 8 cm was reported in LOS conditions, which is high, but no NLOS results were reported, and this system would require special equipment setup in every room. Although Bluetooth is a more popular choice for contact tracing [98], ultrasound has also found its use in preventing the spread of COVID-19. Specifically, a contact tracing system called NOVID combined Bluetooth with ultrasound to improve proximity estimation accuracy in [99].

5.3. Radio-Frequency-Based Technologies

RF technologies are some of the most popular choices for indoor positioning because of their invisibility, low cost, wirelessness and ability to travel through walls. However, a common limitation of RF technologies is that they are sensitive to obstructions and need LOS to perform their best. This is not to say all RF technologies are the same. Each has its own characteristics and trade-offs, and application needs determine which RF technologies are chosen. This section will provide an overview of the most common RF technologies used for indoor positioning.

5.3.1. Bluetooth Low Energy (BLE)

According to [43], BLE is a wireless communication technology that was designed to broadcast small amounts of data encoded as an electromagnetic signal at a constant rate and consume less power compared to Bluetooth. Bluetooth consists of the physical and MAC layers and is used to connect Bluetooth devices within a confined area [9]. Like

Bluetooth, BLE operates on the 2.4 GHz ISM spectrum [64] but has 40 channels instead of 79, the last three of which are used for advertisement and the rest are used for data exchange. Its data rate can reach 2 MBps [66], and its signal can propagate up to 100 m [65]. [100] described the reasons why it is more power-efficient than Bluetooth. First, BLE devices are in sleep mode the majority of the time and only activate when needed. Secondly, BLE only uses three frequency bands compared to 16-32 frequency bands in Bluetooth, which greatly reduces power consumption. BLE is part of the Bluetooth 4.0 standard and was designed specifically for IoT applications. It is mainly used for distance estimation and ranging, i.e., calculating how close the receiver is to a transmitter.

Because BLE devices are relatively cheap and are power-efficient, BLE has been a popular communication technology of choice for indoor positioning among researchers in the last few decades. For example, the authors of [3] designed a tracking system for the elderly and the handicapped based on BLE. They gave the test subjects BLE beacons (either actual beacons or wearable BLE devices like wristbands) and installed eight Raspberry Pis as receivers. Their LOS experiment in a 36 m^2 area yielded an error of less than 1.7 m 90% of the time, and in NLOS conditions, a 90% accuracy was reported. Beacon placement on the body of the subjects did not have a significant impact on the accuracy. Researchers are striving to achieve centimetre-level accuracy in indoor positioning, but BLE alone is not sufficient because of its vulnerability to multipath fading. The signal power at the receiving end is negatively correlated with the squared distance between the receiver and the transmitter [43], meaning that the signal fades faster the further away they are from each other, and this effect is aggravated by obstructions even further.

In recent years, researchers have started to fuse BLE with other technologies. For example, the authors of [48] compared positioning accuracy when using only UWB base stations, only BLE beacons or a combination of both. They found that positioning error was lowest (12.2 cm) when only UWB base stations were used and was highest when only BLE beacons were used (1.21 m). The authors of [101] also conducted a comparative study on BLE and UWB-based positioning and arrived at similar conclusions. They found that UWB performed better, especially in NLOS conditions. Despite this, using UWB alone is expensive because it has a shorter battery life, so combining it with BLE acts as a trade-off between accuracy and power consumption. In [102], an algorithm for fusing ultrasound with BLE in the same IPS was shown to achieve a median error of $0.38 - 0.69$ m. Another common pairing is BLE with IMU, e.g., in [103], BLE and inertial navigation were integrated for indoor positioning, which reduced the error from 1.76 m to approximately 1 m. Another example is [104], where BLE was fused with IMU for 3D positioning, and BLE RSSI data was used to detect landmarks rather than directly for distance estimation to reduce the influence of multipath fading. Most studies usually use RSSI for BLE-based positioning, but Bluetooth recently released a new version of the BLE standard that now supports direction finding using AoA/AoD (angle of arrival/angle of departure) (see sections 7.2.1 and 7.2.2) [105].

BLE has also found wide use in contact tracing systems [8]. For example, the UK National Health Service developed an app for COVID-19 contact tracing using BLE to detect proximity between people's smartphones and exchanging encrypted data between them to notify users whether they have been in contact with infected people [106].

5.3.2. Ultra-Wideband (UWB)

UWB is a wireless radio technology that utilises a large portion of its radio spectrum, allowing it to have a high data rate over short distances. It operates on a $3.1 - 10.6$ GHz spectrum and has a high temporal resolution because of its high bandwidth, making it immune to multipath fading and thus making it more accurate for indoor positioning [67]. According to [69], UWB is characterised by energy efficiency, multipath resolving ability, low cost and centimetre-level accuracy, making it an attractive technology for indoor positioning, especially because UWB is expected to be integrated into smartphones soon [58]. The UWB and BLE radio signal is called CIR (Channel Impulse Response). Because UWB provides more accurate measurements than BLE, it is becoming incorporated into commercial devices such as smartphones [69].

Many studies using UWB for indoor positioning have been conducted in recent years. For instance, the authors of [107] used three UWB transceivers to localise a UWB tag in a 20×20 m^2 area using deep learning and ToA (please refer to section 7.3.1) and achieved a 7 cm accuracy. [108] reported a similar level of accuracy (5 cm at best) by using median and a KF (Kalman Filter). In [109], a 3.6 cm error was achieved using AoA-based localisation. [51] extended UWB-based positioning to use different methods, depending on whether it was operating in NLOS or LOS conditions. The authors achieved a maximum error of 1.3 m and an average error of 47 cm (method with lowest average error) in NLOS conditions. Like BLE, UWB is also sensitive to obstructions, but the amount of variation in its signal is much smaller. Nevertheless, a number of papers have been published on detecting NLOS conditions, usually using machine learning (e.g., [110, 111, 112]) and mitigating the effect of obstructions on the UWB positioning error, e.g., the authors of [113] improved the positioning accuracy from 79% to 87%, and the authors of [114] combined NLOS detection and mitigation in the same method, achieving sub-metre accuracy 90% of the time with NLOS mitigation.

Similar to BLE, UWB is also often used in conjunction with other technologies. For example, in [115], UWB and IMU were combined to correct the long-term drift error of the latter. In line with the work that has been done on detecting NLOS conditions for better UWB positioning performance, the authors of this study stated that UWB-based positioning performed poorly in cluttered environments, so they suggested that IMU be coupled with UWB so that they correct each other's errors. They achieved a maximum error of 20 cm in a $10 \times 10\,m^2$ area. Another noteworthy combination was tried in [116] - WiFi, ZigBee, BLE, UWB and IMU. IMU was used to get the trajectory of the target's movement, whereas the other technologies were used for fixating the target in a location. They conducted experiments in a $1460\,m^2$ area and achieved an error of less than 2 m 90% of the time. The authors' intention was to design a system that would be scalable and suit the needs of both small and large spaces, but the infrastructure required for this system may be cumbersome to install and maintain.

5.3.3. *Wireless Fidelity (WiFi)*

WiFi, also known as the IEEE802.11 standard, is a wireless communication technology that operates on the 2.4 GHz or 5 GHz ISM band, similar to Bluetooth [62]. Its coverage depends on whether it is operating indoors or outdoors. Outdoor coverage can reach 250 m, while maximum indoor range is 75 m, depending on the exact standard [63]. WiFi is mainly used to provide access to the internet for WiFi-enabled devices. Most smartphones, computers and other devices support WiFi, making it one of the most popular technologies for indoor positioning [36].

A large body of research has been done to design methods to take advantage of existing APs and maximise positioning accuracy. Given the wide variety of methods available, the accuracy in the literature also has a wide range – 4.2 mm [45] to 8 m [117] roughly. For instance, the authors of [118] achieved an accuracy of 2 m with nine APs and a smartphone as a target in a $57 \times 20\,m^2$ area, while in [45], a $0.42 - 3.43$ cm accuracy was reached using CSI fingerprinting (see section 8.3.3) in NLOS conditions. WiFi is also often combined with other positioning technologies. For example, the authors of [118] fused WiFi RSS values with IMU data to generate a radio map of the indoor environment and achieved an accuracy of 1.71 m in a $1495\,m^2$ area with 28 APs, which is a good result given the size of the area. As was mentioned previously, smartphones can act as access points as well, and in [119], this fact was used to build an infrastructure-free system with a 90% accuracy using WiFi Direct and IMU embedded in smartphones, i.e., the authors did not use any external access points.

There have been new developments in WiFi communications. For example, apart from RSS, WiFi now supports a more granular type of signal measurements called CSI, which is discussed in section 7.1.3. In short, RSS, as discussed in section 7.1.1, is highly unstable and gives limited information about signal propagation, but more information can be derived from the CSI matrix because it captures how exactly the signal refracted and changed on its way to the destination. There are many studies on WiFi CSI fingerprints for indoor positioning, e.g., [120, 121, 122, 123]. Another promising development is the introduction of IRS for wireless communication, which is discussed in section 4.7. With the WiFi standard IEEE 802.11mc released in 2016, WiFi also now supports RTT-based distance estimation [124].

5.3.4. *Long Range (LoRa)*

A LoRaWAN (Long Range Wide Area Networks) is a LPWAN (Low Power Wide Area Network) whose infrastructure is similar to that of cellular networks but has a larger range (up to 19 km in LOS conditions [74]). Some commercial LPWANs have already adopted LoRa, and it is an emerging IoT technology for indoor positioning. According to [73], it operates on three frequency bands: $433, 868, 915$ MHz. LPWANs are characterised by low power consumption with extensive coverage. This comes at the cost of a lower data rate ($0.3 - 37.5$ kBps [75]), which is even lower than that of BLE and ZigBee, and long intervals between data transmissions, which means that LoRa is not suitable for real-time positioning. LPWANs incur significant deployment costs and require extensive planning effort. Therefore, they combine the functionalities of GPS and short-range communication technologies as they can be used for both indoor and outdoor positioning. When used indoors, LoRa features lower signal attenuation because of its low data rate. When used outdoors, it does not need to communicate with satellites. LoRa uses CSS (Chirp Spread Spectrum) modulation [73], making it resistant to multipath fading, interference and Doppler effects, but implementing it is difficult because of its low bandwidth and large distances [9]. Therefore, LoRa has worse performance for indoor positioning compared to other RF technologies, but, if used in conjunction with GPS, localisation accuracy can be improved.

When it comes to examples from the literature, the authors of [125] evaluated the performance of LoRa for indoor positioning using RSSI fingerprinting and reported an average error between 4 m and 23 m in NLOS conditions, depending on which floor experiments were conducted. [126] reported a better positioning error of 1.6 m and 3.2 m for LOS and NLOS conditions respectively. In [127], a TWR-based (Two-Way Ranging) positioning system achieved a considerably higher accuracy with four LoRa transceivers as anchors - 60 cm 99% of the time in a $40 \times 40\,m^2$ area, but this figure was reported for LOS conditions. In NLOS conditions, the maximum error went up to 8.6 m. Overall, it is evident that even though LoRa boasts the highest coverage out of all indoor positioning technologies, there are better alternatives if accuracy is the main priority.

5.3.5. *ZigBee*

ZigBee is a radio communication technology similar to Bluetooth developed by the ZigBee Alliance. According to [70], it also operates on the 2.4 GHz frequency band, features low power consumption and does not interfere with other 2.4 GHz frequency band technologies. Unlike Bluetooth, however, ZigBee is a low data rate technology (250 kBps) [71]. Most ZigBee-based indoor positioning systems use RSSI for position estimation, similar to other RF technologies like BLE and WiFi. RSSI levels are embedded in data packets sent by ZigBee, making it convenient for developers. According to [9], ZigBee is not a favourable choice for indoor positioning as it is not supported by user devices. Despite this, several studies have been conducted on the use of ZigBee for indoor positioning. For example, the authors of [128] used four ZigBee beacons as reference nodes in a $9 \times 12\,\mathrm{m}^2$ area and achieved an accuracy of 1.15 m using particle swarm optimisation. ZigBee has also been combined with other technologies, e.g., in [129], ZigBee was fused with IMU, yielding an error of less than 50 cm. Another noteworthy ZigBee-based system was built by the authors of [130], where the user's position was determined based on his/her interaction with smart home devices with the help of fingerprinting and proximity-based localisation (please see sections 7 and 8 for a more in-depth discussion of localisation data and methods). Fingerprinting was used to identify which room the user was in, and proximity-based positioning was used to determine the exact location of the user in the room based on which smart sensor he/she interacted with, e.g., fridge sensor, door sensor, etc. The authors also distributed wearable sensors to users so that they would transmit RSSI data, and environmental sensors could distinguish between multiple users. ZigBee is widely used in smart home devices [131], so this IPS can reuse existing home devices and extend their use to indoor localisation. ZigBee was specifically designed to address the need for low-power, low-cost, secure communication technology, which it does, but, similar to other RF technologies, ZigBee-based positioning suffers from low accuracy because of multipath fading [132]. Overall, ZigBee's mode of operation is similar to BLE, but its main disadvantage is that it is not integrated in smartphones, meaning that it requires its own hardware for mobile targets.

5.3.6. Radio Frequency Identification (RFID)

According to [133], RFID is a cheap radio communication technology that is used to transmit data between an RFID transmitter and an RFID reader, which is connected to a device that processes and stores data from the reader. It has already found use in identifying, locating and tracking objects such as assets in warehouses, patients in hospitals, etc., but its widespread adoption is limited due to such factors as privacy, cost and unsatisfactory accuracy. RFID operates on several frequency bands: low-frequency ($125-134\,\mathrm{kHz}$), high-frequency (13.56 MHz), ultra-high frequency ($865-960\,\mathrm{MHz}$) and microwave frequency, and there are two types of RFID: active and passive [72]. An active RFID tag is powered by an internal battery and periodically transmits radio signals, which are captured by an RFID reader. Active RFID tags are more expensive than passive ones, but their range is much higher, so they are more suitable for tracking. Passive RFID tags do not require power to work. Their signal transmission circuit is triggered by a signal sent by a high-power RFID reader. Because of their limited range ($1-2\,\mathrm{m}$), they are used more for identification of objects rather than tracking or localisation. A relatively recent development in RFID technology has been the use of chipless RFID sensors, which have attracted significant attention in the research community because they are suitable for harsh environments and remove chip-associated costs, among other advantages over traditional sensors [134]. Recent studies [135, 136] demonstrate their usefulness in indoor localisation.

RFID is an attractive technology for indoor positioning because of its low cost, but similar to BLE, achieving sub-metre accuracy with RFID remains a challenge. The authors of [137] managed to achieve an error of less than 50 cm over 96% of the time with RFID, but their test area was quite small ($3 \times 3\,\mathrm{m}^2$). They separated transmitters and receivers from RFID readers to save power and used a passive RFID tag as the target. In [138], passive RFID tags were used as well but to correct for IMU drift in asset tracking. They were able to bring positioning error consistently under 3 m, but the range of RFID tags was very small (75 cm). In terms of active RFID, in [139], active RFID transmitters were used as anchors to track wearable RFID readers carried by users, yielding a 2 m accuracy in a high-noise simulated area of $40 \times 20\,\mathrm{m}^2$. Similar to other radio technologies, researchers have tried to combine RFID with other technologies. For example, the authors of [52] distributed active RFID tags to users to carry along with their smartphones so that IMU data from the smartphones could be fused with RFID positioning results. All positioning data was sent to a central unit for processing, and the authors achieved an accuracy of 4 m in a $1600\,\mathrm{m}^2$ area.

5.4. Communication-Free Technologies

A variety of alternative technologies for indoor positioning exist, but this section will only cover some of the most common ones encountered in the literature.

5.4.1. Inertial Technologies

Devices like smartphones and autonomous vehicles have an embedded IMU, which contains orientation sensors, and a typical IMU includes a triaxial accelerometer and a triaxial gyroscope. Some IMUs also contain a triaxial magnetometer because it can output high-precision heading data, but its azimuth estimation is unreliable because of magnetic field disturbances in the environment [140]. Accelerometers detect user acceleration in a specific direction, and gyroscopes help improve this prediction. IMU sensors can be used to predict the next location, speed and direction of a moving object, and this process is referred to as dead reckoning. PDR involves step detection, step length estimation, heading estimation and, finally, position estimation. One of the main problems of PDR is the initialisation issue. PDR can only calculate positions relative to its origin, which is unknown at the start, so other technologies need to be used to localise the target initially, e.g., WiFi [141], which has its own accuracy issues. Another major problem is the accumulation of drift and deviation errors, which leads to progressively worse performance over time [142]. The authors of [143] suggested that the position of the target is re-initialised periodically, but its accuracy depends on the resolution of the initialisation problem. In addition, IMU sensors can be power-intensive and thus be taxing on the battery [37].

5.4.2. Magnetic Field

Magnetic-field-based positioning relies on magnetic field interference, be it artificially generated or stemming from Earth's natural magnetic field (ambient magnetic field), whose strength varies in different parts of the planet. According to [144], some animals, especially birds, rely on Earth's magnetic field for navigation. In outdoor spaces, ambient magnetic field strength does not show much variation over time, but indoors, ferromagnetic elements like iron and nickel create unique disturbance patterns in Earth's magnetic field, and these patterns can be used to identify where one is. The majority of studies rely on ambient magnetic field, i.e., that of Earth, and a magnetometer is used to measure magnetic interference [25]. Earth's magnetic field can be represented using a Cartesian system where any point P is represented in terms of three coordinates: x - direction towards the geographic north, y - direction towards the geographic east and z - direction towards the earth. Magnetic-field-based positioning is a relatively new field of study compared to RF technologies, for example. Some of its most attractive features are high availability and low cost since magnetometers are embedded in devices like smartphones and autonomous vehicles. Moreover, unlike PDR, magnetic-field-based systems do not require another technology for absolute positioning if a magnetic field map of the indoor space is constructed before real-time positioning, making it an attractive choice for infrastructure-free systems [144]. For example, Yeh et al. [145] designed a purely magnetic-field-based IPS with a smartphone-based magnetometer and achieved an average error of 90 cm in a $32 \times 10\,\mathrm{m}^2$ space. Some authors have tried fusing magnetic-field-based positioning with other technologies. For example, Sun et al. [146] combined PDR and magnetic-field-based positioning using genetic particle filtering, which yielded an accuracy of 1.72 m in a 360 m^2 environment. Compared to the previously mentioned study, this system showed worse performance, even though testing conditions were similar, which could be explained by the fact that the two studies used different smartphones. One of the main problems of magnetic-field-based positioning is changes in disturbance patterns caused by the movement of ferromagnetic objects indoors. As was mentioned previously, magnetic-field-based positioning relies on pattern matching, so, if patterns change, positioning accuracy will be adversely affected. Movement of people and non-ferromagnetic objects, however, does not exert a significant influence on the magnetic field. Another major problem is device heterogeneity: different devices have magnetometers from different vendors that vary in precision and tolerance level, meaning that two different devices may produce different estimates for the same position, even if they use the same algorithm [144]. Finally, similar to PDR, using a magnetometer for a prolonged period of time can drain the battery on smartphones [37]. Overall, it seems that magnetic-field-based positioning is similar to IMU-based positioning in that both can be infrastructure-free and are suitable for smartphone-based positioning, but the former does not seem to be as sensitive to interference on the part of the target moving around, making it a more attractive alternative.

5.4.3. Computer Vision

Computer vision refers to the use of machine learning to perform inferences on images. Specifically, in the context of indoor positioning, computer vision can be used to determine the location of a target through a camera using different methods, e.g., by matching pictures from the environment with a database of pictures collated beforehand. Computer-vision-based positioning boasts one of the highest accuracy levels among all indoor positioning technologies but is more expensive and operates poorly in the dark [5]. However, in [147], infrared cameras were used for thermal imaging, removing the need for illumination. The study was motivated by the difficulty firefighters face when navigating fire-afflicted areas. Firefighters participating in the study were given handheld infrared cameras to estimate their direction, velocity and angle of movement, and this information was combined with IMU data, yielding an average error of 2 m, which is rather high for a computer-vision IPS, but handheld cameras can move around frequently, especially in extreme unpredictable environments firefighters work in. An infrastructure-free object-detection-based system by Xiao et al. [148], on the other hand, showed better performance. In their system, a database of the images of reference objects (e.g., doors, windows) was compiled prior to positioning, so that during positioning, a smartphone, acting as a target, could capture pictures of its environment and upload them to a server, which ran an object recognition model to locate reference objects and calculated the target's position based on its position relative to the reference objects. The authors reported an average error of 70 cm. Object recognition models with high accuracy are computationally expensive and need time and effort to train, and these are some of the considerations that should be taken before opting for computer vision solutions for indoor positioning.

6. Network Layer

The network layer presents a higher level of abstraction in indoor positioning systems and focuses on their infrastructure, i.e., what components are required and what roles they are supposed to play. Researchers have used different terms for various IPS architectures, but overall, no uniform classification for them has been proposed. One probable reason is that there are multiple ways to classify them, depending on the perspective adopted. This section presents different considerations to be taken when designing an IPS architecture, based on literature review and trends identified in studies. Figure 7 shows the outline of this section. Different types of architectures are difficult to be classified in a single hierarchy because of overlaps, so a graph-based representation is provided for the reader's reference in Figure 8, where a connection between two nodes means that they are compatible, i.e., not mutually exclusive. When it comes to relationships between system architectures within the same category, e.g., collaborative and non-collaborative, they can

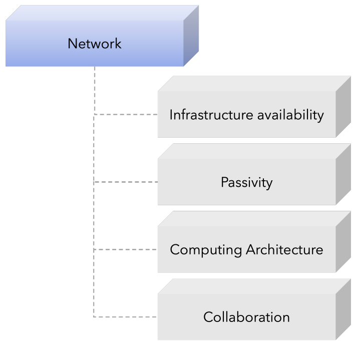

Figure 7: Network layer breakdown

also be combined in the same system, but these relationships are not included in the diagram to avoid confusion. This is applicable to all categories except for infrastructure-based vs infrastructure-free systems, as is explained in section 6.1.

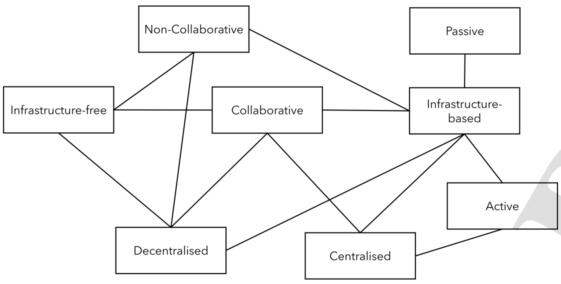

Figure 8: Types of IPS architecture

6.1. Infrastructure Availability

One of the main issues in designing indoor positioning systems is the cost associated with installing and maintaining their architecture, so researchers have been striving to devise systems that either use existing networking infrastructure in buildings, e.g., WiFi access points, or do not rely on any specialised hardware. Another compelling reason why infrastructure-free systems are becoming more popular is that, in emergency situations like earthquakes and fire, infrastructure-based IPSs cannot be relied on since network operation can be disrupted [37]. Some studies call systems that use existing infrastructure infrastructure-free, but, for simplicity and to have a clear definition of infrastructure independence, this work shall restrict the definition of infrastructure-free systems to those that can operate in any indoor environment without relying on external hardware. According to [37], there are three types of infrastructure-free systems: sensor-based, by knowledge exchange and through user interaction. Sensor-based ones are those that rely on smartphone sensors, including IMU sensors (please refer to section 5.4 for a more in-depth discussion of these technologies). The second type is based on the collaboration of network participants to infer their positions based on individual pieces of knowledge about the area to construct its holistic map. It will be covered in more detail in section 6.4. The last type is the most lightweight one in that the user is asked to select a landmark they are standing next to from a finite list of landmarks compiled beforehand and then select a destination from the same list so that a route can be constructed between the two points. This is a navigation scenario rather than a positioning scenario, so only the first two will be considered in the paper. As for infrastructure-based systems, as their name suggests, they rely on a network of devices installed in an indoor environment to perform positioning (examples can be found in section 6.2). Infrastructure-free systems also require devices like smartphones, but the difference is that these devices are portable and do not need to be installed or maintained. In other words, they have lower coupling compared to infrastructure-based systems. In sensor-based positioning, these devices are self-sufficient and can perform positioning independently. Of course, there are hybrid systems where both infrastructure-free and infrastructure-based methods are employed, but these systems shall be considered infrastructure-based because they still use devices that need to be installed and maintained. To avoid repetition, please refer to section 6.4 for examples of infrastructure-free systems.

6.2. Passivity

In Section 4, we discuss the different functions of IPS devices, i.e., some devices are responsible for transmission, some receive the signal and others translate it to positioning information. This is not to say that all IPSs follow the transmitter-receiver model, but the infrastructure of this type can be classified into two categories: passive and active. Overall, IPSs can be classified into three categories based on passivity: passive, active and other, where "other" refers to systems that are not based on the transmitter-receiver model. We define a passive IPS as one where reference nodes act as transmitters and targets passively receive the broadcast signal. In active systems, the roles are reversed, i.e., targets are responsible for sending data, and reference nodes passively listen. In summary, this type of classification is from the perspective of which device(s) is/are responsible for transmission and dictates where position estimation will take place, as was described in section 4. This classification can be found in existing literature. For example, Zafari et al. [9] coined their own terms for the two categories – device-based localisation (DBL) and monitor-based localisation (MBL) respectively.

There are other definitions of passivity in the literature. For example, device-free systems are commonly referred to as passive, e.g., in [149, 60, 150]. [151] defined passive positioning as passive monitoring of tags that start broadcasting data as soon as they enter a certain coverage area, meaning no triggering on the user's part and no ranging is required, which is more energy-efficient. Another definition of passivity can be found in [152], which refers to passive positioning as one that does not require the active collaboration of the user, i.e., positioning can be performed without the user's endorsement. While we acknowledge other definitions of passivity from the literature, we shall use our own definition in this survey.

The choice of infrastructure for this classification depends on the application and devices chosen. For example, a popular configuration is to have BLE beacons attached to the ceiling and a smartphone receiving the signals of multiple beacons to calculate its own position (e.g., [153, 154, 3, 155]). This is a passive framework, but if the application stipulates that using BLE beacons is compulsory, transforming the framework into an active system is not feasible because beacons can only act as transmitters, while smartphones can both broadcast and receive. In addition, if the positioning algorithm is not too computationally expensive, calculating the position locally rather than on a server reduces the positioning delay. This could be one of the reasons why passive positioning is more common in WiFi-based systems as well (e.g., [117, 156, 157]), despite the fact that WiFi APs can act as receivers as well. Ultrasound, however, is more flexible. For example, in [158], three transmitters were attached to the target and sent signals to four beacons acting as ultrasound receivers for 3D localisation. The configuration of a system presented in [159] was similar except that an ultrasound receiver was attached to the target, while four ultrasonic transmitters were attached to the ceiling as anchors for localisation.

6.3. Computing Architecture

As briefly discussed in section 4.3, a trade-off must be made between the computational complexity of a positioning method and positioning accuracy, and it depends on the computing architecture, i.e., how computation is distributed in the network. An important distinction must be made here though. The next section discusses collaboration of nodes in IPSs, and, in this survey, two nodes are said to collaborate if both employ a communication technology, i.e., both directly participate in positioning, and need to be localised. If two nodes simply exchange positioning data so that one node can estimate the location of the other, i.e., where one node simply delegates computation to another node, this is not an instance of collaboration because one node acts as a processor and does not aim to be localised.

In the IoT era, more devices are connected to the internet and need server-based data processing, which puts significant strain on servers, congests the network and increases latency. This can be a problem for large-scale IPSs as well. Although not all IPSs require server-side positioning, as discussed previously, more computationally expensive methods are being used for indoor positioning to handle the complexity of indoor signal propagation. This means that, in anticipation of an increased demand for indoor positioning services, similar to other IoT systems, alternative computational paradigms must be considered.

In recent years, computational paradigms such as edge computing, fog computing, cloud computing and mist computing are becoming more popular. Cloud computing provides elastic computing services and storage on demand [160], so computing is performed on a remote server. In the IoT era, cloud computing cannot keep up with an increasing demand for cloud processing, so edge computing and fog computing paradigms have recently been introduced to address the issue. Edge computing is a computational paradigm where computing is performed at the edge of the network, where an edge can be a smartphone, an autonomous vehicle, etc. [161]. IPSs where tags are localisers can be said to follow the edge computing paradigm if the localisers are self-sufficient, i.e., do not rely on external computation. As for fog computing, according to [162], fog computing refers to a network of servers located between edges and cloud services, meaning they are closer to the edges, which reduces latency. These servers have lower storage and processing capability than cloud servers but they help reduce network congestion. Fog computing is not a replacement for cloud computing because the cloud is needed for long-term storage and computationally heavy operations. Fog nodes aim to service low-resource devices such as IoT devices that need low latency. Mist computing pushes computation even closer to the edges than fog computing [163]. Cloud computing, mist computing and fog computing would be suitable for large-scale indoor positioning systems but for smaller systems, local servers or even edge processing would suffice. Examples of these paradigms in indoor positioning can be found in the literature. For example, [164] defined a fog computing architecture for a BLE-beacon-based indoor navigation system, and [165] designed a WLAN-based (Wireless Local Area Network) IPS with different types of fog nodes, where some were responsible for positioning and others were responsible for forwarding, i.e., wireless routers. Experimental results show that distributed fog computing yielded the lowest latency compared to cloud computing and fog computing with a single fog node, and this effect became more pronounced with larger amounts of positioning data. However, as the number of fog nodes was large enough, positioning latency started to go up again.

6.4. Collaboration

Based on the previous subsection, it may seem that collaboration and centralisation refer to the same concept, but there is a difference between the two. Pascacio et al. [36]

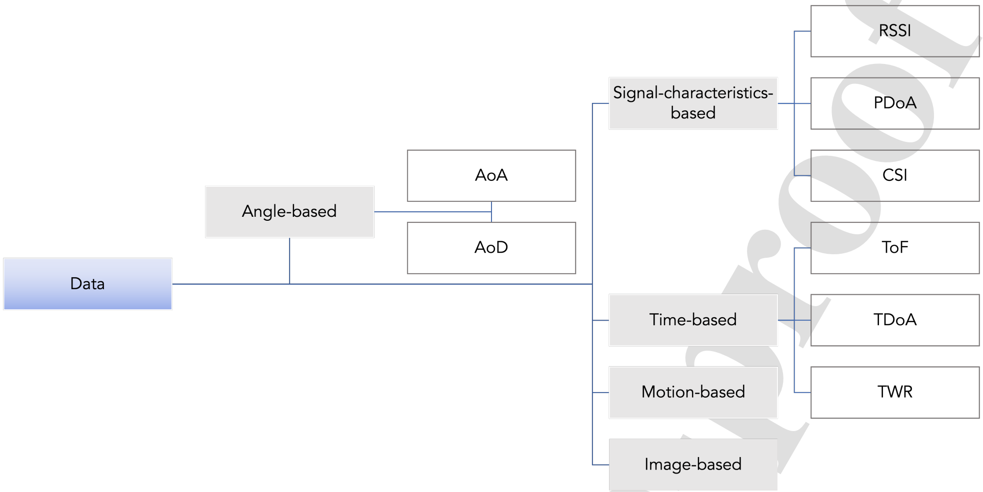

Figure 9: Data layer breakdown

defined a collaborative IPS as a system where independent actors draw information from different sources and share it with each other, assisting in the localisation of every actor. The authors also pointed out that centralised systems can be collaborative, but their implementation is complicated because one must figure out how to make network devices communicate and share their information with a central node and vice versa, which creates additional network delay. The researchers argue that collaborative systems are an evolution of the growing trend of sensor fusion in indoor localisation and present several advantages over traditional systems. First, collaborative systems allow for higher area coverage since users can propagate their positions to their neighbours. Secondly, they decrease the need for costly and/or complex infrastructure since, by definition, users can locate each other without the help of additional hardware. As for the limitations, one of the main drawbacks is the high computational burden incurred by collaborative positioning algorithms, increasing energy consumption of independent actors. Another major concern is privacy. Since collaborative systems imply frequent data exchange, extra measures must be taken to secure communication channels between devices and to make sure no sensitive information is revealed. When it comes to positioning accuracy, it depends on many factors such as the algorithm, data and technology used, so it is difficult to argue that collaborative systems show worse performance than non-collaborative ones. However, examples of collaborative systems from the literature will be provided for reference. The authors of [52] designed a centralised collaborative IPS with RFID transmitters in fixed locations and active RFID tags attached to smartphones (mobile nodes), which sent RSS measurements and step length and heading estimates from their IMUs to a central server for localisation. They tested the system in a $1600\,\mathrm{m}^2$ area and achieved a median error of 2.6 m using a cooperative approach.

7. Data Layer

The data layer delineates the types of data used for indoor localisation, and a high-level overview of this layer is shown in Figure 9. As was mentioned in section 5, a recent trend in indoor positioning has been the fusion of multiple technologies in the same system to improve localisation accuracy and compensate for the limitations of individual technologies, e.g., combining UWB and BLE for increasing accuracy and saving energy respectively. While most types of data are supported by the majority of localisation technologies, it is common to combine them in the same system as well. In general, localisation data can be categorised into several groups: power-based, angle-based, time-based, motion-based and image-based data. This section will provide an overview of the most common types of data that can be used for positioning, compare them against each other and provide examples from literature. The advantages and disadvantages of different types of data for indoor positioning are discussed in Table 7. Please note that these types of data simply provide insight into what data is used rather than how it is handled. These types of data are employed for distance

Table 7
Advantages and disadvantages of different types of data for indoor positioning

-	**Advantages**	**Disadvantages**
RSSI	Low cost and high availability	High sensitivity to noise and limited granularity
CSI	Provides more information on dynamics of signal attenuation, higher accuracy compared to RSSI	Supported by a limited set of communication technologies
AoA	More precise than RSSI	Requires specialised hardware with AoA-enabled antennae
ToA	Simple to calculate	Requires synchronisation between the target and reference nodes; assumes free space signal propagation, i.e., does not account for obstructions; needs the time of signal dispatch from the transmitter for ToF calculation
TDoA	No synchronisation with the target required	Requires synchronisation between reference nodes; assumes a clear LOS
TWR	No synchronisation between network nodes is required, provides high accuracy	Sensitive to clock drifts; assumes a clear LOS
PDoA	Can be fused with other types of data for better positioning performance	Lower accuracy; assumes that the transmitted signal is of sinusoidal form; performs poorly in NLOS conditions
IMU data	Can be collected locally, i.e., on the target, reducing dependency on external infrastructure	Only allows for relative positioning, i.e., it provides information relative to positions it saw in the past; drift error accumulates over time
Images	Good for custom positioning solutions where placement of reference points is significant; can be an effective way of representing fingerprints of data	Not suitable for similar-looking spaces because it is hard to distinguish between them; usually require a database of reference images to match pictures taken during real-time positioning against, and the database needs to be maintained, especially in frequently changing environments

estimation, and many localisation methods are predicated on the availability of distance estimation between different network nodes.

7.1. Signal-Characteristics-Based Data

7.1.1. Received Signal Strength Indicator (RSSI)

RSS is a measure of the power of a signal when it arrives at the receiver. It is an estimate of the average amplitude over the whole channel bandwidth and all antennae [9]. It is one of the simplest, cheapest and most popular sources of data for indoor localisation [166], partly because it does not require additional hardware to measure and is supported by most wireless technologies [71]. RSS is often confused with RSSI, a relative RSS indicator measured in arbitrary units, which are vendor-dependent [9]. As a signal travels from a transmitter to a receiver, its power fades, and, according to [167], RSSI is sensitive to electromagnetic interference, refraction and reflection. In other words, signal power is reduced further by obstacles in its way and thus varies considerably, not representing the true signal power at the receiver by the time it arrives. To address these issues, usually computationally expensive methods are required [9], e.g., KF [49, 168], Gaussian filtering [48]. Another popular technique is to average RSSI values over time, but usually individual RSSI values are so far from the ground truth that average values still give a high error. A new technique to reduce RSS noise has been the use of IRS, e.g., the authors of [169] designed a phase shift optimisation algorithm to improve RSS-based localisation accuracy by adjusting signal phase shifts for multi-user positioning. Moreover, as was mentioned previously, RSSI is vendor-dependent, meaning that different devices may output different RSSI values. Overall, RSSI is a widely available and cheap source of data, making it attractive for indoor positioning, but using it for consistent sub-metre accuracy is a challenge.

7.1.2. Phase Difference of Arrival (PDoA)

A signal travelling between two nodes can be modelled as a wave with a certain amplitude, phase and frequency. Signals transmitted from multiple anchors or the target, depending on where passivity is shifted, are assumed to be of sinusoidal form, having the same frequency and zero offset [9]. When they arrive at different antennae of the receiver, they have different phases, and these differences can be used for estimating the distance between two nodes.

Some VLC-based IPSs have used PDoA (Phase Difference of Arrival) for localisation. For example, the authors of [170] designed a 3D positioning system with four LEDs with a new distance estimation method, which utilised differences in the phases of signals arriving at the photodetector. They tested the new system in a simulated $5 \times 5\,\mathrm{m}^3$ room and achieved millimetre-level accuracy in LOS conditions. Then they simulated noise using two different noise distributions and obtained a maximum error of 4 cm. PDoA was also used with RFID in conjunction with AoA in [171], which focused on designing a system for multipath and NLOS environments. The authors used RSS to isolate top two strongest signals that arrived at the receivers' antennae and calculated their PDoA for better positioning performance. PDoA was also used to calculate the AoA, and both were used to construct a system of equations, from which the coordinates of the target were recovered. The authors reported decimetre-level accuracy in a simulated 100 m^2 area.

7.1.3. Channel State Information (CSI)

According to [172], CSI describes the propagation of wireless signals from the transmitter to the receiver at certain carrier frequencies. It is a 3D matrix that is estimated by the receiver to get insight into how the transmitted signal was transformed into the received signal, which can be represented as a formula: $y = Hx+n$, where y is the received signal, x is the transmitted signal, H is CSI and n is the noise vector. The rows of the matrix represent antennae on the transmitter, the columns represent the receiver's antennae, and within each cell, there are k values for k frequencies of the channel, which makes up the third dimension of the matrix. In other words, it describes the changes that the signal went through on its way to the receiver, which led to its attenuation. As was mentioned in the previous section, RSS averages information over the whole signal bandwidth, whereas CSI is more granular because it can provide information for each frequency and antennae pair (please see [172] for a more detailed discussion of CSI representation). CSI can provide large amounts of data, which needs to be handled in real-time and be adaptable to changes in the environment, so that the system can learn the radio geometry of the network on the fly [173]. CSI measurements are more stable over time than RSSI measurements and are thus more reliable [174]. Therefore, CSI seems to be a promising source of data for indoor localisation because of its high temporal stability, but to achieve marginally better accuracy, computationally expensive methods are required. Another major limitation of CSI is that it is not supported by all devices and can only be extracted from specific Network Interface Cards. Moreover, CSI is still sensitive to signal interference, e.g., from people walking [175].

7.2. Angle-Based Data

7.2.1. Angle of Arrival (AoA)

According to [42], AoA refers to the angle at which the transmitted signal arrives at the antennae of the receiving device. The receiver should have several antennae so that data like time difference of arrival, phase of arrival, etc. can be calculated to estimate AoA. AoA is different from AoD, which is the angle at which the signal starts travelling from the transmitter, please see [42] for an illustration of the difference between AoA and AoD. Unlike other types of data, AoA is not used for range-based methods. Instead, it is used as input to the multiangulation method described in section 8.3.2. Unlike RSS-based positioning, angle-based positioning requires a minimum of two anchors for 2D localisation and a minimum of three for 3D localisation to perform multiangulation [176]. Angle-based positioning boasts higher positioning accuracy compared to RSS methods, but it is not yet supported by smartphones, meaning that it requires special hardware for operation. The authors of [177] explained that there are multiple ways to estimate AoA, including TDoA and PDoA [178], but this depends on the type of device used because some may not support time-based ranging.

AoA is a relatively new type of positioning data, so it comes with its own challenges. For example, antennae arrangement can affect positioning performance, and there are three main ways to do this: ULA, URA and UCA [179]. The first one is a sequential 1D arrangement, which can only be used for 2D positioning because it can only measure the azimuth angle and assumes the target is moving in the same plane. 2D arrangements, however, are capable of estimating both azimuth and elevation angles, making them suitable for localisation in half-3D space. Full 3D space positioning requires a 3D arrangement of the antennae. One of the reasons why integrating angle calculation in smartphones is difficult is because antennae need to be spaced apart to minimise interference, which is also referred to as mutual coupling. Direction finding using AoA is more difficult because, similar to RSSI, it is sensitive to multipath fading. When it comes to examples from literature, the authors of [180] developed a WiFi-based IPS using 13 WiFi APs that support AoA and smartphones that acted as transmitting targets. They connected the APs to a central server that was responsible for position estimation. The system was tested over a floor in a university building and achieved an error of less than 5 m 77% of the time with Android phones. A 50% accuracy improvement was observed using iPhones, which suggests that AoA-based systems are highly sensitive to the type of devices used. Another promising study combined AoA with blockchain for indoor COVID-19 contact tracing [181]. Blockchain was used for secure decentralised BLE packet exchange to address privacy issues, and a CNN (Convolutional Neural Network) was used to localise AoA-enabled mobile BLE receivers, which were responsible for reading signals from BLE beacons acting as transmitters using AoA fingerprints in 3D space. The authors achieved a localisation accuracy of approximately 40 cm in a 100 m^2 area 90% of the time. They also designed a custom credit score system, where the score was calculated based on one's distance to infected people and general conduct (e.g., being transparent about infection status), and users with higher credit scores could mine blockchain blocks faster. The advantage of this system is the low cost of BLE communication, but using a CNN coupled with block mining may be taxing on the users' smartphones.

7.2.2. Angle of Departure (AoD)

As was mentioned in the previous section, AoD is the angle at which the signal leaves the transmitter. The transmitter must have multiple antennas, and the receiver must have one [182]. Another difference between AoA and AoD is that in the latter case, the transmitter must send its coordinates to the receiver as well so that the receiver can estimate its position after processing the signal using IQ sampling [183]. In other words, both AoA and AoD allow one to estimate the direction of the signal, which can be coupled with ranging to achieve better positioning performance. Similar to AoA, AoD can be measured using phase differences of signals travelling from multiple antennae. Please refer to Figure 1 in [183] for an illustration of AoD calculation.

Based on the literature review, AoD is not as popular as AoA. However, one interesting application of AoD can be found in [184], where AoD was used to detect security breaches in indoor positioning by comparing AoA estimated at anchors to AoD estimated at the target tag.

7.3. Time-Based Data

7.3.1. Time of Arrival (ToA)

ToA is simply the timestamp of signal arrival at the receiver. ToA is used to estimate the time it took for a signal to travel between a transmitter and a receiver (ToF). To do this, however, ToA alone is not sufficient; the timestamp at the transmitter, i.e., when the signal was dispatched, must be subtracted from ToA. ToA assumes that the speed of signal propagation is known and requires that the transmitter's and receiver's clocks are synchronised so that ToF estimation error is minimised [185]. ToA is used less frequently than its counterpart, TDoA, because it does not account for indoor signal interference, i.e., it assumes that the signal travels in a straight line, and requires that the timestamp of signal transmission is sent in the data packet [180]. Similar to RSSI, ToA's problem is sensitivity to signal interference. However, the authors of [186] improved the traditional trilateration method using ToA, which can also be used with RSSI, to correct for noise and achieved an error of $5 - 10$ cm in simulated conditions.

7.3.2. Time Difference of Arrival (TDoA)

One of the downsides of ToA is that it needs ToD (Time of Departure) to calculate ToF. One way to address this issue is to take advantage of ToA values from multiple nodes, and this is what TDoA is based on. A single TDoA is simply the difference between ToAs of two nodes, and at least four TDoA values are required for positioning [113]. These TDoA values must be accompanied by the absolute coordinates of the four reference nodes when they are fed to the method layer. Similar to ToA, calculating TDoA requires that reference nodes are synchronised because even a small time difference may yield a high positioning error [180]. Synchronisation with the target, however, is not required. TDoA is a popular technique of choice for UWB-based IPSs. For example, Cai et al. [187] developed a UWB-based IPS using TDoA and TWR and a custom optimisation algorithm. They set up four UWB base stations connected to a central server and used four active tags as targets. They tested their system in a 100 m^2 area and achieved consistent sub-metre accuracy of 36 targets. Of course, the high accuracy was not just because of TDoA or TWR. As was discussed previously, UWB is a highly accurate RF-based technology on its own, but using the right method as well as arranging and configuring devices correctly is also important.

7.3.3. Two-Way Ranging (TWR)

Both ToA and TDoA require precise clock synchronisation among network nodes, which may not always be possible, e.g., when the number of network nodes is prohibitively high. TWR (also known as RToF (Return Time of Flight)) is a time-based type of positioning data designed such that it does not require synchronising network nodes. Similar to ToA, it is used to estimate the ToF between a transmitter and a receiver, but because it does not require synchronisation, it does not rely on any timestamps. TWR's name comes from the fact that a transmitter and a receiver exchange signals back and forth to calculate the ToF. Unlike TDoA, TWR needs a minimum of three reference nodes for positioning [113]. According to [188], although TWR does not require clock synchronisation between devices, its accuracy can be compromised by clock drifts, i.e., when a clock gets behind or ahead of its original state. Even a 1 ns error of ToF can lead to a 30 cm drop in accuracy. Symmetric double-sided two-way ranging is a more popular TWR-based distance estimation technique because it minimises the clock drift error of both devices [189]. A downside of TWR is that it extends the positioning delay because ToF calculation takes more time [190]. TWR has recently been made available in WiFi, and in [191], it was fused with IMU data with the help of the Federated Filter for tracking, leading to a 37.4-67.6% reduction in positioning error compared to EKF (Extended Kalman Filter).

7.4. Motion-Based Data

Previous sections have covered data that rely on signal exchange between two devices. However, the target can predict its next position by collecting information about its movement over time. Modern smartphones are equipped with a wide variety of sensors, including a barometer, accelerometer, IR LED, etc. Sensors from the IMU unit, i.e., accelerometer, gyroscope, magnetometer, light sensor and barometer, can be used to model motion. According to [192], an accelerometer measures the acceleration of a moving object in 3D space, i.e., it produces an estimate in each direction. A gyroscope calculates the angle of the subject's movement in 3D space and is used to determine heading direction. A magnetometer can help calibrate gyroscope readings by providing direction towards the true north from the ambient magnetic field. A barometer is used to measure atmospheric pressure, which decreases the further away one moves from the sea level. Thus, a barometer can be used to measure changes in altitude and is usually used to determine which floor a user is on. Motion-based data is primarily employed in PDR (see section 8.3.4).

7.5. Image-Based Data

Images are primarily used in computer-vision-based indoor positioning, and, in general, they are mostly used as fingerprints (see section 8.3.3. One variation of image-based data is artificially generated images of signal data, e.g., RSSI [193]. Alternatively, images of the environment can be used, but then the database of reference images of the environment will need to be extensive, posing an additional

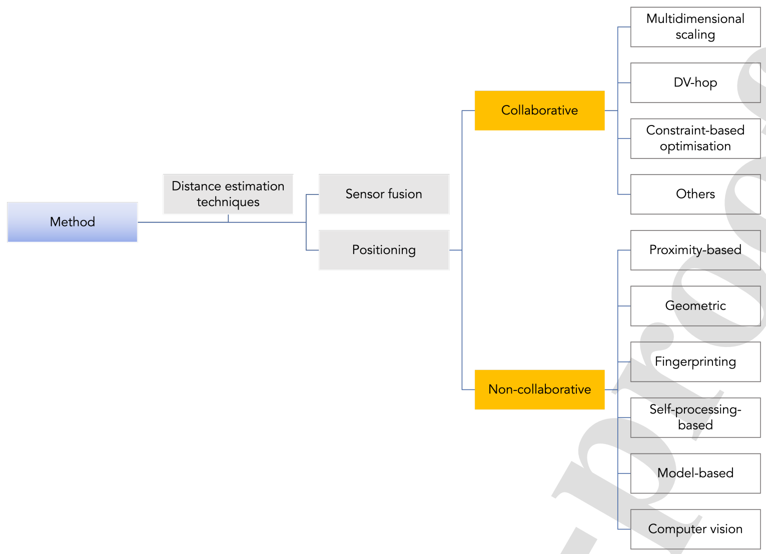

Figure 10: Method layer breakdown

computational burden for the system [192]. Images can be captured from the target's perspective, as is done in robot navigation, e.g., [194, 195], or from the network's perspective, i.e., with surveillance cameras. The perspective adopted determines the localisation method, e.g., fingerprinting in the first case and object detection in the second case. In the former scenario, users can use smartphone cameras to take pictures of their surroundings and match them to a location in a database. A disadvantage of this type of data is that surroundings can change, e.g., doors can be opened, objects can be moved around. Another downside is that some spaces do not have distinguishing features, e.g., most corridors in a building may look the same, so it may be hard to differentiate between similar-looking environments [192].

8. Method Layer

The previous layer mostly covered the types of derived features of the transmitted signal that can be used for estimating the distance between two network nodes, but this alone is not sufficient for localisation. The method layer consolidates the data provided by the data layer and uses it to estimate the location of one or more targets. Please refer to Figure 10 for an outline of this layer. Similar to the network layer, the method layer can be classified differently depending on the perspective taken. The following classifications are an extension of Buehrer et al.'s [196] classification system. A categorisation of common indoor positioning methods based on method type is provided in Table 8.

- **Range-free vs range-based**. One of the most common classifications of positioning methods found in the literature is based on the use of ranging, i.e., range-based vs range-independent algorithms (e.g., [198, 199]). Range-based algorithms are based on direct distance estimation between anchors and target nodes via ranging, e.g., using RSSI, ToF, etc., whereas range-free methods rely on network connectivity and nodes communicating with each other [200]. The latter are usually less accurate but are less costly and less computationally expensive (except for fingerprinting) [201]. Note that if a method uses a type of data that can be used for ranging, such as RSSI, it does not necessarily classify as a range-based method as it may not need to convert RSSI into distances, i.e., it inherently does not rely on inter-node distance measurements. For example, in fingerprinting, RSSI values are simply collected from reference points, they are not converted into distances [202] (see a detailed description of fingerprinting in section 8.3.3).

- **Centralised vs distributed**. Buehrer et al. [196] extended ranging-based classification by introducing four more dichotomies, one of which is based on centralisation. Centralised algorithms delegate localisation of all network nodes to one entity, whereas distributed algorithms allow each node to localise itself. While we recognise emerging computing paradigms discussed in section 6.3, we shall adopt this definition independent of the network layer, meaning that centralised methods are those that require to be run on a processor (see section 4.6), whereas distributed methods are those that only require local information exchange. In other words, how the processor is chosen in the network is irrelevant in the method layer.

- **Collaborative vs non-collaborative**. Similar to network architectures, localisation algorithms can be classified based on the degree of cooperation between

Table 8
Localisation methods and their classifications [36, 24, 196, 197]; N/A means "not applicable"

Method	Collaborative (C) / Non-collaborative (NC)	Centralised (C) / Distributed (D)	Deterministic (D) / Probabilistic (P)	Range-free (RF) / Range-based (RB)	Tracking (T) / Non-tracking (NT)	Sequential (S) / Concurrent (C)
Multilateration	NC	C	D	RB	NT	N/A
Multiangulation	NC	C	D	RB	NT	N/A
Fingerprinting	NC	C	D	RF	NT	N/A
Centroid	C + NC	D	D	RF	NT	S
DV-hop	C	D	D	RF	NT	S
MDS	C	C + D	D	RB	NT	C
Belief propagation	C	C + D	P	RB	T	S
Maximum likelihood	C	C + D	D	RB	NT	S
Semi-definite programming	C	C + D	D	RB	NT	S
PPM (Parallel Projection Method)	C	D	D	RB	NT	S
CV	NC	C + D	D	RF	T + NT	N/A
PDR	NC	D	D	RF	T	N/A

nodes. Collaborative algorithms are different from non-collaborative algorithms in that the former need to handle inter-node communication. According to [24], all collaborative algorithms are range-based.

- **Probabilistic vs deterministic**. This categorisation was also introduced by Buehrer et al. [196]. Probabilistic, or Bayesian, algorithms return a probability distribution of all possible location estimates and tend to be more computationally expensive. Deterministic methods assume there is only one possible location estimate, so they do not provide insights into how confident they are in their estimates. Probabilistic algorithms are typically used for tracking because they take historical information into account [52].
- **Sequential vs concurrent**. This categorisation can be found in [24] and [196]. Sequential algorithms allow freshly localised nodes to act as reference nodes, even if they are mobile, whereas concurrent methods only rely on nodes whose position was known before the localisation process started. The advantage of this approach is that positioning error does not propagate throughout the network, and the opposite is true for its counterpart. It should be noted that this classification is only applicable to collaborative algorithms.
- **Tracking vs non-tracking**. Tracking algorithms are used for mobile targets so that their previous positions can be taken into account to improve accuracy. This categorisation was newly proposed in [196].

Sometimes, it may be difficult to distinguish data and methods as they are so closely related. For example, the fingerprinting method heavily relies on the data it uses, so some papers counted it as both data and a method, e.g., [36]. However, an algorithm is not the same as the data it uses as it is a more dynamic concept, involving a sequence of steps. Hence, for clarity, positioning methods are distilled into a separate layer in the six-layer model. The rest of this section will be classified based on our custom categorisation approach, but first, distance estimation techniques and sensor fusion methods are discussed as distance estimation is an essential part of range-based methods, and sensor fusion methods are considered to be part of the positioning method. It is important to note that distance estimation techniques and sensor fusion methods are not said to be independent localisation methods but rather part of some of them. Broadly, localisation methods are classified as collaborative and non-collaborative. We listed the time complexities of different methods found in the literature in Table 9. Note that the table does not include all methods since we only included those whose time complexity was evaluated in the literature.

8.1. Distance Estimation Techniques

As was discussed in section 8, range-based methods rely on inter-node distance estimation. There are several ways to convert data from the data layer to distance, and these techniques will be discussed in this section.

8.1.1. RSSI-Based Distance Estimation

As was discussed in section 7.1.1, RSSI is a measure of signal power at the receiver. RSSI can be used to estimate the distance between a receiver and a transmitter, and, in general, the higher the distance between the receiver and the transmitter, the lower the received signal power because the signal loses more of its power on its way, and this is referred to as path loss. There are different path loss models. The most popular one is the logarithmic distance path loss model

Table 9
The time complexities of indoor positioning methods from the literature

Method	Time Complexity
Trilateration	$O(n \log n)$, where n is the number of reference nodes [203]
Weighted centroid	$O(n)$, where n is the number of reference nodes [204]
Triangulation	$O(n^2)$, where n is the number of reference nodes [205]
Fingerprinting	$O(n^2)$, where n is the number of fingerprints [206]
DV-hop	$O(n^3)$, where n is the number of anchor nodes [207]
Belief propagation	$O(n^2)$, where n is the number of particles [208]
Multidimensional scaling	$O(n^3)$, where n is the number of access points [204]

[209]. Another common model is the free-space path loss model [210]. This model assumes that there is a clear line of sight between the receiver and the transmitter, hence the name. Since this is not usually the case in indoor environments, the logarithmic path loss model is used more widely.

RSSI is not a reliable indicator of distance because it varies significantly in NLOS conditions. However, it is one of the cheapest and most accessible sources of data, so, if coupled with more sophisticated distance estimation techniques, e.g., based on machine learning, its accuracy can be improved.

According to [98], because of high availability and low cost, RSSI has been one of the most popular types of data for distance estimation in COVID-19 contact tracing. However, many systems do not take measures to mitigate the noise issue, so some infected people at a far distance, at which the risk of contagion is low, may be estimated to be close, leading to unnecessary quarantine [8].

8.1.2. PDoA-Based Distance Estimation

PDoA can also be used for distance estimation between two nodes based on the difference between the phases of the receiver and the transmitter using the following formula from [211] for a single antenna i:

$$d = \frac{\lambda_i}{2} \times \left(\frac{\phi_i}{2\pi} + n_i \right), \tag{1}$$

where d is the distance, $\lambda = \frac{c}{f_i}$ is the signal wavelength, c is the signal speed, f_i is the signal frequency at antenna i, ϕ_i is the difference between the phases of the transmitted and received signal, and n_i is a parameter that needs to be configured. Like other techniques, PDoA-based distance estimation assumes a clear line of sight between the receiver and the transmitter, which is rarely the case in indoor environments. However, it can be combined with other techniques to improve the accuracy, e.g., with RSSI, ToA, etc. [9].

8.1.3. CSI-Based Distance Estimation

[212] extended the free space path loss model to describe the relationship between CSI and distance as follows:

$$d = \frac{1}{4\pi} \left[\left(\frac{c}{f_0 \times \gamma(d)} \right)^2 \times \sigma \right]^{\frac{1}{n}}, \tag{2}$$

where c is the wave speed, σ is an environmental factor that denotes RF baseband gains at the transmitter and receiver and power loss due to shadowing and passing through walls in NLOS conditions, n is the path loss fading exponent, d is the distance, $\gamma(d) = |(\frac{1}{K} \sum_{k=1}^{K} \frac{f_k}{f_0} \times |H_k|)|, k \in \{-15, 15\}$, K is the number of groups of subcarriers ($K = 30$), f_k is the frequency of the k^{th} subcarrier, $|H_k|$ is the amplitude of the k^{th} subcarrier's CSI, and f_0 is the central frequency. The authors of the study compared RSSI and CSI for triangulation using WiFi and found that CSI yielded a lower positioning error - 1.24 m versus 1.54 m, which cannot be considered an instance of sub-metre accuracy. Studer et al. [173] suggested the use of machine learning and mathematical modelling for CSI-based positioning, and Li et al. [213] did just that. They used multi-level fingerprints (see section 8.3.3 for a detailed description of the fingerprinting method) of CSI and fed them to a deep learning model for training. The model generated top five locations closest to the target with an error of 60 cm more than 90% of the time, compared to 4 m using RSSI.

8.1.4. ToF-Based Distance Estimation

One simple way of calculating the distance between two nodes (d) is simply multiplying the speed of the signal (c) by the time it travelled to reach the receiver (ToF).

$$d = c \times ToF \tag{3}$$

If the velocity of the signal is known, then this technique can be used, but its downside is that it does not account for noise. If a signal takes longer to travel because of obstructions, this technique will overestimate the distance covered by the signal. There are two ways to calculate ToF: using ToA and TWR, as described in sections 7.3.1 and 7.3.3 respectively. The choice of data for ToF calculation depends on whether clock synchronisation among network nodes is possible. Because TWR-based distance estimation does not require clock synchronisation, it is a popular technique of choice for UWB-based systems. For example, the authors of [115] used TWR and a fusion of noise filters to minimise positioning accuracy in a system with four UWB base stations and one tag acting as the target, reporting a 20 cm accuracy in a 100 m^2 area.

8.1.5. Image-Based Distance Estimation

Different image-based distance estimation techniques can be found in the literature. For example, [214] described how 3D cameras with depth sensors can be used to estimate the distance between a QR code and a camera. In [40], the authors presented a distance estimation technique between a camera and an LED lamp as follows:

$$H = \frac{f}{r} \cdot R, \tag{4}$$

where H is the distance between an LED lamp and a camera lens, f is the focal length of the image sensor, R is the radius of the lamp and r is the radius of the lamp on the imaging plane obtained by casting a projection from the lamp.

8.2. Sensor Fusion

According to [28, 215], the use of multiple sensors for indoor positioning improves positioning accuracy and positioning service availability, hence, multi-sensor fusion methods are becoming more popular among researchers. Sensor fusion methods are categorised by the level of coupling. [216] defined loosely coupled fusion as fusing the output of multiple positioning methods with a filtering algorithm such as a KF, whereas tightly coupled fusion was defined as a type of sensor fusion where sensor measurements were fused directly. Most fusion-based IPSs are loosely coupled but tight coupling is gaining popularity. Common technology combinations that support sensor fusion are WiFi and IMU (e.g., [216, 191]), BLE and IMU (e.g., [217]), UWB and IMU (e.g., [218, 219]). For example, in [216], an EKF was utilised to fuse PDR-based positions with WiFi-based positions as follows:

$$\mathbf{X}_k = F \cdot \mathbf{X}_{k-1} + \mathbf{\Omega} \cdot \mathbf{U}_{k-1} + \mathbf{W}_{k-1}, \tag{5}$$

where $\mathbf{X}_k$ is the PDR position vector at time k, $\mathbf{U}_k$ is the WiFi position vector at time k, $\mathbf{F}$ is the state transition matrix, $\mathbf{\Omega}$ is the control matrix and $\mathbf{W}$ is the system noise matrix. The equation illustrates that the next PDR position is coupled with both the previous WiFi position and PDR position, creating a tight coupling. [220] also utilised an EKF to fuse UWB position estimates obtained with trilateration and PDR data in a tight-coupling manner to correct for position and orientation drift. The UWB position estimate was loosely coupled with heading estimation and tightly coupled before being fed to PDR-based tracking algorithm.

8.3. Non-Collaborative Methods

Non-collaborative localisation methods have been in place for a long time, and their advantages and limitations have been studied well. In recent years, researchers have taken considerable interest in studying collaborative and infrastructure-free solutions [37] because they have minimal installation and maintenance costs. In addition, many non-cooperative methods suffer from low positioning accuracy, and researchers have been trying to employ machine learning to address the issue [6]. This section will cover non-collaborative positioning methods and machine learning enhancements proposed by researchers for them in recent studies. Examples of machine-learning-based enhancements for non-cooperative indoor localisation methods can be found in tables 10 (communication-free methods), 11 and 12 (communication-based methods).

8.3.1. Proximity-Based Positioning

Closest Neighbour Method Proximity methods simply rely on mapping the position of the target to the nearest reference point. If the target is in the range of one or more reference points, it is assigned the location of the reference point from which the strongest signal is received. Note that this method is also applicable to device-free positioning, i.e., for untagged targets, by defining a threshold on signal measurements, depending on the communication technology, which can be RF-based, sound-based or light-based [31]. This method is simple and is thus computationally inexpensive but is also highly inaccurate [142]. Of course, localisation granularity could be increased by decreasing network sparsity, but, if reference nodes are positioned too close to each other, they may interfere with each other, making it hard to arbitrate between several candidate nodes close to the target. Moreover, if high accuracy is required, the number of reference nodes required may be too high to be practical in terms of deployment and maintenance costs. Proximity-based methods are usually used for context-aware services like targeted location-based advertising and anonymous user data collection in shopping malls [9], i.e., where high accuracy is not required but simply knowing the target is near a certain location is enough. Proximity detection has been instrumental in curbing the spread of COVID-19. Contact tracing applications usually rely on BLE for proximity detection and do not require high granularity in distance estimation. They simply need to track people who have stayed within 2 m from an infected individual [237].

Centroid Localisation (CL) This method is similar to kNN but is not discrete, i.e., the target's position does not need to be assigned to a particular anchor node's position. According to [154], centroid localisation simply refers to taking the average of the coordinates of all anchors detected in the target's range, making it computationally inexpensive. This method's downside is that remote anchors contribute as much as those that are closer to the target, which skews the positioning result. This can be solved by assigning more weight to closer nodes, which is known as weighted centroid localisation (WCL). In WCL, the coordinates of each node are multiplied by the inverse of the distance from that node to the target (each node is given a weight), so that nodes that are further away contribute less to location estimation [238]. This method assumes that the closer two nodes are, the more accurate distance estimation between them is. WCL is simple and computationally inexpensive but fails to measure up to range-based methods in terms of accuracy [239]. Because of its lower accuracy, WCL is often combined with other methods like least squares [240]. CL-based methods

Table 10
Non-cooperative communication-free methods and recent ML enhancements

Method	Description	Conventional problems	Examples of ML enhancements
PDR	The target's movement is detected using an accelerometer, which estimates the number of steps made by the target. Then the target's heading and step length are calculated to estimate the next position of the target relative to its previous location.	• Accumulated drift error due to noise, meaning that PDR is only accurate in the short-term • Only provides relative position estimates, i.e., it needs a reference location, meaning that it needs to be coupled with another positioning method that is able to supply an absolute initial location of the target, which may not be accurate • IMU sensors can drain the battery if used for an extended amount of time	• Wang et al. [221] proposed a pedestrian movement behaviour recognition algorithm to classify different types of gait of a person with an SVM (see section A.2) and use it for better step length estimation. The authors claim to have increased PDR positioning accuracy to 96%. • Abadi et al. [119] designed an MLP (see section A.5) model for collaborative dead reckoning; specifically, they used the model to detect targets whose heading estimations based on their magnetometer readings were within an acceptable margin of error and used these estimations as heading estimates for targets moving in roughly the same direction. If several targets move in the same direction, the magnetic field may not change as predicted for all targets. • Jamil et al. [222] trained an artificial neural network to derive true gyroscope and accelerometer readings from noisy input. They fed gyroscope and accelerometer readings as well as accelerometer readings processed by a KF to the network for training.
CV	• *Object detection*: This method uses a deep learning model, usually a CNN, to detect targets from a video feed. The model must be trained on an extensive dataset of labelled images, but open-source models that have already been trained can be used instead. For custom labels, transfer learning can be used. • *Background subtraction*: In this method, a reference frame with no targets in sight is stored, and subsequent frames are compared to the reference. The difference is subtracted and assumed to be the moving target. • *Landmarking*: either artificial or natural landmarks are set up to assist in portable-camera-based localisation. Object detection is performed to detect natural landmarks and match them to a location. Artificial landmarks can be used in different ways, but usually they contain information about their location, which can be read by the target and used for self-localisation.	• CV-based localisation methods are computationally expensive and may be not fast enough for real-time frame processing • Object detection requires an infrastructure in the form of static cameras • These methods cannot perform well in poorly lit environments and may not be fast enough to handle different angles and orientations of the camera, especially if it is portable	• Punn et al. [223] designed a real-time object detection system for monitoring social distancing via surveillance cameras using a YOLO v3 model for human detection and DeepSort for tracking.

Table 11
Non-cooperative communication-based methods and recent ML enhancements: Part 1

Method	Description	Conventional problems	Examples of ML enhancements
Closest Neighbour	The target is assigned the location of the node closest to it.	• Low positioning accuracy • High number of reference nodes is required for high accuracy, which may be impractical	• Madoery et al. [224] performed feature engineering on BLE RSSI values to improve proximity detection, tested the dataset on random forest, SVM and logistic regression models and achieved a maximum accuracy of 83% with the random forest model. • Su et al. [225] compared random forest, SVM (see sections A.3 and A.2 respectively) and gradient boosted machine models with classical estimation theory algorithms in detecting people who have been in proximity with a person who contracted COVID-19 for more than 15 min and found that classical approaches had a confidence level of 69.6%, while the ML approaches showed a 20% improvement over the classical ones.
Fingerprinting	Consists of two phases: offline and online. In the offline phase, reference nodes are set up equidistantly in the indoor space, and signal readings are collected in each reference node's location to build a fingerprint for each, which are then stored in a database. In the online phase, fingerprints are collected in the target's location and mapped to the closest match in the database to estimate its location using classification algorithms like kNN, SVM, MLP, DT and more.	• Compiling an offline database is labour-intensive and time-consuming • Fingerprints can change with the rearrangement of objects • May be costly if high coverage is required • Accuracy depends on the algorithm used; simpler algorithms have higher error, whereas more accurate algorithms are more computationally expensive, making real-time positioning difficult • Large fingerprints can be hard to classify because of high dimensionality	• DBN (Deep Belief Network) (see section A.8 in the appendix for a description of DBNs) - automated feature extraction for dimensionality reduction [226]. • GAN (Generative Adversarial Network) (see section A.9 in the appendix for a description of GANs) - generation of artificial fingerprints for dataset augmentation [227]. • AE (autoencoder) (see section A.10 in the appendix for a description of AEs) - noise reduction [228]. • CNN (see section A.6 in the appendix for a description of CNNs) - generation of images based on various types of data, e.g., derived AoA from CSI [229], training a deep learning model in the offline phase and predicting the target's location with the trained model in the online phase. • RNN (see section A.7 in the appendix for a description of RNNs) - Hoang et al. [230] trained an RNN based on RSS time-series data from consecutive points on a pre-determined trajectory to take correlation between RSS readings over time into account.

Table 12
Non-cooperative communication-based methods and recent ML (Machine Learning) enhancements: Part 2

Method	Description	Conventional problems	Examples of ML enhancements
Multilateration	Distances from the target to at least three anchors are calculated, a system of equations based on the equation of a circle in 2D space or a sphere in 3D space, with the distances as the corresponding radii, is built and solved for the coordinates of the target.	• Heavily relies on the accuracy of distance estimation because it assumes the supplied distances are the ground truth	• Shi et al. [155] designed a k-means clustering algorithm to filter out extreme RSSI values. • Marques et al. [231] used kNN (see section A.1) to estimate the distance to anchors with RSSI instead of using raw RSSI values. • Li et al. [232] trained an LSTM (Long Short-Term Memory) model for modelling non-linear Bluetooth signal attenuation and mapping a sequence of RSSI values to a distance measurement between two nodes and achieved a localisation error of 1.5 m with trilateration. • Choi et al. [233] designed an unsupervised machine learning approach for range estimation, where cost functions were designed based on network estimation.
Multiangulation	AoAs/AoDs are calculated, and a system of equations based on basic geometry is built and solved for the coordinates of the target.	• Heavily relies on angle estimation accuracy, assuming there is no error • Angle calculation requires specialised hardware not available on all devices	• Alteneiji et al. [234] designed a CNN (see section A.6) whose input was the eigenvector matrix derived from the covariance matrix of the received signal, that estimated AoA using regression. • Khan et al. [235] used a single-hidden-layer neural network (see section A.5), Gaussian Process and regression trees to estimate AoA by means of extracting variances from normalised snapshot data from the MUSIC spectrum.
Centroid	The coordinates of all nodes in the target's range are averaged; the target is assumed to be in the centre of its region of reach.	• Low positioning accuracy • Long communication range required if the number of anchor nodes is low	• Jondhale et al. [236] combined trilateration and weighted centroid localisation estimates and fed them to an artificial neural network for training, which was then used for real-time localisation with an average error of more than 3 m.

tend to be computationally cheap but have high positioning error.

8.3.2. Geometric Methods

Geometric methods can be divided into two categories based on whether they use ranging or not. Range-based methods rely on data exchange (e.g., RSSI, ToA, TWR) between nodes and require network nodes to support ranging, which in turn requires specialised hardware. They are more popular among researchers because of significantly higher accuracy compared to range-free methods. Thus, it could be said that range-free methods are better for more high-level positioning, e.g., which room an object is located in rather than where exactly in that room it is. Range-based geometric methods include multilateration and multiangulation, and range-free methods include DV-hop (Distance-Vector hop), CAB (Concentric Anchor Beacon), APIT (Approximate Point in Triangle) and more. Range-free geometric methods are less accurate because they have a lower localisation granularity. In general, most of these methods try to restrict the search space to a small region where the target could be and calculate the area's centroid as the estimated position, but the target could be anywhere within that region, which means the accuracy could be low.

Multilateration Multilateration is a simple positioning algorithm that relies on simple geometry and is thus one of the least computationally expensive methods. In this method, distances between N anchor nodes, usually at least three, and the target are calculated, assuming that the positions of the anchor nodes are known in advance. Multilateration with three nodes is called trilateration and is often coupled with RSSI-based distance estimation. Then, the Euclidian distance formula in a Cartesian system of coordinates is used to construct a system of equations as in [153]. Distance estimation is an integral part of multilateration, and there are several ways to do this. Please refer to section 8.1 for how different types of data from the data layer can be used to calculate the distance between two nodes.

One of the main problems of multilateration is that it treats distances from anchors to the target as the ground truth, which is rarely the case because distance estimation techniques described in the previous section almost always involve some error. In other words, multilateration assumes that there is a clear LOS between the target and the anchors, which is not always the case in real-world settings. Multilateration can also be performed for 3D positioning, but at least four reference nodes with known positions are required [241]. In 3D positioning, the range of possible target locations for each node is represented by a sphere, and the intersection of four spheres yields the 3D position of the target. Increasing the number of reference nodes does not usually increase accuracy [242].

Studies that use multilateration usually use some kind of filter or machine learning to address the distance estimation error issue. For example, the authors of [155] designed a k-means clustering model that partitioned RSSI readings into three classes based on their distribution: RSSI values of signals weakened by interference, RSSI values that followed the normal path loss model and RSSI values of signals strengthened by external factors like power gain at antennae. They compared their filter to the mean filter, i.e., one that simply averages incoming RSSI values, in a positioning system based on trilateration and found that their filter showed a better performance with an error of less than 1.46 m. The authors of [49] used a KF to smooth fluctuations in incoming RSSI values and combined trilateration with fingerprinting in a system that fused BLE with PDR. The authors managed to achieve an average error of 2.75 m. In [231], kNN was used as a regression model to estimate the distance between reference nodes and the target, thus reducing distance estimation error, and trilateration was used for positioning. In general, it is difficult to achieve high positioning accuracy with multilateration because of the poor ability of distance estimation techniques to account for signal interference present in indoor settings.

Multiangulation Multiangulation is similar to multilateration in that it relies on the presence of reference nodes, but in this case, it uses AoA or AoD to estimate the position of a target, and, as was mentioned in section 7.2.1, two references nodes are enough for this in 2D space. Note that this method is also applicable to device-free positioning, where the target is identified by movement and thus a change in signal measurements [31]. For example, [243] employed phase changes in a CSI signal to triangulate the position of hands. Since this method is one of the most popular indoor positioning methods, readers are referred to [244] for the detailed description of multiangulation. Multiangulation can also be used for 3D positioning, but two angles, i.e., elevation and azimuth angles, are required, which can only be achieved with at least three reference nodes with known coordinates [245].

The advantages and disadvantages of this method are in line with the data it relies on, i.e., AoA/AoD. Similar to multilateration, this method's performance depends on the accuracy of angle measurements as it assumes they are correct, i.e., it does not account for noise (e.g., from nearby antennae). In addition, it requires that receivers are equipped with special antennae for AoA estimation, meaning special equipment is required. However, similar to multilateration, it is computationally inexpensive, though geometric methods are more computationally expensive than proximity-based methods as they require a system of simultaneous equations.

TDoA-Based Positioning Although TDoA makes use of ToA, TDoA is not used for inter-node distance estimation. Instead, TDoA-based positioning itself depends on distance estimation techniques, e.g., using RSSI. This method is also predicated on the simple displacement formula, i.e., velocity times time. In this method, ToA values are recorded from multiple reference nodes (at least four [113]), and a system of equations is constructed to derive the position of the target, but this system of equations assumes that the coordinates of reference nodes are known [246]. The system of equations makes use of the fact that the difference in distances from the target to two nodes j and i is proportional to the difference in the time they had to travel to the target. One of the downsides of this method is that, similar to other range-based methods, it assumes the distances between nodes are correct, i.e., it does not account for error in distance estimation. Similar to other geometric methods, TDoA-based positioning is computationally inexpensive as it is simply based on a system of simultaneous equations.

8.3.3. Fingerprinting

Fingerprinting is one of the most accurate methods for indoor positioning and is thus widely used [247]. A fingerprint refers to a vector of values that acts as a unique identifier for a reference location. Fingerprinting requires a training phase before localisation can occur. This phase is called the offline phase, where the indoor space is divided into equal sectors with reference locations, and fingerprints of data such as RSSI [157, 116, 248, 238, 49, 117], sound

[249], magnetic field data [250], CSI [251] or even images for computer-vision-based positioning [252] are collected over time at each location and stored in a database. Some systems use hybrid fingerprints, e.g., [253] combined CSI and RSS data into fingerprints. Once the fingerprinting database is ready, target nodes can build their own fingerprints, which are then compared to offline fingerprints. A reference location with the closest matching fingerprint is selected, and the target is predicted to be in that discrete location [9]. Because fingerprinting most commonly involves mapping indoor positioning data to a reference location rather than estimating the distance to reference nodes directly, it is classified as a range-free method, as in other works, e.g., [202, 254]. Note that this method is also applicable to device-free positioning, but in this case, fingerprints are based on how the object of interest perturbs the signal [31]. For example, [255] implemented a WiFi-based device-free indoor positioning system that employed domain adaptation to differentiate between CSI variation without the target and with the target for fingerprint-based localisation. [256] also used WiFi CSI for device-free positioning with continuous calibration of fingerprints to account for changes in CSI readings over time compared to the original fingerprint database. The computational complexity of fingerprinting depends on the fingerprint matching algorithm. Simple algorithms like kNN are less expensive than deep-learning-based methods, for example.

One of the major limitations of fingerprinting is the extensive amount of effort and time required to construct the fingerprint database. Another drawback of this method is the fact that fingerprints can change as the arrangement of objects in the indoor environment is altered, meaning that the database should be updated regularly. Thirdly, mapping the target's location to a reading in the database yields a discrete set of coordinates, whereas the target could be anywhere between two reference nodes on a continuous spectrum, so there is a margin of error involved depending on the distance between the nodes. Of course, the number of reference locations could be increased, but this would mean that differences between the fingerprints of neighbouring nodes would be lower than typical online measurement variations caused by noise, making selecting a reference node with the closest fingerprint difficult [9]. Therefore, it is essential to strike a balance between localisation granularity and the number of reference nodes.

Fingerprinting involves mapping an online fingerprint to an offline location, which can be regarded as a classification task. Researchers have tried using different classifiers in recent years for localisation, but simpler ones generally do not perform as well because of a high degree of fluctuation in the fingerprint data, especially RSSI. This creates the need for more high-dimensional fingerprint vectors to model this variability, but simpler algorithms fail to capture the complexity of the input. Therefore, researchers have tried reducing dimensionality using methods like PCA [257] and LDA (Linear Discriminant Analysis) [258]. Even though these methods try to preserve the quality of the original data, some features are still bound to not be represented correctly. Therefore, researchers have recently been more interested in using deep learning, which can perform feature extraction on its own [18]. For example, the authors of [259] employed a convolutional autoencoder to denoise RSS fingerprints and combined it with a CNN for location estimation. The appendix provides an overview of machine learning models used in indoor positioning, either for localisation or to enhance positioning performance. Please refer to that section for information on the types of classification (and regression) models that can be used for fingerprinting-based localisation, which are kNN (section A.1), SVM (section A.2), MLP (section A.5), Naive Bayes (section A.4), CNN (section A.6) and decision trees (section A.3). Each algorithm has its strengths and weaknesses as well as input requirements, which are discussed in the appendix. For example, CNNs are usually used for image-based data, so fingerprints should be converted into images before training.

8.3.4. *Self-Processing-Based Methods*

Self-processing refers to a method being self-sufficient, i.e., not relying on external infrastructure and only utilising its own local resources. Dead reckoning is an example of this because it relies on IMU sensors embedded in smartphones. Magnetometer-based positioning is also self-sufficient, but it either uses magnetometer readings for heading estimation in dead reckoning or uses fingerprints of the readings. Fingerprinting was already described in the previous section, so this section is only going to cover dead reckoning.

According to [142], PDR is a self-localisation method that relies on measurements from inertial sensors. PDR is not capable of absolute position estimation, i.e., its estimates are relative to the point of origin, which should be supplied externally. It involves three steps: heading estimation, step length estimation and step detection. Readers are referred to [142] for a detailed description of PDR.

Similar to other methods, PDR suffers from noise that comes from IMU data. For example, device orientation plays a significant role in estimation quality [260]. Measurement noise in step length estimation using an accelerometer hinders positioning and leads to large errors. Another way is to use a simple linear model, i.e., assuming the target moves in a straight line, and the target's speed, but this method requires knowing the target's height, which is sensitive data if the target is a person. Machine learning can also be used to develop a model that takes multiple parameters into account, i.e., accelerometer readings, the target's speed, ground inclination, etc. Finally, heading estimation is typically performed using a compass or a gyroscope, where the former measures the target's angle of movement with respect to the true north and the latter measures angular velocity. Compass measurements are sensitive to ferromagnetic interference, and gyroscope readings are subject to drift error [142].

8.3.5. *Model-Based Methods*

These methods are mainly applicable to device-free positioning [31]. They generate position estimates based on signal propagation models such as shadowing models that describe RF signal attenuation or the excess path delay model for human presence detection. Then, based on the objective function, an optimisation algorithm such as genetic algorithms or gradient descent is run to find the estimate. These methods have low accuracy because they do not account for environmental noise, so model parameters need to be updated for new locations [31]. For example, [261] used RTI with its shadowing model to estimate the location of a target by generating tomographic images.

8.3.6. Computer Vision (CV)

Computer-vision-based methods are some of the most computationally expensive positioning methods because they rely on continuous processing of images, which often involves computationally heavy machine learning models. They also require offline training and digital map construction of the indoor space, which is labour-intensive. Nevertheless, computer vision is promising in that it provides very high localisation accuracy. Of course, similar to other methods, it is not immune to noise like lack of lighting, objects blocking the field of view, etc. However, if accuracy is of utmost importance, one may consider investing in surveillance cameras, although this is not necessary for all methods. Some studies explore the use of cameras with more advanced features like infrared cameras, 3D cameras and those equipped with depth sensors [262]. In general, computer vision methods rely on the use of cameras, which can either be part of the infrastructure or be carried by the target. Three types of computer vision approaches can be delineated based on literature review: object detection, background subtraction and landmarking.

Object detection is one of the simplest ways to localise an object and is usually performed by CNNs. Open-source models have already been trained to recognise a wide array of common objects like people, books, etc. They can be retrained to recognise custom objects with relatively small datasets with the help of transfer learning. Many object detection models have been developed over the years, including SSDs, RCNNs, YOLO and more [263]. In order to obtain an absolute position of the target, a map of the indoor space needs to be constructed along with a database of static camera locations. If tracking is required, object tracking algorithms like the mean shift algorithm [264] can be used.

Since running an object detection model is computationally expensive if high accuracy is required, some studies have used the background difference method, which takes advantage of the fact that the background captured by static surveillance cameras does not change much. It takes a reference frame with no objects of interest in view and compares each frame to the reference. If there is a difference, it is assumed that the target has caused the background to change, so the difference region is where the target is located. The authors of [265] used the background difference method to detect and track people through static cameras and combined this method with PDR. They used a sliding window approach to make sure the reference frame was updated regularly since lighting conditions and the background could change over time. One of the drawbacks of this approach is that there may be false positives like doors opening, which are hard to detect. However, targets do not have to carry any additional devices since localisation is purely dependent on motion, which means that users do not have to bring their smartphones or install localisation software beforehand.

Finally, landmarking is another popular computer vision-based positioning method. It is similar to fingerprinting in that it relies on building a database of landmarks and their locations in the digital map of the indoor space, but the use of landmarks in positioning the target is slightly different from fingerprinting. Landmarking is usually used in systems where the user carries a camera, i.e., they are not usually used in systems with static cameras. For example, the authors of [266] retrained a VGG19 CNN model for landmark recognition in video frames collected by users to assist pedestrian navigation. Similarly, [267] trained a CNN model based on ResNet50 [268] for scene recognition based on user-taken images and achieved an average error of 1.31 m. In another study [269], the authors used a depth sensor to estimate distances to nearby QR codes, which served as artificial landmarks with their locations encoded on them, and performed trilateration to locate the target. Essentially, this study combined landmarking and trilateration in one system.

8.4. Collaborative Methods

In collaborative methods, all devices (network nodes) participate in localising each other by exchanging information about their absolute or estimated locations, if known, and distances to their neighbours. One of the advantages of collaborative localisation is that infrastructure requirements can be greatly relaxed as devices' positions are incrementally propagated throughout the network, so not all devices need to have neighbours with known positions [197]. With the rising popularity of smartphones, collaborative positioning methods are expected to play an important role in indoor positioning. Let N be the number of unlocalised (agent) nodes, which includes target nodes, and let M be the number of anchor nodes, i.e., whose absolute position is known. In general, cooperative methods can be categorised based on the number of anchors involved in localisation. The first scenario is when the number of anchors exceeds the number of agent nodes, i.e., $M > N$. In this case, collaborative localisation is mainly used to enhance the accuracy of agent nodes' estimated locations. Traditional methods like trilateration can be used to localise agent nodes with at least three nodes, and their estimated locations can then be propagated to their unlocalised neighbours so that they can do the same. The second scenario is when $M < N$. In this case, if network connectivity is low, more sophisticated methods are needed, which usually employ the minimisation of an objective function that captures the joint positioning of all nodes. These methods can be collectively referred to as optimisation-based methods. One of the main problems with these methods is how to obtain an initial solution, and there are several ways to do this, including multidimensional scaling [270] and mean connected anchor initialisation [196]. Alternatively, anchor nodes can be equipped with GPS so that they can position themselves any time, especially if they are mobile, but this is only applicable to outdoor spaces [271]. The last scenario is when $M = 0$ and $N \neq 0$. This is a difficult problem because, according to [272], the number of anchor nodes in a collaborative localisation setting must be at least three. However, it can still be considered as a relative localisation problem, i.e., where each node obtains other nodes' locations relative to itself and the node itself acts as the origin. In general, collaborative positioning methods are relatively new, so more research is needed in this area.

8.4.1. Multidimensional Scaling (MDS)

According to [270], multidimensional scaling is an algorithm used to represent a set of samples in an r-dimensional space given a matrix of dissimilarities between each pair of samples. In the context of indoor positioning, the dissimilarity matrix is the matrix of pairwise distances between network nodes. MDS does not take locations of anchor nodes into account, meaning that it can be used even if all network nodes are mobile. In other words, MDS is an algorithm for fitting a dissimilarity matrix without any additional constraints. MDS is usually performed in a centralised manner and is computationally expensive [273]. However, MDS can be implemented in distributed and semi-centralised systems, lowering its computational load and increasing overall positioning accuracy.

8.4.2. Distance Vector Hop (DV-Hop)

DV-Hop is a range-free distributed localisation algorithm that relies on the arrangement of nodes in the network, whose coordinates are assumed to be known. In this method, the minimum number of hops it would take to reach a node via other nodes is calculated and multiplied by the average distance between two nodes. Readers are referred to [201] for a detailed description of this method.

Like other range-free methods, DV-Hop suffers from relatively low accuracy. To address this problem, improvements were proposed for the DV-hop algorithm by researchers. For example, Cai et al. [274] suggested including several objective functions instead of just one, where one objective function aims to minimise the absolute distance error and assumes that the average hop size for each node is different. They added one more objective function, which introduced a constraint based on the average hop size for all nodes to achieve better convergence. They tested the new model in simulated conditions and demonstrated an improvement over existing 3D DV-hop algorithms. Chai et al. [275] integrated whale swarm optimisation into their DV-hop algorithm to minimise inter-node distance estimation error, which was based on calculating the hop size.

8.4.3. Constraint-Based Optimisation Methods

Belief Propagation (BP) According to [197], belief propagation is a message-passing algorithm where each network node holds a belief about its current state, i.e., its position, but other pieces of data could be included as well, like velocity, in case nodes are mobile, and this state evolves according to a model of the target's behaviour, e.g., a motion model of a person [276], a robot [277], etc. [272]'s simulations showed that the minimum number of nodes with known positions in a collaborative network to achieve a unique localisation solution is three, but, due to node sparsity, the number of anchors in real-world settings should be at least 10, which is quite high.

One of the major advantages of this method is that a node is not required to have three nodes with known locations in its range to localise itself, as is required by triangulation and trilateration. Instead, a node can wait for its neighbours to localise themselves. Belief propagation is an umbrella term for collaborative Bayesian algorithms that rely on message exchange, which include MMSE (minimum mean square estimator) [278], MAP (maximum a posteriori) estimator [279], KF (for linear, Gaussian systems), EKF (Gaussian approximation for non-linear systems, runs faster than a particle filter) [140, 280, 281], UKF (Unscented Kalman Filter) and PF (for non-linear systems) [52, 51]. In general, they rely on calculating the next possible node states based on historical information and a function that determines the next state.

Maximum Likelihood Estimation (MLE) According to [282], MLE (Maximum Likelihood Estimator) is a parameter estimation method similar to the least-squares method. In the context of indoor positioning, it aims to minimise the error between estimated and real distances by taking the probability distribution of measurement noise into account, but, according to [196], the method itself is deterministic, meaning it produces one-shot locations. This method assumes that the probability distribution of measurement noise is known, which may not be the case. If Gaussian distribution is assumed, there may be additional error. Another problem with this method is that not only is this function not linear, it is also not convex, meaning that there is a risk of stopping at local minima while searching for an optimal solution. Therefore, an optimal starting value for the optimisation algorithm used is required, which is difficult to obtain since the search space is unknown. Other local search algorithms like simulated annealing can be used, but the problem of local minima remains. The minimisation function can be transformed into a relaxed version and solved using semi-definite programming [196], which will be described next.

Semi-Definite Programming (SDP) SDP (Semi-Definite Programming) is a collaborative positioning algorithm that helps find the optimum value of an objective function (either maximum or minimum), given a set of constraints in the form of inequalities. As was mentioned in the previous section, it can be used to solve a relaxed version of the collaborative localisation optimisation problem. The derivation of the relaxed version is beyond the scope of this paper. The problem is relaxed such that the cost function becomes

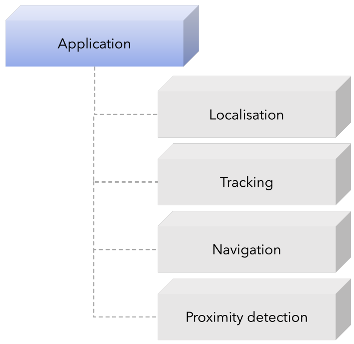

Figure 11: Application layer breakdown

convex but remains non-linear. Because of the relaxation, positioning error increases, but it is generally acceptable and close to the optimal solution [196]. One of the limitations of this algorithm is that it needs some nodes' positions to be known, i.e., with no anchor nodes localisation is impossible. This means that nodes need to localise themselves before semi-definite programming starts.

Parallel Projection Method (PPM) This is a distributed collaborative localisation method with low computational capacity that is also based on minimising the localisation cost function. It achieves high accuracy but needs to have full information on NLOS error, which may be hard to obtain [283]. The non-convex and nonlinear nature of the collaborative positioning problem complicates the search for global optima, as was mentioned in section 8.4.3. According to [284], PPM solves this problem with the POCS (Projection onto Convex Set) method, and the transformed objective function becomes a least squares problem. Before running, however, PPM needs to obtain an initial solution, which determines the quality of the final solution and can be done using multidimensional scaling or mean connected anchor. Then gradient descent is used to update positions of unlocalised nodes in each iteration by averaging the projections of each node's unlocalised neighbours [196]. The algorithm terminates when every node has been localised.

8.4.4. Other Methods

This section will discuss less popular collaborative methods. The first one is the outer-approximation method, which, according to [197], approximates the bounds of the area where the target could be and reduces it to a geometrical shape by finding intersections of the ranges of virtual and anchor nodes. The authors of this study previously used ellipses as location-bounding shapes and used polygons in their new work because they produced tighter bounds. In general, in outer-approximation, each unlocalised node j receives bounding areas from its neighbouring nodes, and the intersection of all these bounding areas becomes j's own bounding area, whose shape remains convex. Once all bounding areas are established, for each node, a random point within each unlocalised node's bounding area is picked as its estimated location. Initially, each node's bounding area is set to a circle whose radius is set to the range of the node, i.e., how far its signal can travel. Outer-approximation-based methods are usually range-free, and range-free methods have a lower accuracy compared to range-based methods [285].

A simpler version of outer-approximation is called APIT. In this method, all nodes in the network exchange data, i.e., their locations and IDs. Then, based on this data, all possible triangles formed by reference nodes are determined, and triangles containing the target are extracted. Then their overlapping area is taken, and its centroid is returned as the estimated position of the target. In terms of examples from the literature, [286] developed an enhanced APIT algorithm, where the authors used APIT to get an initial positioning estimate and then narrowed down the area of the target's possible location based on the tangent circle. One of the major shortcomings of APIT is that it requires high reference node density or a long communication range. Another limitation is that it requires that at least three anchors are in the target's range, otherwise, it yields an error. Similar to other range-free methods, APIT has a low positioning accuracy.

9. Application Layer

Finally, the application layer provides the most high-level perspective on indoor positioning, i.e., in terms of what it is intended to be used for in real-world settings. Based on the literature review, there is not much diversity when it comes to classifying IPS applications. One useful categorisation was proposed in [37], which categorised IPSs by the amount of granularity required by system users, which usually dictates and is dictated by the resources available to system designers. The authors of [238] designed a fuzzy-logic-based scheme that selected a suitable positioning method based on signal strength, room size and the number of available BLE beacons. Winter et al. [37] classified IPS navigation scales into building-level (error of less than 100 m), room-level (error of less than 10 m), furniture-level (error of less than 1 m) and component-level (error of less than 10 cm) navigation, from coarsest to finest. Some applications require extremely high accuracy, e.g., locating small but critical parts within a large piece of equipment, while for others component-level accuracy would be a waste of computational resources, e.g., locating a shop. A person can see where a shop's entrance is, so guiding him/her to the door would be unnecessary, unless the person's vision is compromised. This is just one classification system, but most studies classify IPS applications based on their use cases, industry or both, e.g., [287, 16, 9]. However, a single IPS is not necessarily supposed to be dependent on the domain it operates in. For example, a system used for guiding people to a certain location in a museum should be applicable for guiding people in a library. Classifying IPS applications based on their granularity provides a better generalisation because one cannot be replaced by the other, i.e., they are discrete. Another possible abstraction can focus on the value an IPS brings rather than the industry it operates in, e.g., localisation vs tracking. Thus, in this paper, IPS applications shall be categorised as follows: localisation, tracking, navigation and proximity detection, as depicted in Figure 11. Proximity detection is the easiest task for an IPS to accomplish, followed by localisation and tracking. Localisation and navigation require proximity detection, and tracking and navigation require localisation, so these tasks are related to each other, as is illustrated in Figure 12. This section will also cover examples of special applications related to COVID-19.

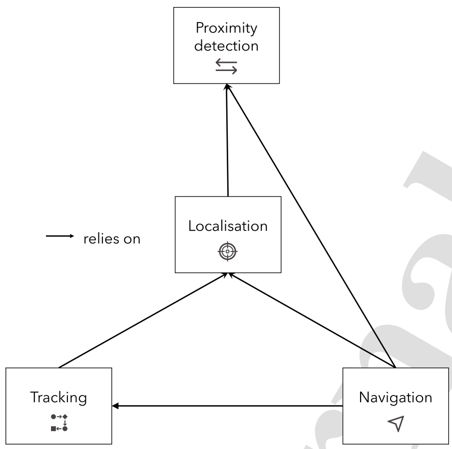

Figure 12: IPS applications

Table 13 lists examples of indoor positioning applications along with their requirements along five dimensions: accuracy (abbreviated in the table as ACC), response time (abbreviated as RT), latency (LT), scalability (SCL) and robustness (RB). Accuracy requirements are based on [37]'s navigation scale, where C stands for component-level, F stands for floor-level, R stands for room-level and B means building-level accuracy in Table 13. The other four requirements are defined as high (H), medium (M) and low (L). No specific metrics were defined for these requirements as we believe exact measurements depend on the use case.

9.1. Localisation

Localisation is a more difficult task compared to proximity detection because if an object is localised, calculating its proximity to another node is trivial, but simply knowing the object is near the node is not enough to provide a precise location estimate. In addition, localisation only provides one snapshot of a target's location, so if one needs continuous updates on the target's location, one may need to look for tracking solutions. Localisation plays a vital role in disaster management for locating victims in risky environments with low visibility such as during natural disasters like tornadoes, earthquakes, etc. For example, the authors of [4] developed an ad-hoc UWB-based IPS named CELIDON for assisting firefighters in localising their teammates, which achieved an accuracy of 30 cm. They proposed an architecture where tracking devices could be integrated into firefighters' equipment such as augmented reality masks and helmets. The authors of [288] designed a WiFi-based IPS for evacuating people trapped in buildings; their locations were stored in a central database for the rescue team to search for them. However, this system relied on internet connectivity and victims carrying smartphones, which may be lost during a disaster, so this system is unlikely to be a robust disaster management solution. Infrastructure-based systems do not guarantee to be functional during a disaster as the network could be disrupted. Thus, disaster management requires infrastructure-free solutions with little coupling. IPSs for dangerous environments can also be used to help victims locate the nearest exit. Apart from this, uses of localisation can be found in healthcare for locating patients, staff and medical equipment, e.g., [289, 290]. AAL (ambient assisted living) systems also need to keep a record of the elderly's location to make sure they do not go outside, e.g., the authors of [291] designed a personalised AAL system based on WiFi RSS fingerprinting with Gradient Boosted trees with AdaBoost, and [292]'s AAL system based on BLE beacons achieved 82% accuracy in zone classification in a building using machine learning, with random forest showing the best performance. In addition, IPSs can be used for localising lockers, rooms, books in a library, cafes in an airport, assets in a warehouse and much more. They are especially useful in multi-story and multi-building spaces.

9.2. Tracking

Tracking is a more difficult task compared to localisation. In a sense, tracking can be viewed as continuous localisation with additional constraints on localisation latency, i.e., if real-time tracking is required, then the time interval between two consecutive localisation attempts should be negligible. IPSs can be used to track the elderly and frail people in general to detect anomalies in their movement, e.g., when they collapse or have a seizure [3]. Tracking patients during COVID-19 quarantine is another new use case that has emerged recently. For example, the authors of [293] built a sensor-based system to monitor the health of patients diagnosed with COVID-19 that were self-isolating. They used wearable biomedical and geo-location sensors for

Table 13
Examples of IPS applications by industry with their requirements.

Industry	Application type	Example	ACC	RT	LT	SCL	RB
Disaster management	Localisation	Localising arson victims in a multi-story building	F	H	L	H	H
	Navigation	Building an escape route for people trapped in a building during an earthquake towards the closest exit	F	H	L	H	H
	Tracking	Tracking a firefighter looking for a victim to make sure he/she is on the right path	F	H	L	H	H
Asset tracking	Proximity detection	Tracking which items get approached the most in a shop	C	M	M	M	M
		Tracking which shops attract most attention in a mall	F	M	M	M	M
	Localisation	Localising lost goods in a large warehouse	C	H	L	M	H
	Navigation	Guiding a staff member to an item in a warehouse	C	M	L	H	M
	Tracking	Tracking an item to make sure it is not dropped off on the way	F	H	L	H	H
Healthcare	Proximity detection	Notifying nurses closest to a patient in case his or her condition is deteriorating	F	H	L	M	H
		Warning a person to maintain social distancing in case he or she comes too close to another person	R	H	L	H	H
		Notifying people who have been close to a confirmed case of COVID-19 for over 15 min to self-isolate	F	H	M	H	H
	Localisation	Localising estranged patients	F	H	L	M	H
		Calculating the probability of contracting COVID-19 in some space before a person decides to walk in	R	M	M	H	M
	Navigation	Building a route and guiding a visually impaired person towards a washroom	R	M	L	M	M
		Constructing a path towards a destination with a minimum number of people infected with COVID-19 on the way	R/B	M	L	H	M
	Tracking	Tracking an old person diagnosed with dementia at home with no caregiver nearby to make sure the person is safe	R	M	L	L	H
		Tracking delivery of prescriptions to patients	F	M	L	H	H
		Sending information about an exhibit to a museum visitor when he/she approaches it	R	M	M	M	M
Context-based assistance	Proximity detection	Sending targeted promotions, coupons or advertisements to a mall visitor depending on the shop he/she is next to	R	M	L	M	M
		Visualising performance of industrial equipment in an augmented reality application for staff as they pass by	F	H	L	M	M
	Localisation	Helping a person locate him- or herself in a large building in case he or she is lost	R	M	M	M	H
	Navigation	A person clicking on a cafe in an airport navigation app, which builds a route towards the cafe based on the person's current location	R	M	M	H	M
Security	Tracking	Tracking soldiers carrying out a mission	R	H	L	H	H
		Tracking military assets	F	H	L	H	H
		Tracking people to detect suspicious activity	R	H	L	M	H
Agriculture	Tracking	Tracking farm animals to make sure they do not go out of the barn or get stolen	R	M	L	M	H

remote health monitoring and WiFi- and GPS-based geofencing during quarantine. IPSs can also be used for tracking people to detect suspicious behaviour and prevent them from entering forbidden areas, e.g., staff, visitors, crime suspects, etc. They can even be used to track farm animals, e.g., the authors of [294] developed a UWB-based IPS for tracking sows in a barn and achieved a localisation error of 37 cm in a $37.5 \times 11.6\,\mathrm{m}^2$ area with seven base stations. There are many IPS instances in the literature that track mobile targets like humans [295, 296], robots [297] and even animals, but they are not limited to mobile objects. IPSs play an important role in asset tracking, especially those using BLE, RFID and ZigBee [298]. Asset tracking is not restricted to warehouses; RFID-based IPSs have been used for asset management in hospitals as well [299, 300]. Asset tracking can also be used to trace the use of items and even detect theft. For example, the authors of [301] built an anti-theft system for e-bicycles, where, if stolen, an e-bike could receive RSSI readings from nearby ZigBee anchors, and these RSSI readings would then be converted into distances and sent to a base station to perform trilateration.

9.3. Navigation

Navigation is defined as building a route from one point to another. While an IPS itself cannot build a route, it is used for deriving the coordinates of the destination, meaning that indoor positioning serves as the basis of indoor navigation. Building a route requires having access to a digital map of the indoor space, which is different from a radiomap of the indoor space because the latter simply stores the locations of reference nodes. Navigation is necessary for a wide range of industries, one of which is healthcare. Indoor positioning can be used to guide hospital visitors and staff to patients. Similarly, museum visitors can pinpoint an exhibit they would like to see in an app so that the app can build a trajectory towards it after obtaining their initial location. Another use case for indoor navigation is assisting visually impaired people and those who operate in low-visibility conditions, e.g., [302, 303]. Indoor navigation is especially widely used to enable autonomous movement of robots and unmanned aerial vehicles, which heavily rely on IMU sensors to avoid obstacles [304]. The authors of [305] performed multisource fusion for automated meal delivery in a restaurant. According to the authors, most meal delivery robots rely on magnetic navigation, which require magnetic strips to be installed and relocated in case the movement trajectory changes. The authors utilised UWB to let the robot obtain its initial location and infrared, ultrasonic and IMU sensors to avoid obstacles as it moved towards its destination.

9.4. Proximity Detection

Proximity detection refers to detecting whether a node is in the vicinity of another node of interest, which is usually an anchor node. Proximity-detection-based systems usually do not require a high level of accuracy because simply knowing a node is within reach is enough. Examples of such applications include location-aware marketing, whereby people walking by shops are sent customised promotions, coupons or advertisements depending on which shops they are close to [306]. These systems can be extended to send context-aware content to users not just based on their location but also on their spending habits, browsing history, age, gender and more [16]. Of course, this comes with privacy caveats, which is beyond the scope of this paper. Another example of context-aware data distribution is assisted exhibit exploration in museums, where information about exhibits is sent to people automatically as they get closer [307]. Proximity detection is also critical in the healthcare sector, where, in case a patient needs urgent help, staff in the patient's vicinity should be detected and notified immediately. Next, examples of COVID-19-specific applications that rely on proximity detection will be given.

9.4.1. Social Distancing

Barsocchi et al. [308] conducted a review of social distancing apps and described their use in three scenarios: before entering a populated indoor space, while being in a populated space and after leaving. In the first scenario, indoor localisation can be used to determine how crowded an indoor space is and inform visitors which places to avoid to minimise the risk of infection. In the second scenario, IPSs can assist in building the safest routes towards a destination, i.e., with the lowest number of infected people on the way. In the last scenario, crowd traffic patterns can be used to design an optimal cleaning schedule. Similar to contact tracing, social distancing applications usually rely on BLE but there are infrastructure-free systems as well. For example, the authors of [309] built a magnetic-field-based proximity detection system for enforcing social distancing, where people were asked to wear special devices with compact magnetic-field-generating hardware that was used to detect if two people were less than 2 m apart from each other with 100% accuracy.

9.4.2. Contact Tracing

Contact tracing is a special case of proximity detection and was defined by [310] as the ability to pinpoint, track and notify past contacts of an infected person so that they can be asked to self-isolate. Contact tracing apps have been developed in the last few years to curb the transmission of COVID-19, which is a new virus that has become a global health threat. Traditional contact tracing involves conducting a test on a patient suspected to have contracted COVID-19, and, if the result is positive, the patient is interviewed to list his/her recent contacts, which can be problematic because the patient may not be able to recall everyone [311]. Therefore, automated contact tracing can be an attractive alternative as it requires no human intervention other than installing an app on a smartphone or a wearable device, reducing the exposure of authorised personnel to possible COVID-19 cases. Braithwaite et al. [312] conducted a systematic review of automated contact tracing and found no evidence of its effectiveness for transmission reduction. They suggest contact tracing may be effective if population uptake of contact tracing apps is increased to at least 56%, but people are hesitant to trust these apps due to privacy concerns. Anglemyer et al. [311] also found that the effectiveness of digital solutions for contact tracing is unproven. They suggested digital solutions were unlikely to replace manual contact tracing completely. Despite this, Ferreti et al.'s [313] study found that manual tracing was not sufficient for containing the spread of COVID-19, and if it was coupled with digital contact tracing and social distancing, the pandemic could be stopped completely because digital solutions could detect possible infection cases much faster and inform affected people immediately. According to [310], Bluetooth is the most popular technology of choice for contact tracing because of its low power consumption and low cost. BLE's signal bandwidth is too narrow to handle ToA and TDoA for distance estimation [314], so RSS-based distance estimation is most suitable for real-time contact tracing, which is consistent with [310]'s findings. [314] found that RSS-based distance estimation in contact tracing was the optimal choice for decentralised systems, which are necessary for preserving users' privacy. In centralised systems, all users' records are stored on a single server, which calculates the probability of infection and notifies affected individuals in case the probability exceeds a certain threshold, whereas in decentralised systems, this probability is calculated locally.

10. Conclusion

In conclusion, we have used a systematic framework based on a six-layer model to provide a comprehensive survey of indoor positioning systems, covering indoor positioning technologies, algorithms, applications and current trends, with examples from recent studies. According to the model, an IPS can be described in terms of six layers: device, communication, network, data, method and application, sorted by increasing level of abstraction. The device layer is the lowest level of the model and delineates the physical devices used in the IPS, i.e., its tangible components, e.g., beacons, servers, smartphones, photodetectors, etc. The second layer of the model is the communication layer, which describes the communication technologies employed by the IPS, e.g., BLE, WiFi, UWB, etc. These are less tangible than the devices they are based on but are still not just a fabricated concept like the next layer (network), which explains the arrangement of IPS devices and how they interact with each other via their communication technologies. This layer is followed by the data layer, which describes what data is used for positioning and how it is processed before being fed into the method layer. The method layer is about positioning algorithms utilised in an IPS for localising one or more targets. Finally, the application layer describes the high-level functions of an IPS, i.e., what exactly it will be used for or where it will be applied in real life, e.g., locating people trapped in a building during an earthquake. Overall, this review shows that indoor positioning is a vast field with great research potential. Currently, there is no one single indoor positioning solution for all applications. The use of machine learning and the fusion of multiple technologies offer promising prospects for the development of indoor positioning. More research needs to be done to minimise IPSs' dependence on infrastructure and increase the distribution of computational power over all network nodes to minimise the risk of network failure. The six-layer model should provide a useful framework for the research community.

11. Remaining Challenges, Open Issues and Future Research

Indoor positioning is still an open research area with many directions for future work. In this section, we highlight some potential future research work.

11.1. Challenges/Open Issues

11.1.1. Noise Reduction

Based on the literature review, one of the most significant issues in indoor positioning research, despite decades of research, remains to be high levels of noise resulting from multipath fading and absence of a consistent line of sight in indoor settings. Although many studies report sub-meter accuracy, no consensus on a single solution has been reached because of considerations like devices available, infrastructure requirements, cost and more. For example, even though UWB shows promise, it is still expensive to adopt and maintain for small businesses. Deep learning methods and the use of advanced filters have already had a positive impact on positioning error, but more research is needed. The recent introduction of UWB into smartphones and the use of IRS for reducing noise in wireless communications shows that advances in hardware are also required, so optimising software and hardware for indoor positioning should be done as a joint effort.

11.1.2. Generalisation

Many IPSs are designed to be suited for specific indoor environments, meaning that they do not generalise to different settings. Researchers should explore how to make adapting to new environments more seamless, e.g., with transfer learning. Another major issue is device heterogeneity, especially in smartphone-based positioning. For example, different models measure RSSI differently, which poses an additional challenge to positioning methods.

11.1.3. Indoor positioning security and privacy

Existing research work on indoor positioning typically focuses on positioning accuracy. Another important issue is security and privacy. In other words, accuracy depends on system security. For example, if fake data are provided, the measurements become useless. Furthermore, there is also a need to protect user privacy while maintaining positioning accuracy. Therefore, as demand for indoor positioning is rising, it is vital for researchers to investigate privacy-preserving and secure positioning solutions.

11.2. Future Research

11.2.1. Blockchain for secure positioning

With the advent of blockchains, they can be used to authenticate IPS network nodes, track decentralized records and ensure positioning data integrity. In other words, it is of interest to investigate the use of blockchains for secure positioning in a decentralised environment.

11.2.2. Deep learning for indoor positioning

Even though there is a significant body of literature on the use of deep learning for indoor positioning already, existing works still have their limitations, such as long inference time, dependence on a central entity for positioning, low adaptability to new environments, etc. That means, more studies are required to tackle these issues. Moreover, deep learning provides a promising solution for dealing with noise inherent in indoor positioning data, but new or enhanced solutions are required to account for security and privacy considerations.

11.2.3. Infrastructure-free collaborative indoor positioning

There is a pronounced need to minimise dependence on complex IPS infrastructure in order to reduce coupling and maintenance costs. This can be achieved by using co-operative indoor positioning, whereby dependence on infrastructure is relaxed because IPS nodes can propagate their locations throughout the system, meaning that remote nodes do not have to a certain number of neighbours to localise themselves. Collaborative indoor positioning has not received much attention compared to non-collaborative indoor positioning. This is a promising area for further research.

11.2.4. Indoor positioning based on hybrid technologies and sensor fusion

Currently indoor positioning research tends to focus on individual technologies. It is of interest to conduct more studies on using hybrid technologies such as BLE/UWB/BLE to enhance the overall performance. Coupling with AI/machine learning, more effective methods can be developed. Tightly coupled sensor fusion approaches are attracting attention in the research community since they can yield better positioning performance than loosely coupled methods.

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A. Overview of Machine Learning Algorithms

In this appendix, we give an overview of commonly used machine learning algorithms. They are used to enhance positioning methods.

A.1. k-Nearest Neighbours (kNN)

In kNN, k vectors from the training dataset that are closest to a test sample are selected, and the most frequent label among the selected vectors is returned as the label of the test sample. Distances between samples can be calculated using different methods, such as Euclidian distance [117, 315], Chebyshev distance [315], cosine similarity [49], etc. When $k = 1$, i.e., only one nearest vector is selected, this is referred to as simply a nearest-neighbour algorithm. Another common version of kNN is called weighted kNN. In kNN, labels of k nearest neighbours are simply averaged if it is used for regression, or the most frequent label is chosen in a classification task, whereas in weighted kNN (WKNN), closer samples are given more weight. WKNN is said to be more accurate than kNN [117]. kNN shows poor performance with high-dimensional data, and, in the context of indoor positioning, the number of dimensions in fingerprints increases with increased data variability, especially with RSSI [16].

A.2. Support Vector Machine (SVM)

SVM is a machine learning algorithm that takes a series of training samples and is trained to find a hyperplane that separates the samples into categories based on their output labels; an SVM can be used for classification and regression tasks, so its output does not have to be discrete. SVM is not as computationally expensive as more advanced machine learning models, but it is powerful enough to handle non-linear feature spaces, making it useful for handling complex signal interference patterns in indoor spaces. However, if the number of support vectors is large, which controls error tolerance, i.e., how closely the hyperplane follows training data, then space complexity may be an issue.

A.3. Decision Trees (DT) and Random Forest

A decision tree is a supervised learning model that learns some decision rules based on the input data features. Each decision path leads to a classification label. Single decision trees tend to perform poorly since they may not be able to effectively identify the most efficient set of decision rules. Therefore, it is common to combine multiple decision trees in a single model called Random Forest. The input data is randomly divided into n partitions, and a decision tree is constructed based on each partition. Then the label returned by the majority of decision trees based on a test sample is returned in a classification task. In regression, the predictions may be averaged or the maximum value could be taken. There are multiple ways to arbitrate between multiple decision trees' votes.

A.4. Naive Bayes (NB)

This is one of the fastest classification algorithms that uses Bayes' theorem to calculate the probability that a test sample belongs to a certain class given its set of features. It assumes that every pair of features is conditionally independent from each other, hence the "naive" label [316]. The probability that an input vector of online readings x corresponds to a label l_i is [316]:

$$P(l_i|x) = \frac{P(x|l_i)P(l_i)}{P(x)}, \tag{6}$$

and l_i yielding the highest probability should be returned, i.e., $\underset{i\in\{1...n\}}{argmax}(P(l_i|x))$, where n is the number of labels. $P(x)$ and $P(l_i)$ are assumed to be known, so the goal is to find an l_i that maximises $P(x|l_i)$.

A.5. Multilayer Perceptron (MLP)

MLP is one of the simplest deep learning models that consists of an input layer, an output layer and one or more hidden layers in between. Nodes in each layer are connected to every node in the previous layer, which is why MLP is also referred to as a fully connected neural network. In the simplest configuration, MLP has only one hidden layer, and the more hidden layers are added, the better the network can model high-dimensional data, but it also becomes more computationally expensive. In the context of indoor positioning, the input layer usually accepts fingerprints of reference locations, and the network is trained to output the coordinates of the corresponding locations with supervised learning. The model is then used in the online phase to estimate online fingerprints' corresponding locations. The hidden layers learn the relationship between the input and the output by updating their weights, so that in the online phase the input can be multiplied by the weights to obtain an estimated output.

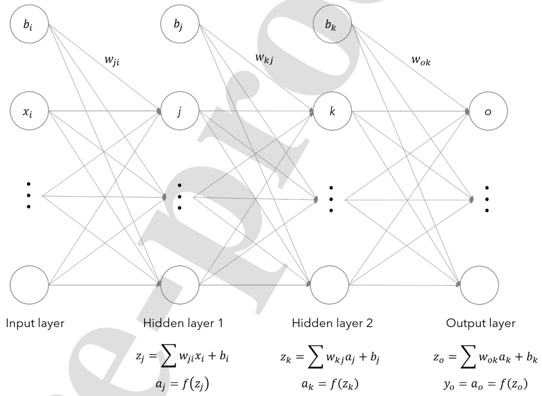

Figure 13: MLP structure

Essentially, an MLP network is like a complex function, where the target is to optimise the weights. This can be done using gradient descent, which minimises the error between network output and real output. Figure 13 provides an overview of the structure of an MLP network. The values of each layer are calculated by multiplying the weights of the current layer by the values of the previous layer, so the general formula for each layer is $a_r = f(\sum w_{rt}a_t + b_r)$, where f is an activation function, e.g., ReLU, b_r is a bias unit, a_r is a value of the current layer, a_t is a value of the previous layer and w_{rt} is a weight outgoing from node t to node r.

Since all layers in MLP networks are fully connected, they are computationally expensive, especially as more layers and units are added, but examples of them being used in the literature still exist. For example, [317] used MLP with RSSI and AoA measurements from BLE anchors for localisation in a $4 \times 4\,\mathrm{m}^2$ area and achieved an error of just over 1 m.

A.6. Convolutional Neural Network (CNN)

CNNs are mainly used for image processing. Since images can be large, running a MLP on images, especially videos, would be slow, so CNNs were designed to reduce the computational load and allow for real-time image processing. A CNN typically includes pooling, convolutional and fully connected layers. A single convolution consists of three steps. First, the input is convolved using a kernel and a sliding window to generate a set of features. Secondly, the features are run through an activation function like ReLU, and finally, the pooling layer reduces the size of extracted features, which speeds up the model. Next, these features are fed into a fully connected layer so that it can map them to a label [318]. In indoor positioning, data like RSSI fingerprints is usually transformed into images before being fed into a CNN. For example, the authors of [157] combined fingerprints of WiFi RSSI with magnetic sensor data to generate images as training samples for a deep CNN. They achieved an error of less than 1 m in a $60 \times 40\,\mathrm{m}^2$ test bed and found that WiFi's lowest accuracy values were worse than those that were generated by a magnetometer, and vice versa.

A.7. Recurrent Neural Network (RNN)

Recurrent neural networks are usually used for sequential data, i.e., something where historical information matters, e.g., stock exchange, speech, music, etc. Taking a stream of RSSI values as an example, most methods assume that RSSI values in a sequence are independent of each other, but RSSI sequences may carry useful information based on how the signal reflects off of objects, e.g., [319]. In an RNN, each node considers the current input as well as historical inputs, i.e., the network maintains "memory" of the data it saw immediately prior to the current input. An unrolled version of a sequence of RNN nodes is illustrated in Figure 14.

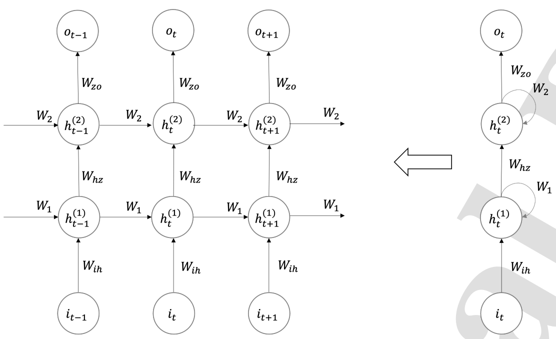

Figure 14: RNN structure (adapted from [320])

$h_t^{(i)}$ refers to the same node $h^{(i)}$ at time t. In general, each node's value is calculated based on the following formula [319]:

$$\begin{cases} h_t^{(1)} = activation^{(h^{(1)})}(\beta_{h^{(1)}} + W_1 h_{t-1}^{(1)} + U x_t), \\ h_t^{(2)} = activation^{(h^{(2)})}(\beta_{h^{(2)}} + W_2 h_{t-1}^{(2)} + V h_t^{(1)}), \\ o_t = activation^{(o)}(\beta_o + R h_t^{(2)}) \end{cases} \tag{7}$$

The formula shows that each unit considers its previous value, i.e., at time $t-1$ and the newly incoming value (x_t for $h_t^{(1)}$, for example), each with its own weight, adds a bias term β and passes the result to an activation function ($activation$), which can be different for each layer, e.g., ReLU for hidden layers and sigmoid for the last layer. o_t is the output unit, which does not have a feedback loop, has its own weights and its own bias term. Note that the weight for the previous value of the current unit (e.g., W_1) is different from the weight for the incoming data from the previous layer (e.g., U).

A.8. Deep Belief Network (DBN)

According to [321], a DBN is an unsupervised learning model formed by stacking several RBMs together such that the hidden node of one RBM (Restricted Boltzmann Machine) acts as the visible node of the next one. An RBM is itself a neural network represented as a bipartite graph with two layers, a visible and a hidden layer, and nodes within the same layer are not connected, but every node in one layer is connected to every node in the other layer, which is in a sense similar to MLP. Each node is a stochastic variable with a value between 0 and 1. An RBM learns a probability distribution of its sets of inputs so that it can learn to reconstruct its input using its weights. DBNs are thus usually used for generative learning tasks like image generation. However, they can also be used for regression, classification and more. The energy function of an RBM is calculated as

$$E_{RBM}(V, H; \theta) = -(\sum_{i=1}^{n} b_i V_i + \sum_{j=1}^{m} c_j H_j + \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij} V_i H_j), \tag{8}$$

where $\theta = \{W, b, c\}$ is the set of model parameters, W is the weight matrix, w_{ij} is a weight connecting a visible node i and a hidden node j, b_i and c_j are the bias weights of visible and hidden nodes respectively, H_j is the value of a hidden node, V_i is the value of a visible node, n is the number of visible nodes and m is the number of hidden nodes [321]. The network calculates the probability of each (V_i, H_j) pair and of a single visible node as follows [321]:

$$p(V, H) = \frac{e^{-E(V,H)}}{\sum\limits_{(V,H)} e^{-E(V,H)}}, \tag{9}$$

$$p(V) = \sum_{H} p(V, H) = \frac{\sum\limits_{H} e^{-E(V,H)}}{\sum\limits_{(V,H)} e^{-E(V,H)}} \tag{10}$$

Here, the activation function is the sigmoid function. The network aims to update its weights so that its output matches the input as closely as possible. Weight update happens based on approximating each $p(V)$ as follows [321]:

$$\begin{aligned} w_{ij} := w_{ij} - \epsilon(\frac{\partial \log p(V)}{\partial w_{ij}}) = w_{ij} - \\ \epsilon(E_{data}[V_i H_j] - E_{model}[V_i H_j]), \end{aligned} \tag{11}$$

where $E_d[V_i H_j]$ represents the expected value over distribution d. In other words, an RBM calculates the probability of a hidden node, which represents a certain feature, given a vector of visible node values $p(H|V) = \prod_{j=1}^{m} p(H_j|V)$. In order to perform classification or regression, one more layer needs to be added after the last hidden layer. In the indoor localisation field, DBNs are usually used for feature extraction. For example, the authors of [226] used a four-layer DBN to normalise incoming RSSI values into a fingerprint that was easier to map to another fingerprint in the offline database. The DBN was trained to capture the behaviour of RSSI values in the test environment.

A.9. Generative Adversarial Network (GAN)

In [227], a GAN is described as a combination of two types of nets: generative and discriminative. Generative nets learn the probability distribution of its input and determine how likely a certain output is in that distribution. This means that the generative part of a GAN learns how to transform an initially random input into a data instance that exhibits the characteristics of a real one. Discriminative nets determine how likely an instance from the generative network to be assigned a certain label, i.e., either fake or real. In other words, a GAN consists of an unsupervised learning model (the generator) and a supervised learning model (the classifier) that are trained together in an adversarial fashion, i.e., the generator is trained such that the discriminator cannot tell if an instance is fabricated about half the time. GANs are usually used for data synthesis, including, but not limited to, images, text, music and more. During training, the objective is to minimise the cost function, i.e., the joint error of the two models [227]:

$$\begin{aligned} \underset{G}{min}\ \underset{D}{max} V(D,G) = E_{x\sim p_{data}(x)}[\log_{10} D(x)] + \\ E_{y\sim p_y(y)}[\log_{10}(1 - D(G(y)))] \end{aligned} \tag{12}$$

The discriminator tries to maximise the number of fake instances it detects, while the generator tries to minimise it. $p_d(v)$ is the probability distribution d of variable v, $D(x)$ is the output of the discriminator, and $G(y)$ is the output of the generator. GANs have been used in indoor positioning for augmenting offline fingerprint datasets because fingerprint collection requires extensive effort. For example, the authors of [227] used a GAN to generate thousands of new fingerprints to cover the entire indoor environment, and they also used a semi-supervised deep neural network to label the new fingerprints based on fingerprints with known labels.

A.10. Autoencoder (AE)

An autoencoder is an unsupervised deep learning network that learns how to transform an input into another representation using an encoder and convert it back to its original form using a decoder. The latent space representation is computed in a layer called the bottleneck. That is why an autoencoder has the same number of input nodes and output nodes. Autoencoders can be used for data compression, anomaly detection, dimensionality reduction and more. In indoor positioning, AEs are used to reduce noise in fingerprints and use the smaller fingerprints to perform regression for position estimation, i.e., the decoder can be replaced with a supervised model [228].

Note: The following biographies may be updated in the final version or shortened if required.

Yerkezhan Sartayeva is a PhD student at the Hong Kong Polytechnic University, expected to graduate in 2025. She received her Bachelor of Science in Computing (First Class Honours) from the Hong Kong Polytechnic University in 2020 and was admitted into a PhD program in Hong Kong a year later under the Hong Kong PhD Fellowship scheme. Her research focuses on indoor positioning, specifically on the use of ultrawideband communication technology for collaborative indoor localisation using smartphones. Before she started her PhD, she worked as a software developer specialising in computer vision and a technical lead for a regulatory affairs database management system at an oil company in Kazakhstan.

Dr Yik Him Ho received his BA in Computing (First Class Honors) and PhD degree from The Hong Kong Polytechnic University in 2014 and 2021, respectively. His research interests include indoor localization, Bluetooth Low Energy, and cloud computing. He has received several local and regional IEEE awards, including third prize in the IEEE Hong Kong Section 2014 (UG) Student Paper Contest, first prize in the IEEE 2015 Region 10 Undergraduate Student Paper Competition, and honorary mention in the 2016 IEEE ComSoc Student Competition "Communications Technology Changing the World".

Henry C. B. Chan received his B.A. and M.A. degrees from the University of Cambridge, England and his Ph.D. degree from the University of British Columbia (UBC), Canada. At Cambridge, he received the Christina Barnard Prize (Girton College) in recognition of his academic achievement. At UBC, he received the NSERC Postgraduate Scholarship, UBC Graduate Fellowship and BC TEL Graduate Scholarship.

Before starting his academic career, he had years of industrial/commercial working experience. From October 1988 to October 1993, he worked with Hong Kong Telecommunications Limited, primarily on the development of networking services in Hong Kong. Between October 1997 and August 1998, he worked with BC TEL Advanced Communications on the development of high-speed networking technologies and ATM-based services. In August 1998, he joined The Hong Kong Polytechnic University (PolyU), where he is now an Associate Head and Associate Professor in the Department of Computing.

His research interests include networking/communications, cloud computing, electronic commerce and computing education. He has co-authored research papers published in various journals such as: Computer Journal, Computer Networks, Computer Communications, Expert Systems and Applications, IEEE Communications Surveys & Tutorials, IEEE Computer, IEEE Journal on Selected Areas in Communications, IEEE Transactions on Communications, IEEE Transactions on Computers, IEEE Transactions on Emerging Topics in Computing, IEEE Transactions on Mobile Computing, IEEE Transactions on Parallel and Distributed Systems, IEEE Transactions on Vehicular Technology, and IEEE Transactions on Circuits and Systems for Video Technology.

He was Chair of the IEEE Hong Kong Section in 2012 and Chair of the IEEE Hong Kong Section Computer Society Chapter between 2008 and 2009. He was the recipient of the prestigious IEEE Computer Society Computer Science and Engineering Undergraduate Teaching Award with the following citation: "for outstanding contributions to computing education through teaching, mentoring students and service to the education community" in 2015. At PolyU, he has received two President's Awards in teaching: 2015/2016 and 2010/2011 President's Award for Excellent Performance/Achievement (Teaching). He has also received 2008/2009 President's Award for Excellent Performance/Achievement (Services) and 2007/2008 President's Award for Excellent Performance/Achievement

(Services - Team Award) (Team Member) and five awards from the Faculty of Engineering. Under his supervision/guidance, his students have received over 50 awards.

Professor Peter Han Joo Chong is currently an Associate Head of School (Research), School of Engineering, Computer and Mathematical Sciences, at Auckland University of Technology, New Zealand. He received the Ph.D. degree from the University of British Columbia, Canada, in 2000. He is an Adjunct Professor at the Department of Information Engineering, Chinese University of Hong Kong, Hong Kong. He was previously an Associate Professor (tenured) in the School of Electrical and Electronic Engineering at Nanyang Technological University, Singapore.Between 2013 and 2016, he was a Director of Infinitus, Centre for Infocomm Technology, at NTU. From February 2001 to May 2002, he was a Research Engineer at Nokia Research Center, Finland. Between July 2000 and January 2001, he worked in the Advanced Networks Division at Agilent Technologies Canada Inc., Canada. His research interests are in the areas of mobile communications systems including MANETs/VANETs, V2X, Internet of Things/Vehicles, artificial intelligence for wireless networks, and 5G networks. He has published over 300 research articles. He is a Fellow of The Institution of Engineering and Technology (FIET).

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Author	**Contributions**
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Him Yik Ho	Conceptualisation, Writing – Reviewing and Editing
Peter H. J. Chong	Conceptualisation, Writing – Reviewing and Editing

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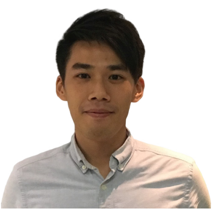

Yerkezhan Sartayeva

Declaration of interests

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: