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Review

Top 10 technologies for indoor positioning on construction sites

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ABSTRACT

Indoor positioning complements the mature outdoor positioning technology, Global Navigation Satellite System (GNSS), by achieving real-time positioning in any environment under a blockage of GNSS signals. In the construction management field, this paper demonstrates that indoor positioning enables five significant applications that considerably enhance work efficiency and safety on construction sites. Without a perfect indoor positioning system and under complicated site environment, developing a suitable on-site indoor positioning system is challenging and essentially user-oriented and environment-specific. This paper analyses the challenges to implement on-site indoor positioning systems, and proposes indoor positioning performance metrics, namely APP-CAT, for evaluating indoor positioning systems. The fundamental indoor positioning principles are first discussed and evaluated. Subsequently, the top 10 indoor positioning technologies, selected by their performance in APP-CAT and their popularity, are thoroughly compared. The promising trends of indoor positioning development, e.g., indoor positioning hybridization, game theory positioning, and integration with BIM models, are highlighted.

1. Introduction

Position and location information is fundamental and significant to realize a considerable number of applications that provides ubiquitous location-based services that can benefit the overall engineering industry. In particular, indoor position and location information has led to the realization of important technological concepts such as Internet of Things (IoT), context awareness, autonomous robots, ubiquitous computing, etc. In the field of construction management, indoor position information has supported promising applications that can considerably enhance the productivity, efficiency and safety on construction sites in five major applications, which are (1) construction safety management [115], (2) construction process monitoring and control [96], (3) inspection of construction structures and materials [104], (4) construction automation with robotics [42], and (5) the use of building information modelling (BIM) technology for construction progress management [16].

Position and location information is acquired by different positioning technologies. In outdoor environment, the mature outdoor positioning technology namely Global Navigation Satellite System (GNSS) has already achieved a positioning accuracy at the sub-meter level. GNSS technology comprises of various outdoor positioning systems, e.g., GPS, GLONASS, Galileo and BeiDou [62], whose services are ubiquitously available on the Earth. However, outdoor positioning systems cannot provide suffer from a poor accuracy wherever there is a blockage of GNSS signals in the environment [101]. These environments include spaces that are completely or partially concealed by building structures, dense urban areas surrounded with tall buildings, and underground environment. It is necessary to develop indoor positioning technologies to complement the mature outdoor positioning technology. In particular, construction sites, which are a semi-indoor environment, require the support of indoor positioning technologies to realize seamless real-time positioning.

In this paper, the term “indoor positioning” encompasses two different approaches, which are localization and positioning. Localization refers to a specific region, like a room, at which the target is located; whereas, positioning refers to the position coordinates of a target with respect to a map. Usually, the terms “localization” and “positioning” can be used interchangeably. For example, both “localization” and “positioning” are used in the titles of numerous references [64], but similar technologies, principles and algorithms are compared. In spite of that, differentiating localization and positioning is useful when it comes to application, because sometimes precise position information is needed, whereas sometimes rough location information suffices. In this paper, however, both localization and positioning are grouped under the term “positioning”, unless otherwise specified.

The extensive research in indoor positioning technologies has led to the development of various categories of indoor positioning

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Table 1
Categories of indoor positioning technologies.

Category	Examples of technologies
RF waves	Wi-Fi
	Bluetooth & Bluetooth Low Energy (BLE)
	Zigbee
	Ultra-wide band (UWB)
	Radio frequency identification (RFID)
	Indoor Global Navigation Satellite System (GNSS)
	Frequency modulation radio (FM-radio)
Non-EM waves	Ultrasound
	Geomagnetic waves
Full-spectrum light	Range imaging
	Visible light positioning
	Laser

technologies, from conventional radio frequency (RF) technologies like wireless fidelity (Wi-Fi), Bluetooth and Bluetooth Low Energy (BLE), Zigbee, radio frequency identification (RFID), ultra-wide band (UWB), indoor GNSS, to non-electromagnetic (non-EM) waves like ultrasound and geomagnetic waves, and to vision-based technologies that utilize the full-spectrum light, like image processing and range imaging. Table 1 summarizes the three major categories of indoor positioning technologies, namely (1) RF-waves, (2) non-EM waves, and (3) full-spectrum light. With the emergence of different technologies, many indoor positioning principles and their corresponding algorithms have also been developed, providing different methodologies to achieve indoor positioning. (1) Technologies, (2) principles and algorithms, and (3) hardware equipment, are the three basic components of an indoor positioning system.

Despite the wide research in indoor positioning, currently there is no single perfect system that can achieve indoor positioning yet. Individual indoor positioning technologies, principles and algorithms have their own strengths and limitations. Therefore, researchers have highlighted the great potential in combining different outdoor and indoor positioning technologies, principles and algorithms to overcome their individual shortcomings to achieve more accurate indoor positioning [110]. Such a combined positioning technique is also referred to as hybrid positioning [110]. The modes of hybridization can be classified into three types: (1) indoor-outdoor positioning technologies hybridization, (2) indoor positioning technology hybridization, and (3) indoor positioning principle hybridization. Notably, indoor-outdoor positioning technologies hybridization usually couples Global Positioning System (GPS) with the widely available indoor Wi-Fi positioning systems [10] to provide both outdoor and indoor positioning services, which are particularly important to semi-indoor environments like construction sites.

Besides hybrid positioning, it is also important to study the supporting techniques that can enhance the accuracy and precision performance of an indoor positioning system. One representative example of the supporting techniques is position tracking. Position tracking usually utilizes inertial measurement units (IMUs), like accelerometers, gyroscopes and magnetometers, to keep track of the position of moving targets. As the position information provided by IMUs is free from electromagnetic interference (EMI), IMUs provide a promising supporting technology on construction sites. For instance, Ibrahim et al. [23] have developed an indoor plus outdoor navigation and tracking system with reliable accuracy for construction applications. Other examples of supporting techniques include moving direction estimation, trajectory clustering, floor plan analysis, crowdsourcing, etc.

In addition to the individual shortcomings of indoor positioning technologies, principles and algorithms, the application of indoor positioning technologies also faces challenges from the indoor environment, especially when the indoor environment is complex and dynamic. Complex indoor environment is filled with a large number of different obstacles that creates many non-line-of-sight (non-LOS) conditions. Dynamic environment indicates that the surrounding obstacles are constantly changing their positions, and hence intractable time-variant noises are produced. Construction sites are both complex and dynamic: they are filled with a large number and large sizes of obstacles, e.g., building envelopes, formwork, columns, heavy equipment, and workers, and some of the obstacles, e.g., construction materials, heavy equipment, machines, and workers, are moving around constantly.

Due to the variety of approaches to achieve indoor positioning, as well as the complex and dynamic environment on construction sites, choosing or developing suitable on-site indoor positioning systems is user-oriented and environment-specific. For example, users should first consider their applications of indoor positioning on the construction site and set the required performance of the system based on their applications before choosing or developing an indoor positioning system according to their needs. The choice or development of indoor positioning systems is also limited by the environment in which they are deployed. For example, concrete walls exist in most indoor environments and concrete walls can weaken the transmitted signals. This can significantly affect the coverage of some types of signals, such as visible light, ultrasound and infrared. Without some reliable performance metrics, it is difficult for users to evaluate the performance of different systems and their component technologies, principles and algorithms under the effect of environmental limitations.

For the last decade, there have been some review papers related to real-time positioning on construction sites. Lu et al. [68] compares three RF-based indoor positioning technologies and discusses the combination of GPS with indoor navigation techniques to achieve positioning and tracking on construction sites. Khoury et al. [53] points out the impracticality of applying GPS on construction sites and evaluates three wireless technologies for on-site dynamic indoor user position tracking, with experimental results showing the high accuracy of indoor GPS. Behzadan et al. [8] discusses indoor-outdoor positioning technologies hybridization of GPS with three indoor positioning technologies based on RF to deliver context-specific information ubiquitously on construction sites. Li et al. [61] discusses and compares seven different indoor positioning technologies that have been used by researchers. Zhang et al. [115] discusses four RF-based indoor positioning technologies and ultrasound, including GPS, to achieve indoor positioning on construction sites for construction safety management. However, there is still a lack of an overview study that discusses and compares not only indoor positioning technologies, but also indoor positioning principles and algorithms, for applications of indoor positioning technologies specifically on construction sites. As principles and algorithms lay the basis for the technologies, the discussion will be centered on the principles and algorithms first, followed by the discussion about the technologies. In light of the lack of a comprehensive study, this paper first provides a general model of an indoor positioning system, then analyses the challenges to apply indoor positioning systems on construction sites. Afterwards six indoor positioning performance metrics, namely APP-CAT in short, are proposed for evaluating suitable on-site indoor positioning systems. As a basis for discussion, indoor positioning principles with their algorithms are first briefly discussed, evaluated and compared using APP-CAT. Subsequently, the top 10 indoor positioning technologies, which are selected according to their evaluation results using APP-CAT, are thoroughly discussed and compared. The promising recent trends of developing on-site indoor positioning systems, such as hybrid positioning, indoor navigation, infrastructure-free positioning, and collaborative positioning are also discussed. The comprehensive discussion of indoor positioning in this paper is intended to help both researchers and practitioners develop suitable on-site indoor positioning systems for engineering and construction applications.

This paper is organized as follows. Section 2 discusses the characteristics of the construction site environment and the challenges in applying indoor positioning systems on site. Section 3 provides a general model of an indoor positioning system. Section 4 presents six performance metrics, namely APP-CAT, for evaluating the on-site indoor positioning systems. Section 5 discusses and compares the three major indoor positioning principles and their algorithms. Section 6 compares and evaluates the top 10 technologies for indoor positioning on construction sites. Section 7 presents five major applications of indoor positioning on construction sites. Section 8 discusses the recent trends in indoor positioning research that can help develop high-performing and suitable on-site indoor positioning systems. Finally, Section 9 concludes the whole paper.

2. Characteristics of construction site environment and the challenges for indoor positioning

2.1. Characteristics of construction site environment

As the types of construction work are diversified, varying from residential and non-residential building construction, industrial construction, road construction, underground construction, heavy construction, etc., the types of construction sites also exhibit different characteristics. However, in the context of indoor positioning, construction sites share three important characteristics, which are summarized below.

2.1.1. Semi-indoor environment

General construction work, such as building construction, industrial construction and heavy construction, are a combination of indoor and outdoor environments. After excavation and foundation works, gradually columns are erected, beams are placed, slabs are laid, and then the building envelope like walls and roofs is constructed. The more the construction process is completed, the larger has the extent of indoor environment the construction site become. The larger extent of indoor environment means that there is more interior blockage inside the environment, which is the sources of noise interference. The construction process hence also reflects an increasing difficulty of achieving indoor positioning. Giretti et al. [36] tested a UWB-based indoor positioning system in a construction site in two stages: (1) just after the completion of beams and columns with some formwork and (2) after the construction of the envelope and of the internal partitions. Stage (2) showed a significantly worse positioning performance than stage (1) since the UWB signals were more easily blocked, reflected and attenuated with the presence of more barriers in stage (2).

In addition, some construction sites are completely outdoor, like road construction without tunnels; whereas, some construction sites are completely indoor, like underground construction such as tunnels and underground railways. For the outdoor construction sites, GPS can still be used because the GPS signals are not blocked by obstacles. For the indoor construction sites, indoor positioning systems must be used. Yet, in most cases, where the construction site is a semi-indoor environment, hybrid positioning techniques that combine indoor and outdoor positioning technologies are required.

2.1.2. Complex environment

Complex environment is filled with a large number of different obstacles. The large number of obstacles produces large noise interference in indoor positioning systems as the obstacles will cause non-LOS condition, significant attenuation and shadowing of signals, diffraction and scattering of signals, and multipath propagation. Construction sites are complex environments, filled with a large number and large sizes of obstacles, including building envelopes, formwork, columns, heavy equipment, and workers. Notably, for underground construction, Woo et al. [106] conducted a study in the Guangzhou Mass Transit Railway, which revealed that tunnel construction sites are even more complex environments: not only are there are many large-sized obstacles, but also the environment has high temperatures and dampness.

2.1.3. Dynamic environment

Dynamic environment indicates that the surrounding obstacles are constantly changing their positions, and hence intractable time-variant noises are produced. These types of time-variant noise are regarded as non-stationary noises, and they may exhibit random walk movement, which make them more intractable and harder to be eliminated by simple statistical methods, such as taking averages. On construction sites, construction materials, large-sized heavy equipment, machines and large number of workers are moving around constantly, which make construction sites a dynamic environment. For instance, in order to overcome the dynamic construction site environment, Park et al. [80] developed a probabilistic local search (PLS) algorithm using BLE technology. The testing results have shown that their developed algorithm outperformed the other two conventional positioning algorithms when the signal interference is high.

2.1.4. Others

Other characteristics of a construction site include a noisy environment, with infrastructure under development, presence of electrical equipment and RF communication systems, and movement of metallic materials and equipment, which create additional challenges to realizing indoor positioning on construction sites. The noisy environment on construction sites produces strong background audible noises, and the performance of sound-based indoor positioning systems is highly affected. In addition, the infrastructure is still under development on construction sites, and there is limited access to the power supply. The portable devices and APs are used in the indoor positioning systems thus have to consume sufficiently small amount of power. For the presence of electrical equipment and RF communication systems, they create EMI and affect the performance of indoor positioning systems using electromagnetic waves. Regarding the movement of metallic materials and equipment, it produces magnetic interference and the performance of indoor positioning systems using magnetic waves is affected [60].

2.2. Challenges for indoor positioning

Based on the characteristics of the construction site environment discussed above and studies of related papers, Table 2 summarizes the challenges and their effects for achieving indoor positioning on construction sites. It shows that achieving indoor positioning on construction sites is not an easy task as many existing indoor positioning are influenced by the challenges in the construction site environment. Design of specialized indoor positioning systems with strict criteria is needed to adapt to the construction sites.

3. A general model of indoor positioning systems

Indoor positioning systems can be viewed as a combination of (1) indoor positioning principles with their corresponding algorithms, (2) indoor positioning technologies and (3) indoor positioning hardware equipment. The three components largely affect the performance of an indoor positioning system. As illustrated in Fig. 1, the general model of indoor positioning systems consists of three major elements (principles and algorithms, technologies and hardware equipment), which affect the system performance in six different metrics. The system performance metrics will be discussed in Section 4. The principles and algorithms will be discussed in Section 5. The technologies will be discussed in Section 6. Hardware equipment will not be discussed in detail due to frequent changes of technology and variation amongst brands.

3.1. Indoor positioning principles and algorithms

Indoor positioning principles refer to the theoretical methodologies, such as trilateration, triangulation and scene analysis (a.k.a. fingerprinting), for estimating indoor positions based on the information

Table 2
Challenges and their effects for achieving indoor positioning on construction sites.

Characteristics of construction site environment	Challenges	Effects
(1) Semi-indoor environment	Presence of blockage	GPS does not work in indoor environment
(2) Complex environment	Non-LOS condition Significant attenuation and shadowing of signals Diffraction and scattering of signals Multipath propagation	The performance of most indoor positioning systems based on signal propagation is highly affected
(3) Dynamic environment	Non-stationary noises interfere signal propagation	Precise control of the positioning accuracy is difficult [36]
	Planning of AP placement is complex	High costs of on-site layout management [36]
	Changes in lighting and background [61]	The performance of vision-based indoor positioning systems is affected [61]
(4) Noisy environment	Strong background audible noises	The performance of sound-based indoor positioning systems is highly affected [61]
(5) Infrastructure under development	Limited access to power supply	The power consumption of indoor positioning systems has to be sufficiently low
(6) Presence of electrical equipment and RF communication systems	EMI is present [19]	The performance of indoor positioning systems using EM waves is affected
(7) Movement of metallic materials and equipment	Magnetic interference is present	The performance of indoor positioning systems using magnetic waves is affected [60]

carried by the technologies. Each indoor positioning principle has its strengths and limitations. Indoor positioning algorithms refer to the computation methods that are run by the computer. With reference to the nature of the indoor positioning principles used, different indoor positioning algorithms have been developed by the researchers. Although the structure of an algorithm is based on its referenced indoor positioning principle, some innovatively and cleverly designed algorithms can improve the limitations of their referenced principles. For instance, Zhuang et al. [118] utilized extended Kalman filtering (EKF) and outlier detection algorithms to largely improve the positioning accuracy of an BLE based indoor positioning system, which usually has an accuracy at the multi-meter level, to < 2.56 m at 90% of the time. Ibrahim et al. [46] introduced a newly developed path loss model accounting for signal de-noising using Kalman filtering. The developed model was tested using four wireless technologies, and the results showed an average of 50% enhancement in the distance estimation accuracy.

3.2. Indoor positioning technologies

Every indoor positioning system makes use of specific types of information to estimate the position of the target. Indoor positioning technologies refer to the system or medium that is used to extract, transfer and provide the specific types of information to achieve indoor positioning. Radio waves, such as Wi-Fi, Bluetooth, Zigbee, RFID and UWB, as well as geomagnetic waves, ultrasound, ordinary visible light, infrared and laser are examples of indoor positioning technologies. The choice of indoor positioning technologies determines not only the waveform, frequency, and bandwidth of the propagating waves, but also the transmission protocol used for signal transfer. In addition, the choice of indoor positioning technologies determines the types of hardware equipment required. For example, Wi-Fi based systems require wireless access points (WAPs), routers and end devices like smartphones; whereas RFID-based indoor positioning systems require RFID tags and RFID antennas with connection to the computer. All these elements determined by the choice of indoor positioning technologies affect the performance of an RF-based indoor positioning system.

3.3. Indoor positioning hardware equipment

Indoor positioning hardware equipment includes all the devices that are used in an indoor positioning system. The quality of the hardware equipment highly influences the performance of an indoor positioning

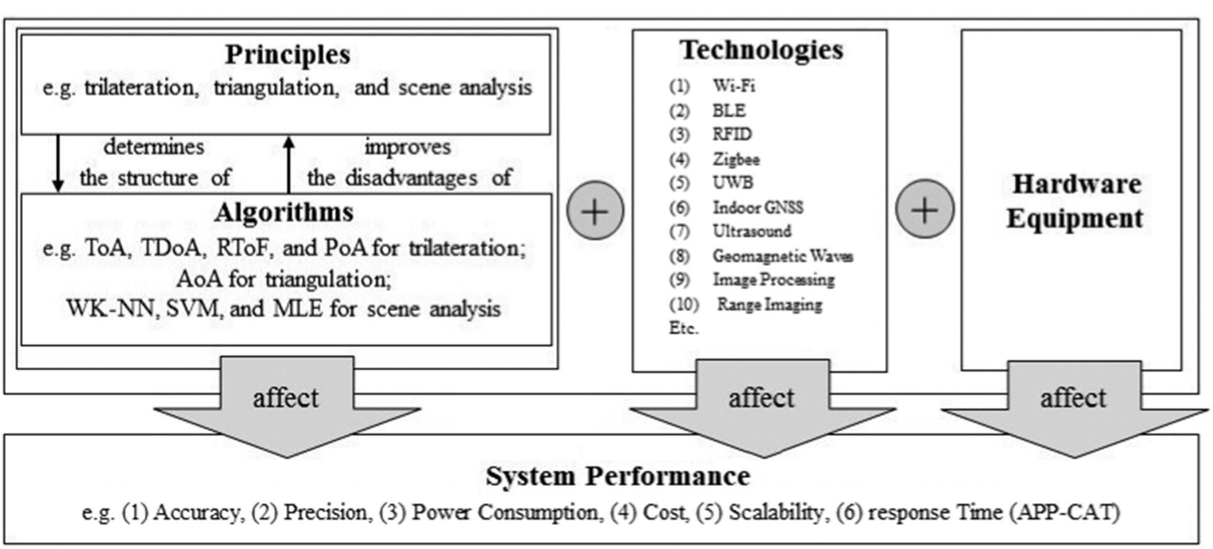

Fig. 1. Structure of the general model of an indoor positioning system.

system. Typical hardware equipment in an indoor positioning system include access points (also referred to as nodes) that transmit signals and end devices, like computers or some portable devices, that can make connection to the access points. If it is a centralized indoor positioning system, computation takes place in one or a few fixed points on the server side, and computers are usually used. On the contrary, if it is a decentralized indoor positioning system, computation is taken place in many separate points on the host side, and portable devices like smartphones are used. A centralized system usually offers better computing power but a higher risk, as the failure of the few fixed points can paralyze the whole system; whereas, a decentralized system has higher safety but usually worse computing power. Further discussion of hardware equipment is not concerned in this paper due to the high diversity of hardware equipment, which depends on factors such as brands, technologies and transmission protocols.

4. Proposed indoor positioning performance metrics (APP-CAT)

Reliable performance metrics are needed for a comparative evaluation of indoor positioning systems. Considering the characteristics of the construction site environment and some benchmarking provided by other review papers [2,64], the performance metrics named APP-CAT are proposed, including the following six criteria: (1) "A"ccuracy, (2) "P"recision, (3) "P"ower consumption, (4) "C"ost, (5) sc"A"lability, and (6) response "T"ime. As indoor positioning systems are user-oriented, the significance (weight) of each criterion is dependent on the users. Notably, the proposed performance metrics can evaluate the whole indoor positioning system and their component technologies, principles and algorithms, as they are contributing factors of the overall performance of the indoor positioning system.

The discussion below focuses on the importance of each criterion for applying indoor positioning on construction sites. In addition, it focuses on how technologies, principles and algorithms influence each criterion. The effects of environmental conditions and hardware equipment are also included, where appropriate.

4.1. Accuracy

Accuracy, which refers to the accuracy of the position information, is a crucial criterion because it adequately reflects the quality of the output position data. As the output data is used by some equipment for further applications, the performance of the equipment will deteriorate if the positioning accuracy is not high enough. For instance, for safety management on construction sites, hazard warning systems combining location, imaging and alerting technologies have been developed by researchers to alert workers when they are close to dangerous zones [38]. False alarms or delayed alarms may occur if the positioning accuracy is low.

The accuracy of an indoor positioning system can be divided to two types: localization and positioning accuracy. Localization accuracy is mostly calculated as the success rate of identifying the exact regions at which the target is located [17]. Such regions can either be provided by the algorithms or defined by the users. Positioning accuracy is usually measured as the positioning error. A higher accuracy corresponds to a lower positioning error. Some research work [69] uses the distance root mean squared measure to record positioning error, which is calculated as:

$$\mathrm{Err_P} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{actual})^2 + (y_i - y_{actual})^2}{n}} \tag{1}$$

where Err_P is short for positioning error, n is the number of measurements taken, (x_i, y_i) are the coordinates of the estimated position, and (x_{actual}, y_{actual}) are the coordinates of the exact position of the target.

Some research work [2] separates the positioning errors to x and y dimensions. Then, the average distance deviations of x and y coordinates are measured respectively, which are calculated as:

$$\mathrm{Err_P}(x, y) = \left(\frac{\sum_i^n x_i - x_{actual}}{n}, \frac{\sum_i^n y_i - y_{actual}}{n}\right) \tag{2}$$

where the coordinates of $\mathrm{Err_P}(x, y)$ represent the positioning errors along the x and y axes respectively.

It is noted that for the discussion above, the accuracy measurements are defined for a 2D space as most of the research work aims at finding an indoor position on a plane. In a 3D environment, the accuracy along the z dimension needs to be considered as well.

4.2. Precision

Precision, which is a measure of the variability of the positioning error, provides a standard for the users to understand the extent of fluctuation of their measurements. For some indoor positioning applications in the construction industry, highly fluctuating position errors are intolerable. For example, many researchers have utilized robotics in the construction industry [33]. When the positioning precision is low, it is difficult for the robots or unmanned aerial vehicles (UAVs) to complete their tasks. Although precision is viewed as part of the accuracy in some papers, it is an individual criterion in this paper, due to the importance of precision in applying indoor positioning on construction sites. To improve the precision, a moving average filter (MAF) can for example be added to the algorithm to smooth out the fluctuations in the signal strength values [40]. For positioning systems, some researchers regard precision as the standard deviation or variance of position estimation [69], as illustrated in Eq. (3).

$$\mathrm{Prec_P} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{average})^2 + (y_i - y_{average})^2}{n}} \tag{3}$$

where is short for positioning precision, and are the average values of and respectively. As an alternative to standard deviation, precision can also be inferred from the cumulative probability functions (CDF) of the positioning error [64].

4.3. Power consumption

Power consumption measures the average power consumed in an indoor positioning system under the same use rate; i.e. under the same number of position queries per unit of time. Both measurements are crucial for applying indoor positioning on construction sites, due to the low availability of the power supply. The choice of technologies determines the communication protocol used in the indoor positioning systems, which affects how much data is sent for each position query. To transmit more data, more energy is consumed. The choice of principles and algorithms determine the amount of memory consumption and computation time to carry out position estimation, which affects the energy consumption per position query.

4.4. Cost

The cost criterion measures the money and time needed to acquire, establish and maintain the indoor positioning system. The cost criterion is important because it reflects the total amount of resources spent to realize the indoor positioning service, and thus it is one of the decisive criteria in choosing the indoor positioning system. To calculate the total cost incurred for an indoor positioning, three different stages need to be considered: acquisition stage, establishment stage and maintenance stage.

In the acquisition stage, the required hardware equipment is purchased. The choice of technologies determines what types of hardware equipment are needed. For instance, the users are required to purchase RFID tags and RFID antennas for RFID-based indoor positioning systems. With the same types of equipment, the brands of the equipment

Table 3
Contributory factors in cost on three stages of indoor positioning systems.

Stage	Acquisition	Installation	Maintenance
Contributory factors	Choice of technologies Brands of hardware equipment Size of the environment	Size and complexity of the environment Choice of principles and algorithms	Quality and number of hardware equipment Use rate Environmental conditions

also affect the prices. Besides, the size of the environment would determine the total amount of hardware equipment needed. In the establishment stage, the indoor positioning system is installed in the application environment. Usually, the larger and more complex is the environment, the more work is required for installation. If the systems require many APs, it may also cause an increase in the cost of layout management [36]. In some systems, establishment of a database is needed, depending on the chosen principles and algorithms. In the maintenance stage, the cost incurred depends on factors such as the quality and amount of hardware equipment, usage rate and environmental conditions of the system. In particular, the environmental conditions are closely related to indoor positioning systems based on scene analysis as these systems rely much on collecting unique characteristics in an indoor environment. For example, if the venue is largely renovated or some APs are replaced or removed, it increases the cost of maintenance as the characteristics need to be recollected. All these factors influence the rate of depreciation of an indoor positioning system. Due to the high variability in maintenance cost, only the acquisition and installation costs are compared in this paper (Table 3).

4.5. Scalability

The scalability criterion measures the maximum number of targets that can be localized or positioned in a time interval with respect to the scale of an indoor positioning system. This criterion is especially important for large-scale construction projects which have a large construction sites and large numbers of workers. In addition, systems with a low scalability require a larger number of APs, which can increase the costs of on-site layout management.

The scale of the system refers to the density of APs in the environment, which can be expressed as the number of APs per the unit area or volume covered by the system. The larger the scale, the lower the density of APs. Given a fixed scale of the indoor positioning system, when the number of targets and position queries increase, the connection links between the hardware equipment become more congested. Therefore, the increasing number of positioned or localized targets per time interval finally reaches a maximum value. A scalable system can still position or localize a large maximum number of targets with increasing scale of the system.

The chosen technology determines the communication protocol and the penetrability of the signal. Some communication protocols are well designed, and they can support a mesh network topology that is not easily congested. The path penetrability of the signal affects the coverage of APs, and hence the density of APs. For example, ultrasound, visible light and infrared cannot penetrate obstacles like walls and thus the indoor coverage is low. As a result, a higher density of APs is needed. Different principles and algorithms require different amounts of information and numbers of APs to perform indoor positioning. In practice, it is hard to compare the scalability across systems as the position distribution of the targets affects the results as well. Most review papers provide a grading system as a standard to evaluate the scalability performance instead.

4.6. Response time

Response time, the reciprocal of update rate, measures how fast indoor positioning systems can update the position information to the user after the position query is sent. The importance of response time is that it can provide timely position information to targets that are in motion. The delayed information results in a poor positioning accuracy. The response time is an important criterion for applying indoor positioning in the construction industry as the targets, such as machines and people, usually work in motion. The accuracy for targets in motion is regarded as dynamic accuracy [98], as opposed to the static accuracy for targets in fixed positions.

Normally, the update rate of position information can be obtained by measuring the time interval between updates. If this information is not available, the dynamic accuracy can also be used as a secondary indicator. However, the major concern of using dynamic accuracy as the indicator is that the error in dynamic accuracy is not only contributed by the delay in updates, but also by other factors that are affecting the static accuracy; i.e., even if the response time is minimal, the dynamic accuracy can still be low.

The contributory factors in response time are complex. The choice of technologies, principles and algorithms, quality of hardware equipment, number of targets to be located or positioned, and environmental conditions may affect the response time. For example, if the computational complexity of the principles and algorithms is high, it needs more computation time. In addition, the choice of technologies determines the communication protocol, the speed of signals, and the types of hardware equipment. The choice of technologies thus affects factors like scan time, transmission delay, queuing delay for position queries.

4.7. Others

Besides the six criteria presented above, there are also some other common criteria for indoor positioning systems, such as robustness, durability, transmission range, and privacy. Robustness measures whether an indoor positioning system can function normally even when some information input is not available, e.g., some signals are blocked. However, this criterion is hard to be quantified and it can be reflected by other criteria like accuracy and precision. Durability is measurement of the long-term performance of indoor positioning systems. Essentially, if an indoor positioning system is not durable enough, it increases the cost of maintaining the system. For example, indoor positioning systems based on scene analysis require regular and usually labor-intensive system maintenance. In other words, the durability of the indoor positioning system is captured under the cost factor in APP-CAT. Transmission range is not one of the six criteria because the influence of the transmission range caused by the choice of technologies has already been captured by the scalability criterion. Furthermore, the transmission range is usually flexible, and it largely depends on the power emission of the hardware equipment. For privacy, it is more of a concern in public areas, but not on construction sites.

5. Indoor positioning principles and algorithms

Different indoor positioning principles and algorithms have been developed throughout the years. In the following, the major positioning principles, and their commonly used algorithms, will be discussed and evaluated. Positioning principles aim to estimate the position coordinates of the target. There are three fundamental positioning principles: (1) trilateration, (2) triangulation and (3) scene analysis. Triangulation and trilateration are also known as range-based

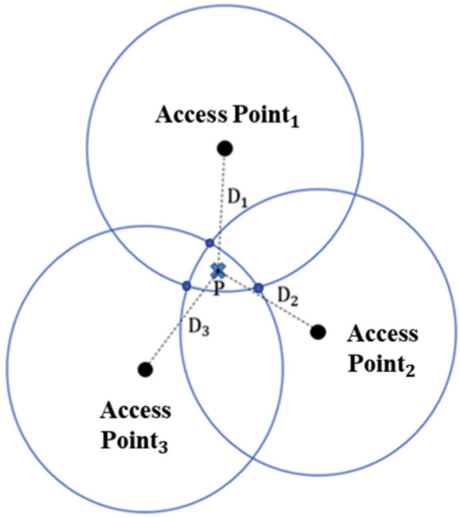

Fig. 2. Illustration of the trilateration.

principles, as they are both capable of deriving the actual distances between the target and the APs. Contrarily, scene analysis can perform position estimation without knowing the actual distance between APs and the target, which makes scene analysis a versatile principle, and has more promising applications in complex and dynamic environments like construction sites.

5.1. Trilateration

Trilateration is a classic principle that estimates the 2D position of a target based on at least three distance measurements between the target and the APs. Some circle equations can be formulated with the positions of APs as the centers of the circles and the respective distance measurements as the radii. As shown in Fig. 2, the position of the target is estimated as the intersection point of the circles. Although two circles are sufficient to determine a single intersection point on a plane, a third circle is needed since the distance measurements usually contain errors and a single intersection point is not formed. With three circles, the linear least square method (LLSM), weighted least square method (WLSM), or a centroid calculation based on the three intersection points near the center can be applied to determine the two coordinates of the position of the target. For 3D position estimation, at least four distance measurements are required. In fact, when more distance measurements are used for estimation, the position estimation tends to be more accurate, as the random errors of individual measurements are mitigated.

Trilateration is theoretically a robust method to achieve very accurate positioning; however, it is prone to the non-LOS condition and other noise interference. The discussion below presents six common algorithms to achieve trilateration.

5.1.1. Time of arrival

Time of arrival (ToA) is the most basic algorithm to achieve trilateration. It measures the time needed for the signals to travel from the APs to the position of the target. The distance between the target and the APs can easily be calculated by multiplying the recorded time durations with the speed of the signals. Despite the simplicity in distance calculation, precise synchronization is required from the transmitting APs and the receiver. Furthermore, the LOS condition is strongly preferred for ToA to achieve high accuracy. If a non-LOS condition exists, depending on the materials of the blockage, it may completely block, significantly weaken, or delay the signals from the LOS paths, causing obfuscation at the receiver when determining the accurate arrival time of the signals.

5.1.2. Time difference of arrival

Time difference of arrival (TDoA) is a modified version of ToA. Instead of measuring the time needed for signals to arrive at the position of the target from the APs, it measures the difference in time when the signals arrive at the position of the target. Since only relative time measurements are needed, it relaxes the constraint that the receiver needs to be synchronized with the transmitting APs, which is easier to be achieved in practice. However, the LOS condition is still strongly preferred for TDoA. Per the experimental results of a UWB-based indoor positioning system in [69], the positioning accuracy decreased by > 200% if the signals from LOS paths are completely blocked when the combined TDoA and angle of arrival (AoA) algorithm was used. The combined TDoA and AoA algorithm is also one example of indoor positioning principle hybridization.

5.1.3. Roundtrip time of flight

Similar to TDoA, roundtrip time of flight (RToF) also relaxes the constraint on the synchronization between the transmitting APs and the receiver, as it measures the time needed for the signal to travel from the transmitters to the receiver, and then back to the APs again.

5.1.4. Phase of arrival

Phase of arrival (PoA) is another method to achieve trilateration. It is also called the received signal phase method [64]. While PoA requires the transmitting APs to send out a sinusoidal pattern of signals, it requires the receiver to process the same pattern of signals by itself. Once the signals from the APs have arrived, the phase difference between the two sets of signals is measured at the receiver to derive the distance between APs and the target. It has one major criterion: the wavelength of the signal must be smaller than the distance between the target and the APs. This method also prefers the LOS condition and high synchronization.

5.1.5. Path attenuation model

Compared with the algorithms discussed above, path attenuation model (PAM) is the most promising one that can work around the non-LOS condition. The path attenuation is a theoretical model to relate the received signal strength with the distance travelled by the signal under signal attenuation. The basic theoretical form of path attenuation is expressed as follows under the LOS condition [11]:

$$L = 10\,n\log_{10}(d) + C \tag{4}$$

where L is the path loss in decibels, n is the path loss exponent, d is the distance travelled by the signal, and C is a constant the captures other losses.

To apply this algorithm under the non-LOS condition, alternative path loss models are needed. Ji et al. [49] classified path loss models to three types, which are simple models, partition models and site-specific models. The simple models only concern the relationship between the signal strength and the distance travelled by the signal. Zhuang et al. [118] used a polynomial regression model (PRM) to determine the relationship between path loss and distance travelled by the signals. It suggests an alternative way to find the relationship between the signal strength and the distance travelled by the signal, in order to mitigate the impact of noise interference on the signal strength. Regarding the partition models, they take the orientations of walls and floors into account and consider the transmission behavior of signals in an indoor environment when they penetrate the walls and slabs. For instance, Du et al. [24] added the third least square fitting parameter to account for the number of walls encountered by the signal. In another work, Du et al. [24] used a path loss model that considers the signal incident angles and the number of intersection of walls to approximate the signal strengths. Bose et al. [11] modified the Hata-Okumara model of path attenuation based on empirical result, and the model considers frequencies of waves as well as transmitting and receiving gains. The site-specific models not only consider the orientations of walls, but also the impact of material types and material thickness. For instance, Ji et al. [49] adopted the site-specific models and they used the ray-tracing method as the basis to simulate the propagation of RF waves. The ray-tracing model considers the attenuation of RF waves at walls and floors due to reflection, transmission, diffraction and scattering.

5.1.6. Channel state information

A more advanced approach than the path attenuation, which is also widely used in current research work, is to utilize channel state information (CSI). CSI can reflect the condition of each channel under the effect of scattering, fading, delay distortion, power decay, and multi-path effect with distance [27]. The CSI collects channel measurements representing the amplitudes and phases at the subcarrier level [107]. As a result, CSI can provide a better estimation of the distance between the APs and the target, even under the non-LOS condition. Yet, CSI requires specialized hardware equipment, the network interface card, to provide CSI.

5.2. Triangulation

Triangulation estimates the 2D position of the target based on angle measurements between the target and the APs instead. To apply triangulation in a 2D space, at least two angle measurements are needed. As shown in Fig. 3, the position is estimated as the intersection point of the angle measurements. For 3D positioning, at least three angle measurements are needed. Similar to the trilateration, least-square-based methods can be applied for more than two angle measurements.

The most common algorithm to achieve triangulation is AoA. At the receiver, an array of antennas measures the phase differences between the signals arriving at different antennas. The arriving angle can then be calculated by finding the included angle between the sides of the phase difference and the distance between antennas by applying trigonometric functions. Since arrays of antennas are used, AoA requires larger and more complex hardware equipment than that required for the algorithms to achieve trilateration. This increases the cost and power consumption of using AoA. In addition, AoA strongly prefers LOS condition to provide accurate positioning. The major benefit is that time synchronization is not required for AoA as no time measurements are taken.

5.3. Scene analysis

Scene analysis, also known as fingerprinting, is a broad and non-range-based principle that can realize position estimation without deriving the distances between the target and the APs. Conceptually

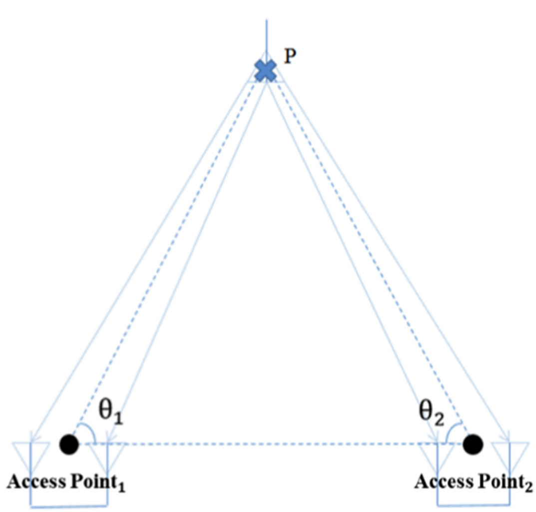

Fig. 3. Illustration of the triangulation.

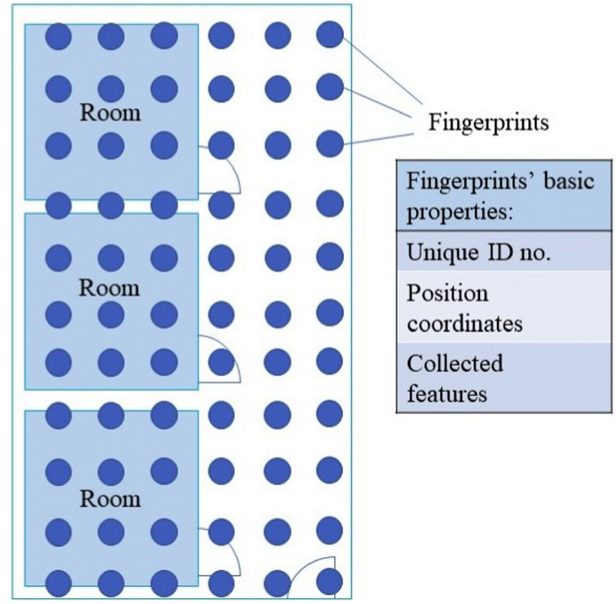

Fig. 4. Illustration of an FM of an indoor environment.

speaking, scene analysis works in two phases: collection phase and matching phase. At the collection phase, a specific technology is used to collect and extract some types of unique characteristics at different positions in an indoor environment. The collected characteristics, as well as the unique identification number of the fingerprint and the position coordinates at the point of collection, are regarded as fingerprints and are stored in a database. A fingerprint database is also called a feature map (FM). The major cost of using scene analysis is usually caused by creating FMs. At the matching phase, the same technology will again collect and extract some characteristics in real-time, which are used to match with the fingerprints collected in the fingerprint database. Per the results of the matching, the best position of the target is estimated. If the size of an FM is large, it also consumes a longer time for matching. Fig. 4 illustrates an FM of an indoor environment.

The major strength of scene analysis is that it does not require the LOS condition. However, it has three major limitations. Firstly, a fingerprint collection process is usually time-consuming. A lot of time and manpower are expended to go to different positions of an indoor environment to perform fingerprint collection, especially when the environment is large. Thus, researchers have developed some efficient fingerprint collection systems. For instance, Huang et al. [45] utilized IMUs to keep track of the moving positions of the fingerprint collector. This can let the collector continuously collect the fingerprints without inputting his or her position information beforehand. To make the collection process even easier, automatic fingerprint collection systems are desired. Such type of system is also related to the next limitation.

The second limitation is that the information contained in FMs is fixed and it is not changed after collection. However, if the environment is dynamic, the information contained in the FMs will provide inaccurate information for matching as the characteristics of the environment have changed. Therefore, some systems which can update the FM dynamically have been developed in [4]. In these cases, received signal strength index (RSSI) is collected as the features in the environment, and this type of FM is called a received signal strength map (RSSM). These systems aim at estimating the whole RSSM with some anchor APs. Different regression methods, such as geography weighted regression and Gaussian process regression, were used to deduce the overall changes of the RSSI in the environment based on the information collected at some anchor APs. Besides using anchor APs, another approach is to use different types of path loss models to simulate the whole RSSM without any anchor APs, but the simulation results usually have limited accuracy. Dynamic update of FM has also solved the automatic fingerprint collection problem, because dynamically updating the fingerprints is the same as automatically collecting or recollecting the fingerprints. In addition, dynamic update of FM can substantially lower the cost for using scene analysis.

The third limitation is to achieve 3D positioning with the same set of APs based on scene analysis. In a multi-floor environment, it is difficult for scene analysis to identify at which floor the user is located because the uniqueness of the characteristics collected in a fingerprint at a position is only preserved within the single floor only. In other words, the uniqueness of fingerprints is largely lost if multiple floors are considered for position estimation [93]. To address this problem, three different methods have been proposed. The first method utilizes the idea of indoor positioning principle hybridization by combining the trilateration or triangulation with scene analysis, as trilateration or triangulation can perform 3D position estimation. The second method is to combine scene analysis with the IMUs to identify the floor on which the target is located. This method is not a real 3D positioning, and it should better be referred to as multi-floor positioning. Ye et al. [113] utilized IMUs such as an accelerometer and a timer to identify motions like going up the stairs or using the elevator based on the acceleration value, step counting and travelling time of elevators, as the travelling time of elevators is assumed to be distinct between any two floors. Yet, the initial floor of the user has to be known in advance. The third method is to utilize machine learning algorithms to let the computer learn how to differentiate the floors. Campos et al. [13] used the backpropagation artificial neural network (ANN) and unsupervised clustering, like K-medians and Kohonen layer for floor identification. The results show that the accuracy of successful floor identification ranges from 91 to 97%. Sun et al. [93] used another type of machine learning algorithm, linear discriminant analysis (LDA), to achieve an average 94% floor identification accuracy.

The essence of scene analysis is to decide: (1) what types of characteristics should be collected, and (2) how to match the characteristics collected in real-time with that in the database. To solve these two questions, researchers have developed different algorithms. The discussion below further divides scene analysis into five main categories, which are (1) RSSI analysis, (2) phase difference analysis, (3) spectral difference analysis, (4) multipath effect analysis, and (5) image-based feature analysis.

5.3.1. Received signal strength index (RSSI) analysis

RSSI analysis, or called received signal strength analysis, is the most common way to achieve scene analysis. In RSSI analysis, RSSI values, which can reflect signal strength levels of the received signals, are collected as a vector to form the fingerprints in an RSSM. To compare RSSI values, different machine learning algorithms are used. They can be classified as deterministic and probabilistic types.

The Weighted K-Nearest Neighbor (WK-NN) algorithm is the most basic deterministic machine learning algorithm used to complete RSSI analysis. Assuming that each AP is uniquely identifiable, when some RSSI values are received from a set of APs in real-time, they are usually compared with the RSSI values of the same set of APs in the RSSM based on the Euclidean metric. The smaller is the Euclidean distance between the RSSI values in real-time and that of a fingerprint indicates that the target is closer to that fingerprint. The position of the target is then estimated as the weighted average of the positions of the k nearest APs. Here, the weight assigned is disproportional to the measured Euclidean distance.

Although most studies use the Euclidean metric for WK-NN, other metrics such as the Minkowski metric, Sørensen distance, Earth Mover's Distance, etc., are also used and tested [98]. Torres-Sospedra et al. [98] intensively tested 53 metrics based on more than ten thousand fingerprints collected in the public UJIIndoorLoc fingerprint database [97]. The results showed that using the Sørensen distance can improve the 2D positioning accuracy by 1.7 m compared with Euclidean metric. Besides WK-NN, other deterministic algorithms such as the decision tree, support vector machine (SVM), and neural networks [59,99] are also used.

To use probabilistic algorithms, rather than collecting a single RSSI value at each position, the user needs to collect a probability distribution of RSSI values at each position as the fingerprint in the collection phase. The idea is that signal strength at a certain position can vary with time due to noise interference and collecting a probability distribution of RSSI values provides more information to enhance the positioning accuracy. The basic probabilistic algorithm used to complete RSSI analysis is the maximum likelihood estimation (MLE). Using MLE, Youssef et al. [114] developed an indoor positioning system that performs positioning by finding the best matched probability distribution of RSSI.

Besides MLE, other popular probabilistic algorithms such as expectation-maximization, Gaussian process, Bayesian network, and conditional random field, kernel direct discriminant analysis [23,88,108] are also used to achieve high positioning accuracy. In general, probabilistic machine learning algorithms offer much better localization performance [23]. However, probabilistic machine learning algorithms have higher computational complexity in achieving the better performance. This results in a longer response time and a lower dynamic accuracy in the indoor positioning systems.

However, the position estimation given by the algorithms above are not the optimal approaches as they discretely estimate the position of the target at each time interval. Due to the presence of noise interference, the position estimation can fluctuate to a position with similar collected RSSI values. The more advanced methods utilize the aforementioned algorithms for continuous analysis of the position of the target. To achieve this, there are two approaches: temporal signal pattern continuous analysis (TSPCA) or spatial signal pattern continuous analysis (SSPCA).

TSPCA continuously collects the RSSI values with time such that the moving direction or the moving trajectory of the target is known. The moving direction or trajectory information can be used to calibrate and constrain the position of the target. [57] is an example of positioning systems using TSPCA. SSPCA, as a type of indoor positioning principle hybridization, integrates position information of APs to improve the positioning accuracy. The idea is that if the AP is located nearby, it will propagate strong signals such that the receiver will collect dominant RSSI values from that AP. As such, the strongest AP is the landmark of the nearby region. From this information, the position of the target can be calibrated to the AP landmarks according to the strength order of RSSI values. SSPCA makes use of the position information (the nearest AP) to calibrate the position of the target, and it is thus a hybridization of localization and positioning principles. [102] is an example of positioning systems using SSPCA.

5.3.2. Phase difference analysis

Phase difference analysis (PDA) offers another approach to collect the characteristics of the environment. The arrival of signals from different APs will create phase differences at the receiver. To measure the phase difference, specialized hardware equipment is required. Hekimian-Williams [44] used Universal Software Radio Peripheral (USRP) software-defined radios to acquire the phase differences of RFID signals. Their experiments have shown that PDA offers high positioning accuracy and can be used for 3D positioning as well. Yang et al. [112] used PDA with a RFID-based positioning system, achieved a high positioning accuracy at the centimeter level when tested at Beijing Capital International Airport and Sanya Phoenix International Airport. Yang et al. [112] created a novel algorithm called differential augmented hologram, which was specifically applied for PDA.

5.3.3. Spectral feature analysis

While RSSI analysis uses the received signal strength of the carrier frequency of the signal only, spectrum feature analysis (SFA) aims at matching the more types of features from the signals for fingerprinting.

Basically, since signals can be represented in either frequency or time domain, specialized hardware equipment can be used to obtain the power spectral density of the signals over a time period or a frequency range. Or, a time-frequency representation of signal strength called a power spectrogram can be matched. From the power spectral density and power spectrogram, different signal features are matched. Normally, if too many features are included, the computational complexity will largely increase, which lengthens the response time of the indoor positioning system and hence reduces the dynamic accuracy. Galván-Tejada et al. [34] identified 46 spectral features from the geomagnetic waves. By using the genetic algorithm, the five most significant signal features to optimize the positioning accuracy were determined. Guo et al. [39] also utilized SDA as one of the classifiers in a multi-classifier and visible-light-based indoor positioning system.

5.3.4. Multipath effect analysis

Multipath effect analysis (MEA) is a novel strategy to collect the features in the indoor environment. Wang et al. [103] were the first to propose multipath effect analysis. Normally, multipath effect is considered as a detrimental noise interference source in the indoor environment, which influences the performance of a majority of indoor positioning systems. However, Wang et al. [103] exploited the multipath effect to accurately locate RFID tags. The intuition of their design was that different targets in the indoor environment experience different patterns of multipath effect, as the angles and strengths of the incoming multipath signals are different. The different features of multipath effect construct a unique multipath profile at a specific position in an indoor environment. Dynamic time warping techniques are then utilized to compare the similarities between multipath profiles. The experimental results from a deployment of 200 commercial RFIDs in their university library demonstrated that their design is able to locate misplaced books with a median accuracy of 11 cm.

5.3.5. Image-based feature analysis

Image-based feature analysis (IBFA) is specifically used by indoor positioning systems based on image processing. IBFA describes the processes of matching the features of images. The images and position information extracted from the environment is first stored in the FM, which is also called an image map in this case, and then IBFA is conducted to perform position estimation using the images captured by the targets and data in the image map.

Since processing images formed by signals can be time-consuming, fast algorithms are needed for IBFA. Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) are initially used for IBFA [7]. SIFT utilizes Gaussian blur with matching of local extreme features of the images. These local extreme features are obtained from the surrounding areas of the local extreme features. SURF is a faster algorithm than SIFT as SURF is based on identifying the extreme features globally in the images only. Although SURF runs faster SIFT, it sacrifices some matching accuracy compared with SIFT [105]. Kawaji et al. [52] used principal component analysis and SIFT, combined with fast nearest neighbor search based on locality sensitive hashing, to achieve a faster IBFA than SIFT, and a more accurate IBFA than SURF.

However, the largest limitation is that currently IBFA still needs 0.56 to 1.6 s of processing time using a laptop computer [52], which means IBFA is unlikely to achieve real-time positioning on devices like smartphones with even less computational power. This limitation becomes more severe with a larger size of environment, which requires a larger image map. As a result, studies like [92] used Convolutional Neural Network (CNN) to reduce the complexity of the image matching by adding an image clustering process; i.e., the comparison set in the image map is filtered and refined before image matching takes place.

5.4. Comparison and discussion

Trilateration and triangulation usually require the LOS condition to reach a high positioning accuracy. Triangulation can also achieve high precision as it is not prone to the variations caused by the time-synchronization issue. However, under noise interference and the non-LOS condition, trilateration and triangulation perform poorly in terms of accuracy and precision. Utilizing CSI and the path loss model are two approaches to overcome the non-LOS condition to achieve better accuracy.

Scene analysis is more adaptable for an environment with stationary noise interference as it captures the characteristics of the environment; however, its accuracy is lowered under the presence of non-stationary noise interference. Dynamic update of FMs is a measure to cope with the dynamic environment with non-stationary noise interference. In terms of precision, scene analysis has a moderate performance as it can easily be influenced by noise interference.

Triangulation has the highest cost and power consumption as it requires special hardware equipment. Trilateration and scene analysis have comparable cost and power consumption. The major cost of scene analysis comes from the creation of FMs at the installation stage. Such cost can be largely reduced with dynamic update of FMs.

In terms of response time, scene analysis usually requires a longer time for large amount of data comparison in RSSM. The response time for trilateration and triangulation ranges from short to moderate, depending on the specific algorithm used.

Scene analysis has a moderate scalability as it usually requires a large number of APs to create distinct fingerprints in the environment. Although trilateration and triangulation do not need many APs, they require APs to send packets of information to the receivers, and they become easily congested when the number of users largely increases. In addition, in some centralized indoor positioning system, packets are also sent to the receivers under scene analysis, but the size of these packets are usually smaller as they contain position information only.

The performance comparison of positioning principles is summarized in Table 4.

5.5. Others

All the indoor positioning principles discussed above aim to estimate the precise coordinates of the target position. However, there is an alternative principle named region-based proximity (RBP) principle which estimates the location of the target in a region with certain shape and size. This principle is a simple method that approximates the location of the target to some specific areas, e.g. particular floors, rooms, or pre-defined zones.

There are two common types of algorithms to achieve RBP. The first type is based on assigning to the location of the target to the nearest AP. The nearest AP can be easily found by finding the RSSI value of the strongest strength. Another type is based on the scene analysis principle. It is similar to the nearest AP method, but the location of the

Table 4
Performance comparison of the positioning principles.

Principles	Accuracy	Precision	Power consumption	Cost	Scalability	Response time	Corresponding algorithms
(1) Trilateration	Moderate to high	Moderate	Moderate	Moderate	Moderate	Short to moderate	ToA, TDoA, RToF, PoA, PAM, CSI
(2) Triangulation	Moderate to high	Moderate to high	High	High	Moderate	Short to moderate	AoA
(3) Scene analysis	Moderate to high	Moderate	Moderate	Low to moderate	Moderate	Moderate to long	RSSI analysis, PDA, SFA, MEA, IBFA

target is assigned to the location of the nearest fingerprint instead. In other words, the 1-NN algorithm can be used in this case.

However, this method is subjected to great source of error. For example, if the position of the closest AP or fingerprint is at the next room, the target location will be assigned to the wrong room. This error is difficult to be mitigated. One possible mitigation measure is to place the APs or fingerprints closer to the center of the region.

6. Top 10 indoor positioning technologies for construction sites

In the development of indoor positioning, different technologies have been utilized and tested in many studies [53,64,68]. According to their evaluation results using APP-CAT, and their popularity amongst the indoor positioning studies, the top 10 technologies for indoor positioning, which are the most promising and the commonest, are chosen. In the following, the top 10 technologies for indoor positioning, and their commonly used principles and algorithms, are discussed. Amongst the top 10 technologies, a large proportion of them are RF technologies, including (1) Wi-Fi, (2) BLE, (3) RFID, (4) Zigbee, (5) UWB and (6) indoor GNSS. Besides RF technologies, (7) ultrasound and (8) geomagnetic waves are also used. The two remaining technologies, (9) image processing and (10) range imaging, mainly utilize ordinary visible light, infrared light and laser to form images for indoor positioning. These two technologies are also referred to as the computer vision based indoor positioning. Although ultrasound is both used in image processing and range imaging, it should be noticed that images are not formed when ultrasound is used solely. The discussion below will focus on the strengths and limitations of each technology.

6.1. Wi-Fi

Wi-Fi is now the most common wireless communication technology in the world. Due to its ubiquitous existence, Wi-Fi is the most widely used technology for indoor positioning systems. In addition to academic research, Wi-Fi based indoor positioning systems (hereinafter simply referred to as Wi-Fi systems) have also attracted close attention of industry practitioners.

The most significant strength of Wi-Fi systems is that they usually do not require purchase of new hardware equipment due to the high availability of WAPs. Another strength is that most Wi-Fi systems do not require modifications of WAPs. Yet, some systems which provide dynamic update of RSSM, require modifications of the firmware of WAP. As modification of firmware is not easy, Atia et al. [4] placed the wireless monitor beside each AP instead. Another major strength of Wi-Fi systems is that smartphones can be used as the receivers. These main strengths of Wi-Fi systems show that they have a very low cost. Wi-Fi systems also have high scalability as Wi-Fi supports a mesh network topology. However, Wi-Fi systems usually show a rough positioning accuracy at the multi-meter level. The experimental results conducted by Zhao et al. [116] showed that the maximum positioning error of Wi-Fi systems is 10 m and the average error is 5.3 m. The precision of the systems is moderate as well. In addition, the power consumption of Wi-Fi systems is high. The scanning rate of Wi-Fi systems is slow as it is limited by the passive scanning of end devices like smartphones. The scan time takes about 1 to 4 s [116]. Assuming that the computation time for positioning is less than the scan time, the response time of Wi-Fi systems is approximately the same as the scan time.

The most common principle used in Wi-Fi systems is based on RSSI analysis, which is well known as Wi-Fi fingerprinting. The process of Wi-Fi fingerprint collection is simple, and it can be easily implemented on smartphones. Trilateration is also often used for Wi-Fi systems [11], but it requires some specialized commercially available off-the-shelf (COTS) hardware equipment with modification in the physical layer of Wi-Fi. For localization principles, the RBP is used.

6.2. Bluetooth Low Energy (BLE)

Bluetooth and its new sibling, BLE (Bluetooth 4.0), are common short-range wireless communication technologies in the public domain. Thus, it has also gained the attention of the researchers for developing BLE-based indoor positioning systems (hereinafter simply referred to as BLE systems).

Both the Bluetooth and BLE use the same carrier frequency (2.4 GHz) as Wi-Fi, but the main difference between Bluetooth and BLE is that BLE has much lower power consumption. A BLE sensor advertising beacon messages a rate of 10 Hz can run for over a year using a coin cell [116]. With this advantage, BLE is more commonly used than Bluetooth today. The cost of BLE systems is low because COTS BLE APs, like iBeacons, are available at a cheap price [118]. In addition, BLE is available on most smartphones today. In terms of scalability, BLE systems also have a good performance with a Bluetooth mesh structure. However, in terms of accuracy and precision, BLE systems perform better than Wi-Fi systems by 27%, but such accuracy is still low compared with other technologies [116]. The experimental results conducted by Zhao et al. [116] showed that the maximum positioning error of BLE systems is 8 m and the average error is 3.8 m. The response time of BLE systems is very short. COTS BLE sensors can achieve an update of about 30 to 50 Hz [116,118]. Assuming that the computation time for positioning is less than the scan time, the response time of BLE systems is equal to the scan time.

Scene analysis is commonly used for BLE systems as it can easily be achieved with smartphones, and modification of the BLE hardware equipment is not needed [118]. Trilateration or triangulation is more often used in Bluetooth-based indoor positioning systems but not in BLE systems. RBP is also commonly used in BLE systems, particularly for commercial purposes [118]. The reason is that COTS BLE APs, like iBeacons, have a small size and can easily be implemented.

6.3. Radio frequency identification (RFID)

RFID is a historical short-range communication technology that has a wide range of applications, including animal tracking, aircraft identification, supply chain management, inventory tracking, and electronic-toll collection. It was not until 1998 that the researchers in Massachusetts Institute of Technology proposed that RFID could be used for tracking and identifying moving objects between different positions [5]. Since then, many RFID-based indoor positioning systems (hereinafter simply referred to as RFID systems) have been developed.

Typical RFID systems consist of three components: RFID tags, RFID antennas and a host computer. RFID antennas are connected to the host computer and the computer will estimate the position of the target. RFID antennas and the host computer can be combined in hand-held devices called RFID readers [5]. In RFID systems, both RFID tags and RFID antennas can be the positioning target, depending on the design of RFID systems [5].

When humans or robotic machines are exploring an indoor environment, they are usually equipped with RFID antennas and a computer. Thus, RFID antennas will be the positioning target and they can instantly give position information to the persons or machines. However, if some objects are to be positioned in the environment, with humans being outside of the environment to monitor the objects, RFID tags are attached to the objects as the positioning targets [76].

There are three types of RFID tags: active tags, passive tags, and semi-passive tags. All of the tags have been used by researchers to develop RFID systems [76]. Active tags have the longest range ($<$ 1 km under the LOS condition) amongst the three [5]. Yet, they are equipped with a button cell battery that needs to be replaced. Passive tags are much cheaper than active tags and have no batteries, and they only start transmitting signals when activated by the incoming RFID signals. However, passive tags have a much shorter transmission range ($<$ 10 m under the LOS condition) [5]. Semi-passive RFID tags combine the advantage of both active and passive tags: while semi-passive RFID tags are activated by the incoming RFID signals, they are equipped with a battery to allow a longer range of transmission. Thus, semi-passive tags are also the most expensive tag amongst the three. In addition, passive and semi-passive RFID tags of ultra-high frequencies are not detectable by smartphones unless an additional antenna is attached, which incurs moderate additional costs [71].

RFID systems usually give moderate to high accuracy and precision performance, and some specially designed RFID systems can attain very high accuracy at the sub-centimeter level under the LOS condition [112]. However, RFID systems have low scalability as they generally require a linear search on the back-end database for identifying a tag, which may cause a burden on the response time of RFID systems. As a result, some protocols utilize a tree structure for RFID key storage to reduce the search time [67]. The cost and power consumption of RFID systems depend on its design and the tags used, which can range from low to moderate. RFID systems can achieve a short response time. The results in [112] showed that it takes about 30 ms each time when the reader interrogates a tag, and the short read time also depends on the well-designed anti-collision algorithm in the study. Although actual response time for positioning depends on the structure of individual RFID systems, it is the same as the read time in the RFID systems presented in [112].

Due to the wide applications of RFID, different types of RFID antennas have been developed and RFID systems are very diversified. Trilateration, triangulation and scene analysis are all used in RFID systems. Notably, the RFID systems are the most common systems that utilize PDA [44,112].

6.4. Zigbee

Zigbee is specifically designed to be used in personal area networks in a small area. It has also attracted the attention of the researchers for implementing Zigbee-based indoor positioning systems (hereinafter simply referred to as Zigbee systems) in small areas like houses. Zigbee is widely known for its low power consumption. It is specifically designed as a low data rate, low power, low cost, and secure technology for short-range communication [117]. Zigbee supports network topologies like star, cluster, tree, and mesh networks. The mesh topology of Zigbee makes it a scalable technology. In a Zigbee mesh network, a special node called a Zigbee coordinator is responsible for initiating the network and for selecting the key network parameters. However, in terms of accuracy and precision, Zigbee has a moderate performance at the sub-meter level only. In addition, the response time of Zigbee is short. Testing results conducted by Gezer et al. [35] showed that the scan time in a Zigbee mesh network took about 60 ms, which is assumed to be equal to the response time of Zigbee systems. One other limitation of Zigbee interfaces is not commonly available on smartphones.

Trilateration can readily be used for Zigbee systems because some COTS Zigbee products can support the use of path attenuation for position estimation [3]. Scene analysis is also used in Zigbee systems.

6.5. Ultra-wide band (UWB)

UWB is a communication technology that is specially designed for high data rate transmission. UWB has now become an emerging and widely used technology for indoor positioning as UWB-based indoor positioning systems (hereinafter simply referred to as UWB systems) can offer considerable advantages.

In general, UWB systems achieve the best performance in terms of accuracy and precision out of the ten technologies. Due to the wide bandwidth of UWB, UWB systems usually can still perform accurate and precise positioning under strong noise interference caused by multipath effect [2]. Typical UWB systems have an accuracy and precision at sub-centimeter or even submillimeter level under the LOS condition [14]. UWB systems also have a low power consumption. The scalability of UWB systems can be either moderate or high as only some specially designed UWB systems support a mesh network. For example, Ridolfi et al. [86] developed a UWB system on top of a WiFi ad-hoc mesh network to achieve a highly scalable UWB system. COTS UWB hardware equipment is usually sold in a package of the whole UWB systems for industrial applications, and hence the cost is high [2]. Yet, the small-sized hardware equipment and programmable UWB system offered by Decawave has a medium cost, and it is suitable for the purpose of research and development. In addition, the testing results conducted by Jiménez et al. [50] showed that the response time of the UWB system made by Decawave is about 300 ms, which is of a moderate response time.

Trilateration, triangulation and scene analysis can all be used for UWB systems [2].

6.6. Indoor Global Navigation Satellite System (GNSS)

GNSS comprises of different outdoor positioning systems, e.g., GPS, GLONASS, Galileo, BeiDou, which are available everywhere in the world [62]. However, this type of outdoor positioning service is not applicable indoor due to the blockage by the building structure. To overcome this problem, indoor GNSS systems have been developed by the researchers. Typical indoor GNSS systems are based on RF waves to carry GNSS signals, but some specialized indoor GNSS systems are laser-based instead.

There are three types of architectures for indoor GNSS systems: pseudolite, repeater and repealite [31]. Pseudolites are just like GNSS satellites. Pseudolites send GNSS signals by themselves, but they are implemented on the roof of the building or other high-level places [87]. Repeaters do not send GNSS signals themselves. They first collect signals from GNSS satellites, and then amplify and retransmit the signals to the indoor environment without further treatment [31]. However, pseudolites are subjected to problems like clock asynchronization, multipath effect, and near-far effect; repeaters reduce the aforementioned problems but cannot solve the problems completely. Repealites combine the architectures of both pseudolites and repeaters to overcome the aforementioned problems [111].

The main advantage of indoor GNSS systems is that the positioning targets can use smartphones to seamlessly position themselves indoors and outdoors using the GPS signals. Indoor GNSS systems also have high scalability as the system can operate with four APs installed on the roof to achieve 3D positioning [87]. However, one limitation is that if the indoor environment is a tall building with many floors, the signals cannot penetrate the lower floors. To rectify this limitation, more APs have to be installed on the ceiling of each floor. In terms of accuracy and precision performance, laser-based indoor GNSS systems can achieve a very high accuracy and precision at deci-millimeter level [100]. RF-based indoor GNSS systems with a pseudolite architecture can also achieve a high performance at the sub-centimeter level using an advanced approach called carrier-phase measurement. Another system in the work of Xu et al. [111], which used repealites, can only achieve an accuracy of about 1 m. However, typical indoor GNSS systems using repeaters have accuracy and precision at sub-meter level only [48]. indoor GNSS systems also have a long response time. The testing results conducted by Chowdhury et al. and Ma et al. [20] showed that the update rate of GPS receivers is about 1 Hz on typical smartphones, and the positioning accuracy reduces if the update rate is larger than 1 Hz. Certainly, specialized and expensive GPS receivers can achieve much higher update rates, like 10 Hz with a pseudolite architecture or 40 Hz with a laser-based indoor GNSS system, without the loss in accuracy. In terms of power consumption, indoor GNSS systems have a moderate performance. The price of indoor GNSS systems can range from moderate to very high, and it depends on the level of accuracy.

Trilateration is usually used in indoor GNSS systems [48], which indicates that indoor GNSS systems are subjected to the influence of the non-LOS condition.

6.7. Ultrasound

Ultrasound is a traditional technology that has wide range of applications. It is even used in the natural world for navigation or communications by animals [111]. Therefore, the mature ultrasound technology has also attracted researchers for developing ultrasonic indoor positioning systems (hereinafter simply referred to as ultrasound systems).

Ultrasound systems can be divided into broadband or narrowband systems. Broadband ultrasound requires more power consumption but can achieve a higher accuracy and precision. To implement ultrasound systems with smartphones, an external analog multiplier is connected to the smartphones using the Jack input connector.

In an environment with little noise interference, ultrasound can achieve very high positioning accuracy and precision at the sub-millimeter level [74]. However, the accuracy and precision performance decrease significantly with the presence of noise. The most serious limitation of ultrasound systems is that ultrasound cannot penetrate walls and has a low coverage [74]. Thus, a large number of ultrasound APs have to be deployed in the environment in ultrasound systems, which leads to a low scalability. A study has specially designed the distributed positioning algorithm for efficient installation and placement of ultrasound APs [75]. In terms of cost, ultrasonic hardware equipment is usually cheap [85], and the power consumption is low [74]. The response time of typical ultrasound systems is as short as about 70 ms. Notably, as ultrasound is seriously subjected to multipath effect, ultrasound can only be transmitted after the previous signal is completely attenuated. With a broadband system, and a well-designed modulation scheme, the response time of ultrasound systems can be even shortened to 25 ms [43].

Trilateration and triangulation are commonly used for ultrasound indoor positioning systems [75].

6.8. Geomagnetic waves

The novel idea of utilizing geomagnetic waves to achieve indoor positioning has appeared in recent years. Geomagnetic waves exist everywhere in the environment. The inner structure of the building interferes the magnetic waves, and hence geomagnetic waveforms are unique at different positions in an indoor environment.

Developing accurate and precise indoor positioning systems based on geomagnetic waves (hereinafter simply referred to as geomagnetic wave systems) is very challenging. Geomagnetic waveforms have a low discernibility [91], which makes geomagnetic fingerprints not unique enough to accurately determine the position of the targets. In addition, geomagnetic can vary both horizontally or vertically [60]. Hence, in addition to the magnetometer, other IMUs like accelerometers and gyroscopes, are also used to provide extra information for positioning. However, the accuracy and precision performance of geomagnetic wave systems using smartphones are at sub-meter level only [60,91]. Despite the varying nature of geomagnetic waveforms, the low accuracy and precision are also partially attributable to the cheap IMUs utilized on smartphones, which are of poor quality. In addition, the movement of metals indoor, such as elevators and other machine equipment, will interfere the geomagnetic field with non-stationary noises [60]. The main strength of geomagnetic wave systems is that no APs are required; i.e., it is an infrastructure-free indoor positioning technology. Thus, geomagnetic wave systems have a low cost and very high scalability. In addition, the power consumption of geomagnetic wave systems is very low as IMUs consume very little battery power. Furthermore, geomagnetic wave systems developed on smartphones have a moderate to short response time. Common magnetometers on smartphones can achieve a moderate to high sampling rate of 10 to 30 Hz, while accelerometers and gyroscopes has a sampling rate of 30 Hz and 50 Hz respectively [63]. The sampling time is assumed to be the response time of GWIBSs for comparison.

Geomagnetic wave systems only use scene analysis and RBP to achieve indoor positioning [60,91]. In particular, SFA can be used for geomagnetic wave systems to improve the accuracy [34].

6.9. Image processing

Image processing is a promising and still developing technology that has vast applications. Image processing technology is also utilized by researchers to develop indoor positioning systems based on image processing (hereinafter simply referred to as image processing systems). These systems are also called image-based indoor positioning systems [52]. Image processing systems are mostly developed using visible light cameras and they are usually developed on smartphones today [105]. Other than positioning, image processing systems can also provide a 6D object pose estimation (3D position and 3D orientation). In particular, Feng et al. [30] proposed a new registration algorithm and computing framework, the KEG tracker, for estimating a camera's position and orientation. The proposed method improved the real-time 6D pose estimation accuracy of image processing based indoor positioning.

Most image processing systems are marker-less and thus infrastructure-free, as they only utilize the built-in characteristics in an indoor environment for positioning [52]. The essence of marker-less image processing systems is that they utilize IBFA to locate or position the targets. Some other image processing systems are assisted with markers for positioning. Kim et al. [56] utilized augmented reality techniques with marker detection and image sequence matching for localization. As the markers have a higher detection accuracy than built-in indoor characteristics, the accuracy and precision of marker-assisted image processing systems increase. In addition, there are some marker-based image processing systems that only use visual markers for positioning [52].

For marker-less and marker-assisted image processing systems that largely depend on built-in indoor characteristics for positioning, they have very high scalability and a low cost; whereas for marker-based image processing systems, they have a low scalability instead. Image processing systems can achieve moderate accuracy at sub-meter level when the environment is static and there is little noise interference [52]. However, when there are dynamic changes of lighting and background in the environment, or the markers are blocked under the non-LOS condition, the accuracy of the systems can reduce significantly. Thus, image processing systems generally have a low precision. In addition, since the camera on smartphones can only capture images at a single direction, the orientation of the smartphones also affects the accuracy and precision. Therefore, IMUs are needed to determine the orientation of the camera [105]. Assuming that the direction of the camera is the same as that of the positioning target, the orientation of the positioning target can also be determined. The response time of image processing systems is long because additional time is needed to perform IBFA. The experimental results using a laptop computer conducted by Kawaji et al. [52] showed that the scan time of their an image processing system ranged from 0.22 to 1.51 s, and the response time of the an image processing system was about 2 to 3 s with IBFA. The computation time is likely to be even longer if an image processing system is developed on smartphones, and thus image processing systems are difficult to achieve real-time positioning. In addition, the power consumption in image processing systems is high due to the use of cameras and heavy computation work.

For image processing systems, scene analysis and RBP are usually used with IBFA. Although the IBFA shares high similarity with the RSSI analysis used in Wi-Fi fingerprinting, it is difficult for image processing systems to dynamically or efficiently update the image database, which is also a considerable limitation to installing image processing systems. Kawaji et al. [52] used an omnidirectional camera as a means to increase the efficiency of creating the image map.

6.10. Range imaging

Range imaging is another promising and still developing technology that has gained wide attention for applications in industrial metrology as well as robot and pedestrian navigation. Range imaging is a kind of device-free positioning as no receivers are placed at the positioning targets. Other than positioning, range imaging can also perform 3D positioning with motion detection, providing a 6D object pose estimation (3D position and 3D orientation) [12]. Although range imaging also uses cameras as in image processing systems, range imaging differs from image processing systems that range can determine the distances at every point of the positioning targets on the images from the range camera. Range imaging based indoor positioning systems are also called optical indoor positioning systems [73]. The main limitation to range imaging systems is the strict requirement of LOS conditions. As the 3D range cameras capture waves with low penetrability, such as ordinary visible light, infrared and laser [12], the presence of the LOS condition is highly important.

The range cameras used in range imaging systems can be divided to three types: stereo cameras, structured light cameras and time of flight (ToF) cameras. Stereo cameras perform position estimation based on triangulation. The stereo cameras work similarly to the binocular vision of human eyes, as they use two or more cameras to capture the scene at different angles. The images formed by the cameras demonstrate subtle shift of the positioning targets and background on the scene, and this phenomenon is known as parallax. In these images, only the center line at the distant background is not shifted. Thus, stereo cameras need to solve the correspondence problem, which is about identifying similar points in the images and determining the position of the center line. The specific angles of the positioning target with respect to the cameras can then be calculated based on the field of view (FoV) of the cameras, and the triangulation problem is solved. However, solving the correspondence problem is difficult if the scene has very similar colors and light intensity. Stereo cameras with high resolution can thus achieve a more accurate positioning.

Structured light cameras also utilize triangulation for positioning. The structured light cameras first project a special pattern of light is projected onto the surface of the positioning targets. By sensing and analyzing the pattern of light on the targets, the angles with respect to the light projector and light sensor are determined, and then triangulation is applied. ToF cameras are also equipped with a light projector and sensor. The ToF cameras project lines of light on the positioning targets, and the positions of the targets are determined based on the time travelled by the signal, when it is reflected back to the sensor from the targets.

Range imaging systems that are based on visible light and infrared can usually have a very high accuracy at the sub-centimeter level [73]. Laser-based range imaging systems can achieve an even higher accuracy at multi-millimeter or submillimeter level [32]. Range imaging systems can also achieve high precision. However, range imaging systems require a high power consumption due to the use of cameras and heavy computation work. As 3D range sensors are restricted by the FoV of the cameras and they have limited coverage, range imaging systems have a low scalability. A dense placement of 3D range sensors is needed to ensure continuous tracking of the positioning targets. Thus, the cost of range imaging systems ranges from moderate to high, depending on the interior structure of the indoor environment. In terms of response time, range imaging systems using ToF cameras or structured light cameras have a short response time. Lu et al. [66] showed that one of a widely used ToF camera, Microsoft Kinect v2, has 60–80 ms of latency but has a low frame rate of 30 Hz. It thus adopted a “Hybrid High Frame Rate Depth” prototype that generates useful depth images at maximum 500 Hz with minimum 20 ms of latency. Testing results conducted by Livingston et al. [65] showed that the average response time of a structured light camera, Microsoft Kinect v1, is about 125 ms with a frame rate of 30 Hz at the best conditions. However, range imaging systems using stereo cameras require a longer response time because additional time is needed to solve the correspondence problem. The testing results conducted by Kuhnert et al. [58] showed different algorithms of solving the correspondence problem, with the time-optimized version of the algorithm named “Winner Takes It All” having the shortest latency of 470 ms.

However, there are some more limitations to range imaging systems using structured light or ToF cameras. The closely positioned obstacles, and positioning targets with specific shapes can cause unwanted signal scattering and reflections. In addition, when the ToF and structured light cameras have overlapped coverage areas, signal interference can occur. The signal scattering, reflections and interference will affect the accuracy and precision of range imaging systems. Therefore, it is recommended to mount the range cameras on the ceiling with specific coverage areas, and to use range imaging systems for positioning large objects like humans or machines. One more significant limitation of using range imaging systems is related to ambient sunlight interference. Natural sunlight consists of infrared, visible, and ultraviolet light with high intensity, and hence the ambient sunlight is a major interference source if range imaging systems are used in semi-indoor environment.

6.11. Comparison and discussion

UWB systems and range imaging systems can both achieve very high accuracy and high precision. Range imaging can also achieve motion detection other than positioning, achieving a 6D object pose estimation. The orientation estimation can provide additional information for trajectory prediction, which can be used for improving positioning accuracy. However, as range imaging systems strictly requires the LOS condition for positioning, range cameras have to be mounted on the ceiling. In addition, range imaging systems using structured light and ToF cameras are prone to the influence of ambient sunlight in a semi-indoor environment like construction sites. Both systems have comparable costs. Range imaging systems using structured light and ToF cameras have a comparably short response time with UWB systems, but range imaging systems using stereo cameras have a moderate response time. In terms of energy consumption, range imaging systems require a high power consumption, whereas UWB systems consume much less power. This is beneficial to developing indoor positioning systems in places with limited power supply as the construction sites. UWB systems also outperform range imaging systems in terms of scalability, which can reduce the costs for on-site layout management.

RFID systems and typical RF-based indoor GNSS systems can both achieve moderate to high accuracy and precision. Specialized indoor GNSS systems and RFID systems can both achieve a short response time, but indoor GNSS systems using smartphones have a long response time instead. The high scalability of indoor GNSS systems reduces the costs for on-site layout management. However, to achieve a high accuracy, indoor GNSS systems are much more expensive than RFID systems. Notably, the laser-based indoor GNSS systems can achieve very high accuracy but are highly expensive.

Ultrasound systems, image processing systems and geomagnetic wave systems share some important similarities. Although ultrasound systems can achieve a higher accuracy than image processing systems and geomagnetic wave systems, the three systems have a low precision as they are easily subjected to noise interference. In addition, the three systems have low costs. Marker-less and marker-assisted image processing systems, as well as geomagnetic wave systems, have high scalability; whereas marker-based image processing systems and ultrasound systems have a low scalability instead. The major difference is that of image processing systems have a much longer response time and consume much more power compared with ultrasound systems and geomagnetic wave systems. The largest concern of applying these three systems on construction sites is the low precision. Notably, image processing systems can also achieve 6D object pose estimation as range imaging systems, but it is less convenient for image processing systems to achieve it because images have to be captured at heights.

Zigbee systems and BLE systems are highly similar systems. Both systems have a low cost, low power consumption, short response time and high scalability. However, Zigbee systems can usually achieve better accuracy and precision than BLE systems. These advantages make Zigbee systems a suitable choice for developing indoor positioning systems in places with limited power supply as the construction sites.

Similar to BLE systems, Wi-Fi systems also perform poorly in accuracy and precision. However, the power consumption of Wi-Fi systems is much higher than BLE systems. The scalability of Wi-Fi systems is also as high as BLE systems but the response time of BLE systems is much shorter. The main advantages of Wi-Fi systems are high availability of WAPs, low cost, ready availability on smartphones, and the easiness of fingerprint collection. These advantages make Wi-Fi systems using Wi-Fi fingerprinting be a preferable choice for establishing an experimental indoor positioning system on construction sites.

The performance comparison of the top 10 technologies is summarized in Table 5.

6.12. Others

Using Frequency modulation radio (FM-radio) to achieve indoor positioning has drawn the attention of researchers in recent years. Some research has focused on experimenting with the performance of FM-radio-based indoor positioning systems (hereinafter simply referred to as FM radio systems), such as [84]. The commonly used principle for FM radio systems is scene analysis [17]. Ongoing research is still concerned with developing FM radio systems. One major advantage of FM radio systems compared to Wi-Fi systems is that FM-radio waves have lower frequencies than Wi-Fi signals. Wi-Fi signals operate at 2.4 GHz, as commonly used by many other devices, which make Wi-Fi signals more prone to noise interference [72]. Thus, some searchers have combined FM radio systems with Wi-Fi, showing an improvement in positioning accuracy [72].

Both LoRa and Dash7 are two promising wireless communication technologies to realize the idea of IoT. While LoRa is regarded as a long-range (2–5 km in urban areas and 15 km in suburban areas), low-power and low data rate technology, Dash7 is also regarded as a low-power and low data rate technology, but with a medium range of transmission (~2 km) [1]. Due to the very narrow bandwidth of LoRa, it will cause very poor positioning accuracy under complex and dynamic environments with various noise interference. Simulation results have shown that the positioning error is about 8 m on average [1]. Dash7 has a better performance in terms of positioning accuracy than LoRa. Some test results have shown a median positioning error of about 4 m [10].

Li-Fi is a novel wireless communication technology that uses visible light, or in conjunction with ultraviolet and infrared, for data transmission [6]. Li-Fi is also considered as a potential complementary to Wi-Fi in developing the fifth-generation (5G) wireless communications. The extra-large bandwidth of Li-Fi makes it a very promising technology to be used for indoor positioning to provide high accuracy positioning. Some researchers have developed a 50 Gbps bidirectional indoor optical wireless communications link with an integrated localization and tracking system [37]. With a ± 30° FOV and a range of 3 m, the positioning accuracy is 0.05° (~2.5 mm), which is highly accurate. However, Li-Fi performs very poorly under the non-LOS condition as visible light, ultraviolet and infrared cannot pass through most objects. In addition, Li-Fi is prone to the noise interference of strong external light source. These make Li-Fi an inferior choice of indoor positioning technology in complex and dynamic environments with exposure to sunlight. However, if the non-LOS condition is not frequent, it is possible to combine Li-Fi with other indoor positioning technologies.

Laser-based indoor positioning technologies, such as the

Table 5
Performance comparison of the top 10 indoor positioning technologies.

	Indoor positioning technologies	Accuracy	Precision	Power consumption	Cost	Scalability	Response time
1	Wi-Fi	Low (multi-m; < 10 m)	Low	High	Very low	High	Long (~1–4 s)
2	BLE	Moderately low (multi-m; < 8 m)	Low	Low	Low	High	Very short (~20–30 ms)
3	RFID	Moderate to high (sub-m to sub-cm)	Moderate to high	Low to moderate	Low to moderate	Moderate	Short (~30 ms)
4	Zigbee	Moderate (sub-m)	Moderate	Low	Low	High	Short (~60 ms)
5	UWB	Very high (sub-cm to sub-mm)	High	Low	Moderate to high	Moderate/high	Moderate (~300 ms)
6	Indoor GNSS	Moderate to very high (sub-m to deci-mm)	Moderate to high	Moderate	Moderate to very high	High to very high	Short/long (~25–100 ms/~1 s)
7	Ultrasound	Moderate to very high (sub-m to sub-mm)	Low	Low	Low	Low	Short/very short (~70 ms/~25 ms)
8	Geomagnetic waves	Low to moderate (multi-m to sub-m)	Low	Very low	Very low	Very high	Moderate (~300 ms) to short (~100 ms)
9	Image processing	Low to moderate (multi-m to sub-m)	Low	High	Very low	Very high/low	Long (~2–3 s)
10	Range imaging	Very high (sub-cm to sub-mm)	High	High	Low	Moderate to high	Short/moderate (~60–125 ms/470 ms)

aforementioned laser-based indoor GNSS systems and laser-based range imaging systems, as well as total stations and laser trackers, are specifically used for achieving very accurate and precise positioning [100]. The positioning principle of total stations and laser trackers are similar to range imaging, which also uses the ToF algorithm. However, laser stations and trackers do not capture any visual images. Total stations have a very high accuracy at the submillimeter level. On construction sites, total stations are usually used for surveying purposes. Total stations can be controlled manually or they can follow the positioning targets automatically. Laser trackers have an outstanding positioning accuracy at one micrometer level [100]. The highly accurate laser trackers are mainly used in the aerospace industry for inspection and assembly. Both laser trackers and laser-based indoor GNSS systems have a very high cost, which make them a rare choice for indoor positioning systems.

7. Major applications in construction

Five major applications for utilizing indoor positioning on construction sites are identified. The discussion below focuses on the importance of these applications to the construction industry, and the related research work is described.

7.1. Real-time construction safety management

Real-time construction safety management (RT-CSM) is the most effective way for preventing accidents and casualties on construction sites. RT-CSM is able to provide instant warnings to workers so that they can avoid unnoticed danger. Sensor-based technologies, including indoor positioning technologies, vision-based sensing and wireless sensor networks, are greatly utilized in RT-CSM [115]. indoor positioning technologies are particularly important in two aspects of RT-CSM: safety design and accident forewarning system. Safety design concerns predicting the trajectory of machinery equipment and workers so that collision accidents can be avoided by better planning beforehand [115]. Position information on machinery equipment and workers is needed for trajectory prediction. An accident forewarning system gives alerts when accidents are upon to happen. These accidents include entering to unnoticed dangerous zones, collisions, and objects and people falling from heights.

For example, Cheng et al. [18] developed an automated trajectory and path planning analysis UWB system, which can generate optimal paths for workers and vehicles on construction sites. Lin et al. [63] utilized Wi-Fi system and ANN to develop algorithms that can assess the danger to the workers in real-time. If a worker enters a dangerous zone, a warning message will alert the worker and his or her coworker, or the supervisor nearby. Dzeng et al. [25] developed a system for detecting falling objects with acceptable accuracy rates, with the objective of reducing fall accidents on construction sites. Chen et al. [15] developed a real-time 3D crane workspace update system using a hybrid visualization approach. A wide-angle camera is mounted on a crane boom to track moving objects on the construction site during lift scenarios. The captured 2D image frames were aligned with a laser-scanned point cloud, and the corresponding 3D bounding boxes for tracked objects were updated dynamically. Yet, the study did not implement a warning function in the system to alert the crane operator in case any potential collision accident may happen.

7.2. Real-time construction process monitoring and control

Real-time construction process monitoring and control (RT-CPMC) is vital to the success of construction projects. Real-time monitoring can provide instant information on the current project status, work task performance and contingency circumstances on construction sites. Based on the information, near real-time decisions can be made by site managers and engineers to control construction processes efficiently and effectively. If the construction processes along the critical path are not well monitored and controlled, they will delay the finishing time of the whole construction project.

Location information is very important to RT-CPMC. Every construction process requires coordination of labor, equipment and material. Thus, location information for labor, equipment and material is needed for resource procurement and allocation. In light of this, indoor positioning technologies have been utilized by researchers to develop RT-CPMC systems. Teizer et al. [96] tested UWB system on a construction site to track workers and materials for monitoring the work task productivity, where UWB tags were attached to steel columns to monitor the steel erection process. Costin et al. [22] implemented an automated bi-directional construction monitoring RFID system on > 50 construction workers and equipment. The system not only collected and analyzed data from the workers and equipment, but also returned automated feedback to the workers and managers. Kim et al. [54] experimented an RFID system to position the construction materials on a construction site. Afterwards, the Zigbee technology was used to effectively deliver the information to the end users. A combined system of RFID and Zigbee technologies can potentially be used for improving the existing management processes for construction resources on construction sites. Kim et al. [55] developed an adaptive detector and tracker for positioning heavy equipment on construction sites using functional integration and online learning. While a detector focuses on finding out the targeted construction equipment using image processing technology, the tracker focuses on analyzing the continuous movement of the equipment to keep track of their positions. The online learning platform then keeps labelling the new incoming data to improve the detection accuracy recursively. The validation results from using video stream data collected from four different construction sites showed that the average precision, recall rates, and data sampling accuracy were 86.53, 86.21, and 79.35% respectively.

7.3. Autonomous and efficient inspection of construction structures and materials

Inspection of construction structures and materials on construction sites is important for ensuring that the quality of construction structures and materials are in line with the standards. Inspection also ensures whether the workers have followed the safety requirements. However, inspection is usually time-consuming and is prone to errors. Indoor positioning technologies can improve inspection on construction sites in two ways. Firstly, if one person has found some problems during inspection, the person can report the problems more efficiently by providing his or her current position information. Wang et al. [104] developed an RFID-based quality inspection and management system to manage and deliver data related to quality, and the laboratory test results showed that the system can enhance the effectiveness of information management in concrete specimen quality testing.

Secondly, a more efficient approach is to achieve autonomous inspection using robotics, without human intervention. Researchers have developed prototype systems that utilize robotics to carry out efficient inspection on construction sites. For instance, Irizarry et al. [47] utilized UAVs with a large-size interface to develop a safety inspection system. The study included a comparative test on the accuracy of counting hardhats. The test results showed that the developed system had comparable accuracy but better efficiency than the safety manager with a clear view of the construction site. Although not tested on a construction site, Pereira et al. [82] utilized UAVs with an embedded image processing system for detecting cracks on building facades. In both studies [47,82], autonomous navigation is a recommended feature for the UAVs, which uses an image processing system for indoor positioning and navigation.

7.4. On-site construction automation with robotics

The idea of using robotics to realize on-site construction automation appeared early in 1980 in Japan [42]. The International Association for Automation and Robotics in Construction was founded in 1990, in an effort to promote robotics on construction sites for improving the low labor productivity in the industry [42]. For the last forty years, many automated construction systems using robotics have been intensively researched. The biggest challenge for achieving construction automation is that every construction project is unique. Unlike the manufacturing industry, where most production processes are repetitive and standardized, construction processes are more complex and dynamic in the sense that they are more information-intensive, requiring judgement, sensing and adaptability. Thus, robots that automate construction processes have to be more 'intelligent'.

The first step to create intelligent robots is to install sensors on the robots, so that they can obtain sufficient information for analyzing the current situation and making judgements about what to do in the next step. One of the most vital piece of information is the position information. Incorporating position information to robotics has led to the development of different automated construction systems as described below.

In the late 1990s, autonomous road pavers and asphalt compactors equipped with GPS receiver are developed for positioning and autonomous navigation [83]. Besides road construction, construction automation has also been widely applied in tunnel construction. Sensors like lasers, gyrocompass, level-gauges and inclinometers are used in tunnel boring machines for navigation [89]. For the last two decades, research has also been focused on bringing automation to building construction. On-site construction processes such as foundation construction, frame erection, wall assembly, and indoor works can all be automated using robotics with the assistance of accurate positioning techniques. Every movement of the robots, including grabbing, lifting, erection and assembly of materials, as well as navigation, require accurate position information. The accurate positioning techniques not only include accurate laser-based indoor positioning technologies like total stations, but also include accurate positioning devices like rotary actuators.

Recent work has also focused on using indoor positioning technologies for supporting construction work, such as material delivery and waste removal. Park et al. [81] presented an integrated mobile robot navigation system using BIM and UWB to navigate in indoor areas of construction sites. The test results showed that the system can plan efficient paths for robots and the robots can navigate through the planned path properly to reach different destinations on a complex construction site. Robotic material delivery is one of the direct applications of their systems. For example, Tardioli et al. [95] developed a robotized dumper for debris removal in tunnels under construction. The robotized dumper can position itself and navigate autonomously using IMUs, semantic geometric features, and the signal strength propagation in tunnel scenarios.

7.5. Real-time or near-real time visualization and update of BIM models for construction progress management

In recent years, with the mature development of BIM, the construction industry has acquired an information-rich and highly integrated platform for different parties in the same project. The parties in a construction project, such as the client, site managers, architects, engineers, construction workers can access and share important information, and communicate and collaborate with each other at planning, design, and construction phases of buildings. Different simulation analyses such as clash detection, energy use, lighting, ventilation, scheduling and budgeting can all be realized using BIM models. Particularly, at the construction phase, the visualization of BIM models can help on-site and off-site parties perform overall construction progress management. Although using BIM models for construction progress management has some overlapping with the RT-CPMC or RT-CSM discussed above, the BIM-based construction progress management approach discussed here aims at tracking the overall construction progress using the BIM technology, rather than focusing on the efficiency and performance of individual work tasks, and the use of BIM technology enables the sharing of information across all parties in the project.

The BIM-based construction progress management approach can potentially enhance the efficiency of construction projects, but the major problem facing this approach is that the information contained in the BIM models are not up-to-date. Some researchers have pointed out that BIM models are at risk of being "blind and deaf" if the contained information is not able to be synchronized with ongoing building processes in a real-time manner [16]. As a result, real-time or near real-time visualization and update of BIM models for construction progress management are desired. Throughout the years, some researchers have focused on acquiring real-time data to update the information contained in BIM models. El-Omari et al. and Omar et al. [26] have summarized various advanced data-acquisition technologies for construction progress management that can be categorized to enhanced information technologies, geospatial technologies and imaging technologies. Imaging technologies, such as 3D-laser scanning, photogrammetry, and video-grammetry, can model constructed structures and perform the BIM-based construction progress management at a high level of detail.

To utilize the imaging technologies, one solution is to install stationary sensors on construction sites. However, the size and number of these sensors can make the stationary installation a less preferable solution on construction sites. Another solution is to integrate these imaging technologies with indoor positioning technologies. The integration of imaging technologies with an on-site indoor positioning system allows users to obtain the real-time data by imaging technologies, and the information is extracted from the data for real-time or near real-time update of BIM models based on the position of the users. However, the complex data processing and transfer, data interoperability, and compatibility between programs will be the concerns of this solution. In spite of that, integrating imaging technologies with indoor positioning technologies offer some other benefits. The on-site indoor positioning system allows on-site users to visualize the BIM models more efficiently based on their current positions. Mantha et al. [70] introduced a framework that used autonomous mobile indoor robots for gathering actionable building information in real-time, in which the information can then be used for various analyses and critical decision-making. Furthermore, the on-site indoor positioning system enables autonomous robots and UAVs, instead of human users, to perform more efficient construction progress management using imaging technologies. Fig. 6 illustrates the flowchart of the BIM-based construction progress management approach.

To illustrate how the BIM-based construction progress management approach works, three related studies are discussed in the following. Fang et al. [28] developed a novel point cloud-vision hybrid approach for 3D location tracking of mobile construction assets. Their novel approach utilized UAVs to first obtain the point cloud of the baseline 3D geometry in construction sites, and then recognize and update the positions of labelled mobile assets in construction sites according to the 3D geometry data. The results of the field test have demonstrated that their developed approach was able to reconstruct the site and update the location of mobile assets accurately and reliably. Although their research focuses more on RT-CPMC, their approach can be extended to the whole BIM-based construction progress management.

In another example, Fang et al. [29] developed a BIM and cloud–enabled real-time RFID indoor localization for construction management applications. The system consists of the passive RFID localization system, the BIM visualization system, and the cloud computing system. With a full-scale implementation on an actual construction site, the testing results has shown good localization accuracy ranging from

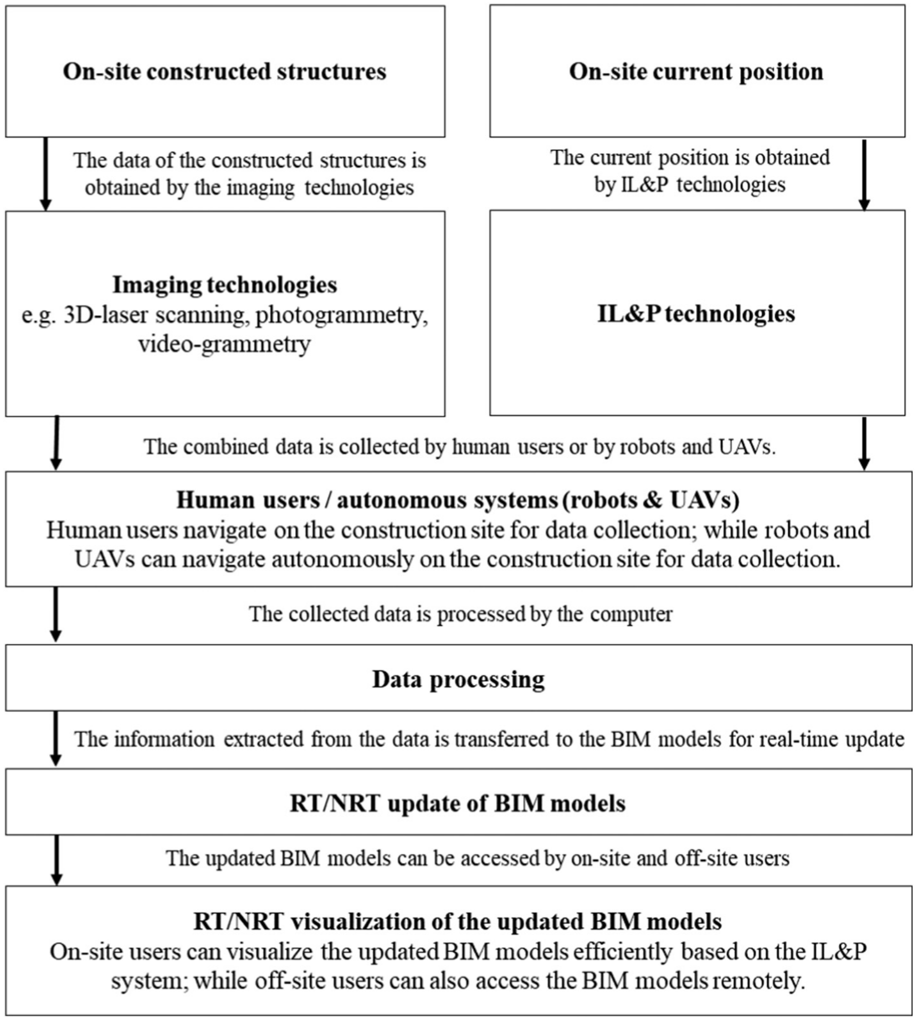

Fig. 6. Flowchart of the BIM-based construction progress management approach.

about 80% to 97%, and a minor time delay of 2 s compared to the actual worker location. Yet, this study does not reply on imaging technologies to update the BIM model in detail. The workaround is to divide the construction workplace to different zones, such that the update process becomes much simpler.

In the third example, Park et al. [79] developed an on-site safety management system which integrated BLE-based location detection technology, BIM-based hazard identification, and a cloud-based communication platform. Potential unsafe areas are defined automatically or manually in a BIM model. Worker locations are monitored and analyzed to determine whether the workers are exposed to predefined risks in the real time. The analysis results are then communicated over the cloud for effective safety management. The testing results of a real-world construction site case study demonstrated that the system is capable of detecting unsafe conditions, as well as collecting and analyzing the trajectories of workers with respect to potential safety hazards. However, the study has assumed that the BIM model is continuously updated as construction proceeds. If there is no efficient way to update the system, it is likely to underperform when the construction project is subjected to frequent changes.

8. Recent trends

Recently, there are some promising trends in indoor positioning research that can help develop suitable on-site indoor positioning systems, such as (1) indoor positioning technology hybridization, (2) indoor positioning principle hybridization, (3) integration with indoor navigation, (4) infrastructure-free positioning and collaborative positioning, (5) game theory positioning, (6) device-free positioning, and (7) integration with BIM models.

8.1. Indoor positioning technology hybridization

One common type of indoor positioning technology hybridization is to combine RFID with Wi-Fi. Combining RFID and Wi-Fi is considered as a promising solution to realize IoT, especially for context-aware systems with indoor positioning capabilities [109]. As RFID systems can achieve higher positioning accuracy and Wi-Fi is more scalable, combining both technologies can create an indoor positioning system with better performance. There are two ways to combine Wi-Fi with RFID. One way is to use RFID systems and Wi-Fi systems to perform position estimation separately, which is then fused together to achieve better accuracy. Such combination of position estimation by various systems is also referred to as fusion-based positioning. For example, Hasani et al. [41] used statistical method to calculate both system the weights for the position estimation obtained from the RFID and Wi-Fi systems respectively. The combined position estimation showed better positioning accuracy than using RFID systems or Wi-Fi system alone. Another way is to combine Wi-Fi system with RFID tags, where RFID tags are used as accelerometers to perform position tracking. SBF can be utilized to improve positioning accuracy recursively [109,110].

Another common type of indoor positioning technology hybridization is to combine image processing with Wi-Fi systems to achieve fusion-based positioning. The combination of the two technologies can yield better positioning accuracy and precision. [9] combined an image processing system with a Wi-Fi system for indoor positioning and used different statistical methods to compute the most probable position of the target from the information provided by both an image processing system and Wi-Fi system.

Niu et al. [77] presented a special type of indoor positioning technology hybridization, utilizing Zigbee radio to assist Wi-Fi systems for Wi-Fi fingerprint collection. A novel method was proposed in the study for detecting Wi-Fi APs to create Wi-Fi fingerprints from the signals collected by ZigBee interfaces. The highlight of this type of indoor positioning technology hybridization is that it takes advantage of the low power consumption of Zigbee, and integrates with the Wi-Fi systems, with the disadvantage of a high power consumption, to lower the overall power consumption. The results showed that their Zigbee-assisted Wi-Fi system is able to save energy by 68% on average compared with the approach based on Wi-Fi interface.

8.2. Indoor positioning principle hybridization

A few studies have combined trilateration and triangulation. As a result, the combined AoA and TDoA algorithm [21] or combined AoA and ToA algorithm [94] has been developed. Cong et al. [21] combined the TDoA measurements from the forward link pilot signals with the AoA measurement from the reverse link pilot signal. In the work of Taponecco et al. [94], it is assumed that the first arriving path signal at AP (BS) experiences a unique dominant scatterer. A nonlinear optimization procedure is used for position estimation under non-LOS condition. In both studies, it is found that the combined systems can achieve better accuracy than systems based on trilateration or triangulation only. In addition, if individual APs are able to measure the time travelled by and the angle of the signal, each AP can estimate the position of the target itself.

Another type of hybridization is to combine scene analysis with trilateration and triangulation. It not only enables 3D positioning for scene analysis, but also shows an improvement in performance of indoor positioning systems. The simulation results conducted by Kabir et al. [51] indicated that their proposed hybrid method achieves better positioning accuracy under NLOS condition than triangulation or scene analysis only. However, by combing scene analysis with trilateration and triangulation, it will expose the indoor positioning system to the influence of the non-LOS condition.

The third type of hybridization is to incorporate location information into indoor positioning, or to incorporate position information into indoor localization. The former type is exemplified by SSPCA, which integrates location information of APs to improve the positioning accuracy, while the latter type is exemplified by using the room detection algorithm to convert position information to location information, and hence a better localization accuracy is achieved. Both examples have already been elaborated previously.

8.3. Integration with indoor navigation

With position information at their initial position, robotic machines can keep track of their position and navigate in an indoor environment, following some predefined or random paths to complete their mission. The most common way to perform position tracking is using IMUs and it is also called inertial navigation.

Certainly, the initial position can be given by installing indoor positioning systems, but this requires some additional costs. The most important objective of indoor navigation is to allow robotic machines to explore the environment autonomously; i.e., the robotic machines should be able to map the environment and position themselves at the same time. This idea is well known as simultaneous localization and mapping (SLAM).

To achieve SLAM, sequential Bayesian filtering (SBF) is applied. This principle has two processes: prediction and correction. At the prediction stage, the posterior probability of the current position of the target is estimated. It can be assumed that the posterior probability is only conditioned on the immediate previous position of the target; i.e., it has the Markov chain property. At the correction stage, the prediction process is improved by the probability estimation at the current positions. Thus, the position estimation can be refined recursively over time by the prediction and correction processes. To perform the sequential Bayesian filtering method, algorithms based on Kalman filtering and particle filtering can be used.

Notably, even when mapping is not needed, SBF can also be used to refine the positioning accuracy with indoor positioning systems and IMUs. Xiong et al. [110] used Kalman filtering with indoor positioning systems and IMUs to improve positioning accuracy. In addition, RFID tags can also be used to substitute IMUs as a type of accelerometer. As a result, combining RFID tags with other indoor positioning technologies can also utilize SBF to achieve better positioning accuracy [110], and it is also a type of indoor positioning technology hybridization.

8.4. Infrastructure-free and collaborative positioning

Infrastructure-free positioning refers to indoor positioning systems that can operate without the placement of any APs. Infrastructure-free positioning is crucial for applying indoor positioning on construction sites, as the installation of APs could bring a high cost to on-site layout management [36]. Technologies such as geomagnetic waves, range imaging and image processing can achieve infrastructure-free positioning directly without further effort. However, for RF technologies and ultrasound, they can be regarded as AP-based technologies as APs are normally required. As discussed below, collaborative positioning is a promising way to achieve infrastructure-free positioning for AP-based technologies.

Collaborative positioning involves utilizing the position information provided from neighboring positioning targets to improve positioning accuracy. With the information provided, relative distances between neighboring positioning targets can be derived, thus adding some constraints on optimizing the position estimation of individual positioning targets. The additional constraints can improve the positioning accuracy. In other words, collaborative positioning can acquire the optimized positions of the targets by using the provided information from the neighboring targets only, without the placement of APs. Collaborative positioning can thus be used for achieving infrastructure-free positioning for AP-based technologies. For instance, Noh et al. [78] developed a collaborative indoor positioning scheme that leverages peer-to-peer Wi-Fi beaconing and accurate position tracking using IMUs. With a simulated RSSM, the targets can find a set of their possible positions indoor using RBP. The information provided by position tracking using IMUs will further refine the set of possible positions until convergence. The positioning accuracy is usually high when the stride length profiling technique is used, but the accuracy still depends on the routes of the targets. However, the limitations are that the convergence may fail, and precise positioning is not achieved.

8.5. Game theory positioning

Game theory has been a reliable mathematical method for designing protocols for wireless networks [90]. The use of game theory is a promising application in indoor positioning as game theory positioning provides another aspect in considering collaborative positioning. In collaborative positioning, it is normally assumed that neighboring targets are willing to provide their position information to other targets to improve their positioning accuracy. However, this in fact consumes the power from neighboring targets as they need to be alive for collaborative positioning. In game theory, as assumed by economic theories, the players in the game are rational and they will always optimize their own net benefits. In the case of collaborative positioning, the increase in positioning accuracy is a type of benefit, and the power consumption is a type of cost. Game theory positioning is objected to create a mechanism that can optimize the net benefits of all the positioning targets when they optimize their individual net benefit.

8.6. Device-free positioning

Contrary to infrastructure-free positioning, device-free positioning aims at removing the receivers, e.g., portable device or tags, at the positioning targets, which makes indoor positioning more convenient and less costly. Device-free positioning can be applied in circumstances where the positioning targets do not need the position information themselves. Some applications of indoor positioning system on construction sites can be improved by utilizing device-free positioning. For instance, considering a forewarning system for construction workers, the workers only need the warning signal when they are in danger. In this case, the workers do not need their position information. Besides the convenience, incorporating device-free positioning with forewarning systems also has a significant advantage in terms of safety; i.e., the workers can be alerted even if they forget to bring their portable devices. 3D image ranging is an example of device-free positioning technology, but the disadvantage is that it cannot work under the non-LOS condition. Analyzing CSI and body radio reflections can also achieve device-free positioning, and they can still work under the non-LOS condition [107]. However, knowing the identity of the positioning targets is a challenge for device-free positioning. For range imaging, one solution is to add face and object recognition techniques in computer vision for unique identification of the targets, but this solution is still subjected to errors.

8.7. Integration with BIM models

The rich geometric and semantic information provided from BIM models of high level of development (LOD) can improve indoor positioning systems in various aspects. One important improvement is the increase in positioning accuracy. The geometric information in the models can provide geometric constraints to eliminate some impossible position estimations, or provide accurate information for IBFA in image processing systems, which can refine the positioning accuracy. The geometric and semantic information in the models can be used for optimizing the AP placement in the indoor environment. The optimized plan of AP placement is a low-cost and promising solution for improving indoor positioning systems, which can increase the accuracy and reduce the cost of the systems [24]. In addition, detailed material information and accurate geometric information can potentially be used for improving the accuracy of RSSM simulation. With an accurate RSSM, the accuracy for indoor positioning systems with dynamic update of RSSMs can be improved. An accurate RSSM can also benefit the infrastructure-free and collaborative positioning systems for AP-based indoor positioning technologies in [78].

9. Conclusion

In conclusion, this paper has comprehensively reviewed the application of indoor positioning on construction sites. Currently, there is still no single perfect system that can achieve indoor positioning. The essence of applying indoor positioning systems is that they are user-oriented and environment-specific; i.e., it largely depends on the requirements of the users and the limitations in the environment. In light of this, this paper has analyzed the challenges in applying indoor positioning systems on construction sites. In addition, this paper has proposed six indoor positioning performance metrics (APP-CAT) for evaluating suitable on-site indoor positioning systems, including their technologies and principles. Fundamental indoor positioning principles with their algorithms are first discussed, evaluated and compared using APP-CAT. Subsequently, the top 10 indoor positioning technologies, which are selected according to their evaluation results using APP-CAT, and their popularity amongst the indoor positioning literature studies, are thoroughly discussed and compared. Other promising techniques like indoor navigation and hybrid positioning are also discussed.

Five major applications in construction of indoor positioning are also discussed, including RT-CSM, RT-CPMC, autonomous and efficient inspection, on-site construction automation with robotics, as well as real-time or near real-time visualization and update of BIM models for construction progress management. With reference to the studies in these five applications, the discussion has demonstrated the importance of the application and their great potential in enhancing the productivity, efficiency and safety on construction sites. Lastly, the recent trends of developing indoor positioning systems are also discussed. These trends, e.g., indoor positioning hybridization, infrastructure-free positioning, collaborative positioning, game theory positioning, device-free positioning, and integration with BIM models, are helpful in developing suitable on-site indoor positioning systems. In this paper, the comprehensive discussion of indoor positioning, from the aspects of the challenges on the construction sites, the six indoor positioning performance metrics (APP-CAT), the top 10 indoor positioning technologies and their principles, the promising applications in the industry, as well as the recent trends in indoor positioning, should be able to help academics, researchers, and practitioners develop high-performing and suitable on-site indoor positioning systems for improving various engineering and construction applications.

Declaration of competing interest

The authors declare that they have to competing interests.

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