Toward Persistent Spatial Awareness: A Review of Pedestrian Dead Reckoning-Centric Indoor Positioning With Smartphones

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***Abstract*— Navigating to a destination using smartphones has recently become a primary way in people's daily lives. Positioning is the prerequisite condition before efficient path planning can be achieved. In urban environments, people can self-localize with the aid of the global navigation satellite system (GNSS). However, last-mile navigation is still a challenge for pedestrians as current indoor positioning techniques cannot provide an accurate position. For the past few years, many researchers in academia and industry have thrown themselves into smartphone-based indoor positioning. Various solutions have been proposed to enable accurate and reliable position solutions. Pedestrian dead reckoning (PDR) is a popular positioning method as it is self-contained and outperforms inertial navigation. Also, other information from sensor data features and infrastructures, such as radio frequency (RF), can ensure the positioning service. At present, there are various indoor positioning reviews available to summarize current techniques. However, they focus primarily on separate positioning methods rather than integration. This article aims to comprehensively review PDR-centric indoor positioning using smartphones. It covers the basic concept of PDR and its integration with other information, examining both infrastructure-free and infrastructure-dependent approaches. Furthermore, this article outlines key considerations for conducting a comprehensive comparative analysis of the algorithm. Finally, the challenges and future research trends are given. This article can help readers understand the features of different PDR-centric integrations. It also contributes to the design of more robust solutions to satisfy the ever-increasing demand for indoor positioning.**

***Index Terms*— Indoor positioning, infrastructure-dependent, infrastructure-free, pedestrian dead reckoning (PDR), smartphones.**

NOMENCLATURE

DR	Dead reckoning.
MEMS	Micro-electromechanical systems.
DVL	Doppler velocity log.
LiDAR	Light detection and ranging.
RF	Radio frequency.
UWB	Ultra-wideband.
STFT	Short-term Fourier transform.
CWT	Continuous wavelet transform.
PCA	Principle component analysis.
VLP	Visible light positioning.
SVM	Support vector machine.
VA	Viterbi algorithm.
SLM	Seed landmark.
ICP	Iterative closest point.
MHT	Multiple hypothesis tracking.
DNN	Deep neural network.
CNN	Convolutional neural network.
GRU	Gated recurrent unit.
TCN	Temporal convolutional network.
DTW	Dynamic time warping.
VIO	Visual-inertial odometry.
RMSE	Root-mean-squared error.
RTE	Relative trajectory error.
RSS	Received signal strength.
LNSM	Log-normal shadowing model.
NLOS	Non-line-of-sight.
CSS	Chirp spread spectrum.
LTE	Long-term evolution.
LED	Light-emitting diode.
NHC	Nonholonomic constraint.
IMU	Inertial measurement unit.
PDR	Pedestrian dead reckoning.
FOV	Field of view.
BLE	Bluetooth low energy.
GPS	Global positioning system.
FFT	Fast Fourier transform.
DWT	Discrete wavelet transform.
GNSS	Global navigation satellite system.
HAR	Human activity recognition.
HMM	Hidden Markov model.
LSTM	Long short-term memory.
OLM	Organic landmark.
PGO	Pose graph optimization.
AI	Artificial intelligence.
INS	Inertial navigation system.
RNN	Recurrent neural network.
SVR	Support vector regression.
GMM	Gaussian mixture model.

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SFM	Structure from motion.
APE	Average position error.
ATE	Absolute trajectory error.
AP	Access point.
RTT	Round trip time.
FTM	Fine timing measurement.
LOS	Line of sight.
NFC	Near-field communication.
VLC	Visible light communication.
CMOS	Complementary metal–oxide–semiconductor.
GPU	Graphics processing unit.

I. Introduction

PORTABLE indoor positioning service for pedestrians has received extensive attention for years [1], [2], [3]. It offers significant convenience for quickly navigating in mega malls, airports, and metro stations. In daily life, people tend to carry their smartphones anywhere at any time. Furthermore, modern smartphones are integrated with multiple sensors in a compact form, offering a significant advantage in indoor positioning [4].

In various positioning methods, the DR is comparatively reliable as it is independent of external sources. Inertial navigation is one specialized form of the DR based on the IMU [5]. With the rapid progress of MEMS-based IMU, IMUs with smaller sizes can be installed in smartphones to offer a lightweight localization solution. However, inertial navigation via MEMS-IMU tends to suffer from rapid error accumulation over time [6], rendering it unsuitable for long-term applications. Although the ZUPT can be employed to restrain error accumulation [7], [8], it is often used in foot-mounted pedestrian navigation rather than smartphone-based positioning. Another DR form uses odometer-like sensors to obtain the position. It is common in land and underwater vehicular navigation via wheel speedometer [9], [10] and DVL [11], [12]. As the position is calculated by one integral in this manner, the positioning accuracy can be superior to traditional inertial navigation. Although smartphones are not equipped with odometer-like sensors, the pedestrian step can be detected by accelerometers. Subsequently, the step length can be estimated to calculate the displacement [13], [14]. The pedestrian current position is reckoned by combining the displacement from the last epoch and the heading. This approach is referred to as PDR. While PDR is a self-contained localization tool and can achieve satisfactory positioning performance, its position error still accumulates with movements. This characteristic limits its effective use in long-distance navigation scenarios [15]. Therefore, various auxiliary methods have been developed to correct the PDR error. These are primarily categorized into two approaches: infrastructure-free and infrastructure-dependent. In this article, the infrastructure refers to the physical hardware or equipment present in the environment, including but not limited to Wi-Fi routers, UWB anchors, and LED lights [16], [17]. Next, the fundamental concepts of infrastructure-free and infrastructure-dependent methods will be introduced.

In infrastructure-free methods, only carrier's sensors are needed, such as accelerometers, gyroscopes, magnetometers, barometers, and cameras. Although these sensors cannot be solely used to offer absolute positioning information, some location-related features can be extracted from their data to suppress the error accumulation. For instance, smartphones can be employed to recognize human activities [18], [19], [20], such as taking turns or elevators. These activities predominantly occur when the pedestrian is at a corner or inside an elevator. If an indoor floorplan can be known, the human activity can be mapped into the floorplan to derive the position [21]. In addition, human kinematic features can be learned via machine learning [22]. More accurate pedestrian displacements can be directly regressed from IMU raw data, achieving better trajectory estimations than classical PDR. In recent years, visual and LiDAR-based navigation methods have been widely investigated in the robotics community [23], [24], [25]. Perception information has been exploited to aid pedestrians' indoor positioning. Currently, cameras have been core components for smartphones, and they can be leveraged to achieve indoor positioning [26], [27]. Although some types of smartphones have been equipped with LiDAR, indoor positioning using smartphone LiDAR has yet to be proven effective due to its short detection range and narrow FOV.

In infrastructure-dependent methods, external communication facilities are required to offer observation information. RF signal-based indoor positioning, including Wi-Fi [28], [29], [30], BLE [31], [32], and UWB [33], [34], has been extensively investigated in academia as well as industry.

At present, RF signals are prevalent and serve as key solutions for indoor positioning. However, their effectiveness is often compromised by environmental factors such as interference, jamming, and spoofing, which confines their use to specific scenarios. On the contrary, PDR uses proprioceptive sensors to determine pedestrian locations. It operates independently of external environments and is consistently available. PDR is quite reliable for indoor or densely urbanized areas although it experiences drift over time. In this regard, PDR can be employed as the backbone and aided by other auxiliary information, forming a PDR-centric indoor positioning solution.

This work focuses on PDR-centric indoor positioning with smartphones. It reviews existing works from two perspectives: infrastructure-free and infrastructure-dependent PDR-centric indoor positioning. The abbreviations throughout this article are summarized in Nomenclature.

A. Existing PDR-Related Reviews and Our Contributions

Currently, there have been several PDR-related reviews. Hou and Bergmann [35] systematically reviewed PDR with wearable sensors, focusing on PDR methods involving sensors attached to the body. Wang et al. [36] presented a detailed introduction to pedestrian inertial navigation via smartphones. The overview of PDR, including step detection, step length, and heading estimation, is summarized. Vezočnik and Juric [37] reviewed typical step length estimation models based on inertial measurements, and their performance is analyzed and compared. Moreover, the influence of different walking speeds and phone placements is researched. Harle [38] distinguished between inertial navigation and PDR, analyzing techniques incorporating maps and hybrid systems to restrain PDR errors. Gobana [39] concentrated on different PDR models and summarized the data fusion for PDR, including Kalman filter, particle filter, graph optimization, etc. Davidson and Piché [32] surveyed the main indoor positioning methods using smartphones, including Wi-Fi, BLE, magnetic fingerprinting, map, and PDR. Guo et al. [40] concentrated on fusion-based indoor positioning, reviewing commonly used information sources and their corresponding fusion methods.

Based on the reviews mentioned above, their comparison with this article is shown in Table I. It is observed that current PDR-related reviews mainly focus on PDR itself, including step detection, step length estimation, and heading computation. These topics will not be discussed in detail in this article. Moreover, although some articles involve multiple sources and fusion for indoor positioning, PDR is just a component with brief consideration. Many current navigation systems, such as the GNSS-IMU [41], odometer-IMU [42], visual-IMU [43], and LiDAR-IMU [44], regard inertial measurements as the core information to ensure persistent spatial awareness. PDR is a self-contained positioning method. When integrated with additional data, it can offer a seamless and precise indoor positioning, establishing a PDR-centric solution. However, there is no corresponding article.

Therefore, this article initially provides a systematic review of PDR-centric indoor positioning with smartphones. The overview of this article is given in Fig. 1. Significantly, with the wide distribution of wireless signals, infrastructure-dependent indoor positioning has become mainstream. Consequently, many articles have focused on it. Although these approaches prove to be effective, they require prior deployment, leading to limited flexibility and application. Hence, this article also reviews infrastructure-free PDR-centric indoor positioning approaches and notably highlights their roles.

The main contributions of this article are as follows.

1) *Review of Infrastructure-Free PDR-Centric Indoor Positioning:* This article systematically reviews existing infrastructure-free PDR-centric indoor positioning methods. They are presented from four perspectives: activity matching, data-driven odometry, magnetic fingerprinting, and visual perception.
2) *Review of Infrastructure-Dependent PDR-Centric Indoor Positioning:* This article gives an in-depth overview of infrastructure-dependent PDR-centric indoor positioning methods from the RF, VLP, and ultrasonic positioning perspectives.
3) *Challenges of PDR-Centric Indoor Positioning:* This article discusses challenges in current methods and concludes with future research trends.

B. Organization of This Article

The rest of this article is structured as follows. Section II presents the basic concept of PDR. In Sections III and IV, infrastructure-free and infrastructure-dependent PDR-centric indoor positioning approaches are introduced. In Section VI, challenges and future research trends are presented. Finally, Section VII concludes this article.

II. Pedestrian Dead Reckoning

PDR was first proposed by Levi and Judd [45] in 1996. It was designed to provide foot travelers with an autonomous navigation solution when a GPS is unavailable. PDR uses accelerometers and gyroscopes, sometimes magnetometers, to obtain pedestrian position and orientation. PDR is independent of additional infrastructure, making it a primary tool in indoor positioning. PDR mainly comprises step detection, step length, and heading estimation [46].

Step detection is a critical part of PDR. It typically involves approaches from the time domain, frequency domain, and feature clustering [39], [47]. Time-domain methods refer to using statistical data features to achieve step detection. Typical time-domain approaches for smartphones include thresholding [48], peak detection [49], and autocorrelation [50]. Frequency-domain methods convert time-domain information to the frequency domain by STFT, FFT, and CWT/DWT [51], [52]. The feature clustering approaches use machine learning to perform step detection [53], [54], [55].

Step length estimation refers to calculating the displacement based on step detection results. It is mainly classified into model-based [56], [57], [58] and machine learning-based approaches [59], [60], [61]. Model-based approaches can be divided into constant, linear, and empirical models. The step length is obtained in the constant model by dividing the pedestrian walking distance by step numbers [62]. However, the estimation performance of this method seriously drops when pedestrian motion states vary. The linear model is formed by analyzing the relationship between step length and step frequency [63], [64], [65]. Moreover, the coefficients in the linear model can be determined based on typical contexts [66], such as walking, climbing and descending stairs, and running. This allows for the calculation of a more precise step length. To further improve the model accuracy, researchers have developed nonlinear empirical models [57], [58], [67], which can better reflect motion characteristics in actual situations.

The step length is along the pedestrian moving direction, and it needs to be projected to the coordinate for navigating. Consequently, the heading estimation becomes another essential issue in PDR [68]. Integration based on gyroscope data is commonly used to obtain the heading. However, pure integration can result in drift. Therefore, the accelerometer and magnetometer are introduced to achieve the correction [69], [70], [71]. Frequently used fusion methods involve the Kalman filter [72], extended Kalman filter [70], and complementary filter [73]. In addition, given that the smartphone can be arbitrarily put, its heading is inconsistent with the pedestrian. PCA is often employed to eliminate the offset between the pedestrian and the phone [74], [75].

To integrate the aforementioned components, the 3-D PDR model can be expressed as

$$\begin{aligned} p_{x,k} &= p_{x,k-1} + l_k \cos\theta_k \\ p_{y,k} &= p_{y,k-1} + l_k \sin\theta_k \\ p_{z,k} &= p_{z,k-1} + v_k \end{aligned} \tag{1}$$

TABLE I
COMPARISON OF PREVIOUS WORKS AND THIS ARTICLE

Content	Category	[36]	[37]	[38]	[39]	[32]	[40]	This
PDR-related Algorithm	/	S	S	S	S	S	W	M
Auxiliary Information Coverage	/	W	W	W	W	S	S	S
Fusion Algorithm	/	W	W	M	M	M	S	M
PDR-related Integration	W/O Infrastructure	M	W	M	W	W	W	S
	W/ Infrastructure	W	W	M	W	W	M	S
	Summary	M	W	M	W	M	W	S

* S-Strong; M-Moderate; W-Weak

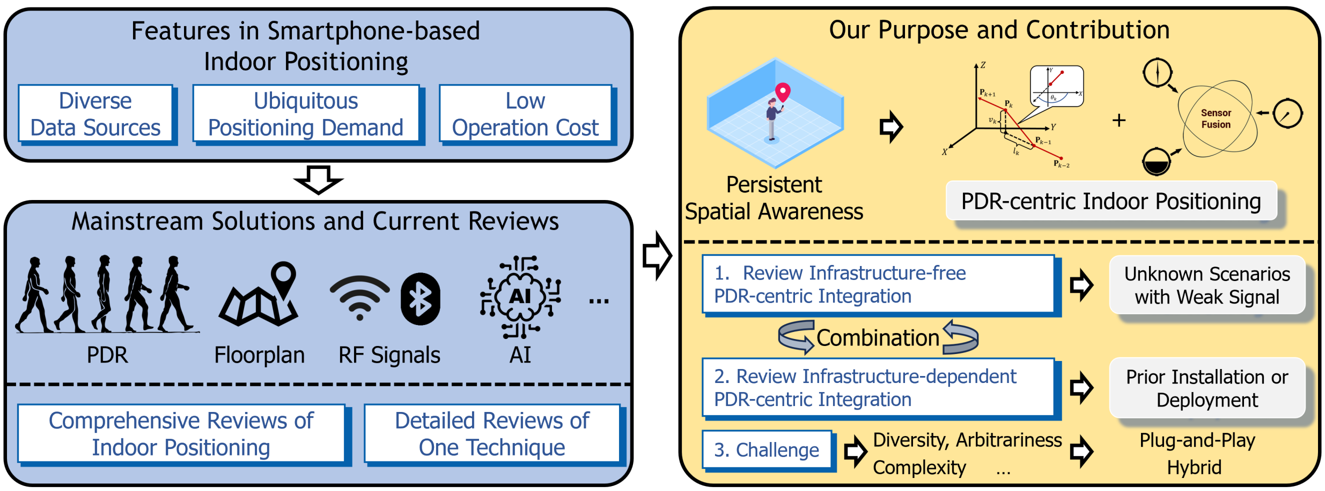

Fig. 1. Overview of this article. PDR can be used as the backbone to formulate a PDR-centric indoor positioning solution, ensuring persistent spatial awareness. This article reviews existing PDR-centric indoor positioning from two perspectives: infrastructure-free and infrastructure-dependent.

where $\mathbf{P}_i = [p_{x,i}, \ p_{y,i}, \ p_{z,i}]^{\mathrm{T}}$ represents the pedestrian position at the ith instant. l_k and v_k denote the step length and height difference [76], [77], respectively. θ_k is the heading that is mainly offered by gyroscopes and magnetometers [78], [79], [80]. In most cases, PDR is mainly used for 2-D scenes as the accurate height difference estimation is difficult to obtain with only smartphones. Therefore, the pedestrian height is generally determined by barometers [81], [82], [83] and wireless signals [84], [85], [86].

III. Infrastructure-Free PDR-Centric Indoor Positioning

Modern smartphones are integrated with multiple sensors in a compact form, which can be classified into proprioceptive and exteroceptive sensors [87], [88]. Proprioceptive sensors are used to measure the motion state of the carrier, such as accelerometers and gyroscopes in smartphones. On the contrary, exteroceptive sensors perceive external information from the environment, such as the smartphone's built-in RF module, magnetometers, camera, and barometer. It is observed that the absolute position cannot be directly obtained via the aforementioned sensors without the aid of infrastructure. Therefore, existing infrastructure-free PDR-centric indoor positioning methods use extended features derived from raw sensor data to aid PDR, as shown in Fig. 2. Also, comparative aspects of infrastructure-free indoor positioning are shown in Fig. 3. In general, data-driven odometry is based on pure DR. As such, its error continuously accumulates with the distance traveled, making its localization accuracy inferior to other methods. The localization accuracy for activity matching is at the meter level, while the approximate localization accuracies for magnetic matching and visual perception are at the decimeter level. However, the error in VIO is related to the distance traveled.

Among infrastructure-free methods, activity matching and data-driven odometry can provide human mobility information. Yang et al. [89] conducted a review of methods for measuring human mobility to aid in wireless positioning. Human mobility includes trajectory, locomotion modality, and activity landmarks. These elements can be fully used to enhance wireless localization in terms of accuracy, cost, and contextual understanding of the location. Magnetic fingerprinting and visual perception can provide ubiquitous global correction and abundant semantic understanding. These methods can ensure persistent spatial awareness in multiple scenarios.

A. Activity Matching

HAR using smartphones for pedestrian navigation has been systematically reviewed in [4]. Human activities are typically related to specific locations in indoor scenes. For example, taking escalators or elevators can only happen when the

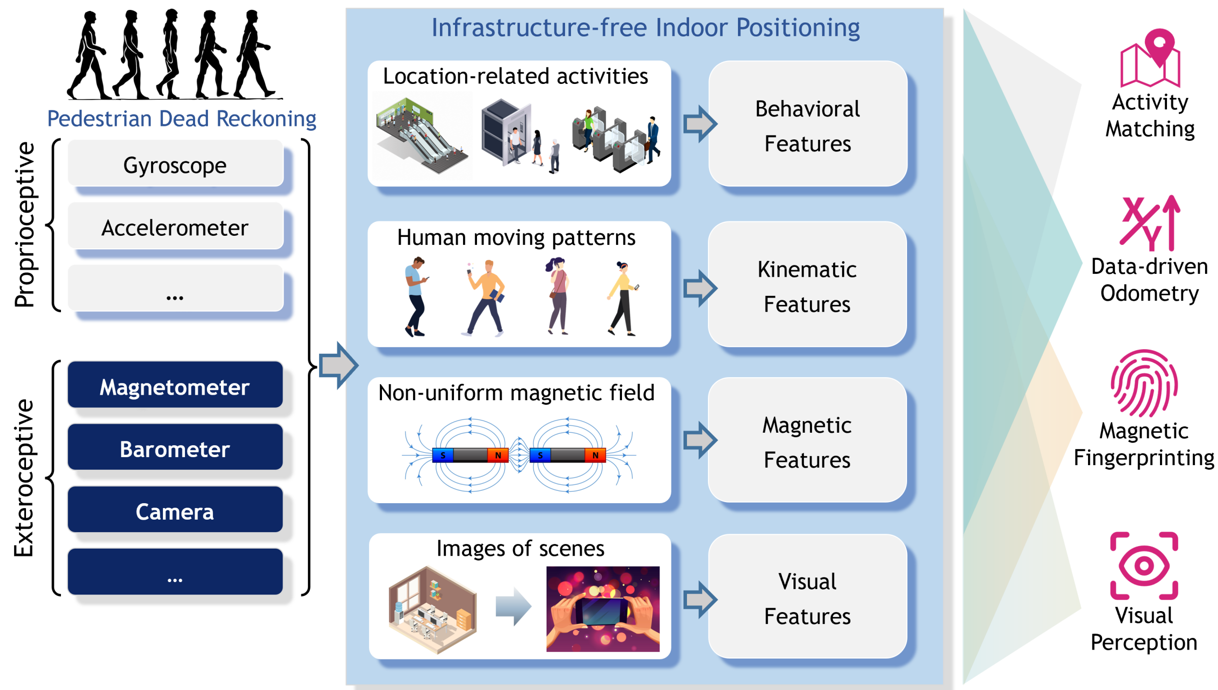

Fig. 2. Infrastructure-free PDR-centric indoor positioning, which is mainly based on data representation reflected by raw sensor data, such as behavioral, kinematic, magnetic, and visual features, leading to activity matching, data-driven odometry, magnetic fingerprinting, and visual perception.

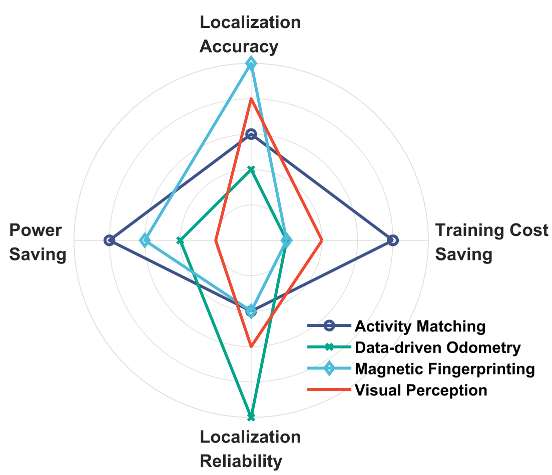

Fig. 3. Comparative aspects of infrastructure-free indoor positioning (the corresponding ability is enhanced from the inner to the outer circle).

pedestrian is at corresponding sites. This method matches recognized human activities with a map to obtain the current position. It is divided into two categories: with a prior map and without a prior map.

1) With a Prior Map: When a preexisting map is available, the locations where a pedestrian is presumed to have passed, based on human activity, can be obtained from the map for correction.

Common locations utilized for map matching mainly involve immanent structures, such as corners, stairs, escalators, and elevators. Gusenbauer et al. [90] introduced a self-contained indoor and outdoor positioning solution using mobile phones. The positioning information in indoor scenes is deduced by combining the PDR and activity-based map matching. Different activity types are classified from accelerometer measurements using an SVM. The estimated position is then matched with the closest vertical links on a map according to the specific activity. In this method, the nearest point is employed to do the matching, but it can easily cause a mismatch if the sensor error is too large. Hence, a sequence-to-sequence activity matching scheme is developed to improve the reliability of matching. Zhou et al. [91] proposed a human activity sequence-based indoor positioning using smartphones. Five different types of human activities are detected based on raw data from the accelerometer, gyroscope, barometer, and magnetometer. These include turning at a corner, turning around, taking the elevator, taking the escalator, and walking on the stairs. With the aid of an indoor road network, an HMM [92] is used to match the activity sequence with the specific sites of the map to correct PDR errors. Lu et al. [93] introduced a context-recognition-aided method to aid PDR. The turning activities are aligned with the prestored context in the database. This alignment uses the HMM and the recursive VA for matching. Gu et al. [94] presented a context-based map matching for indoor scenarios. In mode detection, accelerometers and gyroscopes raw data are combined to differentiate between walking in the corridor and shopping in the store, using LSTM [95]. The barometer is leveraged to recognize vertical displacement-related activities. Gyroscopes and PDR are jointly utilized to detect the turning activity. Then, the activity matching is achieved through HMM.

In addition to direct location-related activities, the collision between the pedestrian trajectory and the floor plan can also be considered an activity that corrects the PDR [96]. This is referred to as geometric map matching. Lan and Shih [97] designed a map matching based on the geometric similarity between the walkable trajectory and the floor plan, to calibrate PDR error. Luo et al. [98] explored the impact of different map-matching methods on commonly used spatial characteristics. In geometric map matching, PDR is utilized to provide initial positioning results. It has been found that corners and narrow corridors can enhance the accuracy of positioning. Zhou et al. [99] presented a method for indoor positioning using smartphones based on activity semantics. The displacements of a pedestrian are determined by employing an RNN, while a CNN is used to identify the activities. Displacements, which include multiple activity points, are matched with a map. The degree of similarity between the displacements and the map network is then used to determine the match. Finally, a factor graph is utilized to fuse the PDR and matching results.

To sum up, with the aid of a prior map, the human activities can be matched with the map to obtain the absolute position. Moreover, ambient signatures with unique features can be observed and dynamically added to the map to improve positioning accuracy. However, a prior map is only sometimes available. Furthermore, the internal structure may change after artificial reconstruction. In these situations, the performance of this type of method will be seriously affected.

2) Activity SLAM: In this method, the map is automatically built based on human activity. Park et al. [100] presented a pedestrian tracking approach using smartphones in indoor corridor environments. Corners are detected using magnetometer readings, and a new landmark is built each time a new corner is found. At each corner, current heading and location information are compared to the stored data to determine whether it is a known landmark. Pedestrian location can be revised when a stored landmark is revisited. Wang et al. [101] developed the UnLoc on the Android mobile phone. This article defines the SLM and OLM to represent specific structures and ambient signatures, respectively. SLMs include elevators, escalators, and stairs. OLMs refer to the site where the smartphone can overhear the RF signals or unique interference. These landmarks are combined to correct the PDR error. Liu et al. [102] proposed a collaborative Simultaneous localization and mapping (SLM) using the turning as the landmark. The ICP is utilized to detect whether the current turning can be matched with the known map. PGO is then leveraged to revise the pedestrian position using tuning-based loop closure. In the above approaches, the matching criterion for activity landmarks is based on the nearest object matching or similarity between current and past navigation information. However, it easily fails if the PDR error is too large. There may be instances where a match is not triggered, and mismatches can occur, leading to entirely incorrect results.

To solve this issue, researchers applied MHT [103] to activity-based SLAM to avoid the failure from ambiguous data associations. Grzonka et al. [104] proposed an indoor mapping approach via the movements of the door opening and closing events. Human activities are detected by wearable IMU suits. MHT is leveraged in the SLAM framework to deal with the high data association uncertainty. Grzonka et al. [105] extended their work to 3-D environments involving walking up and down staircases. Hardegger et al. [106] presented ActionSLAM, wherein location-related activities, such as door opening and sitting on a chair, are built as landmarks. ActionSLAM is built from FastSLAM [107], [108], utilizing a particle filter for state estimation. It maintains multiple particles to represent different hypotheses. Hardegger et al. [109] extended their work and formed SmartActionSLAM. The phone is used to detect sitting and standing activities. Moreover, the smartphone can be solely employed to offer PDR results. A Rao-Blackwellized particle filter is used to update the current pedestrian position and the map. Abdelnasser et al. [110] proposed SemanticSLAM, also based on FastSLAM, employing SLMs and OLMs to reset the PDR error. Shokry et al. [111] introduced DynamicSLAM, a method where the relative distances between two users serve as human-based anchors. This approach enhances anchor density and increases accuracy. Bai et al. [112] employed factor graph optimization to achieve smartphone-based indoor pedestrian SLAM, using turnings as landmarks. This approach demonstrates superior position estimation accuracy compared to the conventional particle filter.

To sum up, human activity-based SLAM methods have been paid much attention as they can run even without the prior map. However, the performance of activity-based SLAM relies heavily on the accuracy of PDR, as original landmarks are built based on PDR results. Moreover, this type of method requires pedestrians to revisit observed landmarks, which limits its application in some large-scale scenarios.

Based on the above reviews, the summary of existing PDR with activity matching is given in Table II.

B. Data-Driven Odometry

AI has recently been widely studied in indoor positioning, aiming to mitigate errors caused by sensors and models. Among various indoor positioning methods based on AI, one popular approach is employing IMU measurements to regress human motion, leading to data-driven odometry.

In classical PDR, the movement is determined by step detection and a step length model. However, in a data-driven odometry scheme, the step length or displacement along humans' moving direction can be directly regressed using IMU raw data. Chen et al. [113], [114] developed the IONet, which utilizes a bidirectional LSTM to regress changes in distance and heading from a sequence of raw IMU data. Then, the regressed change in distance and heading are applied within a PDR framework to obtain the position. On this basis, Chen et al. [22] introduced a lightweight DNN called L-IONet by considering the efficiency when deployed on low-end devices. A dataset for human tracking is also released. Cortés et al. [115] formulated a learning-based INS. The momentary speed is inferred by the CNN using a window of IMU measurements. It is then used to constrain the inertial navigation error using an extended Kalman filter. Cho et al. [116] suggested a multiscale CNN and RNN based on GRU using an outdoor dataset to learn the pedestrian's speed. GPS is the ground truth to train the model [117]. Feigl et al. [118] combined CNN and RNN to estimate human speed, robust to multiple motion states in dynamic situations. On this basis, Feigl et al. [119] extended their work by using

TABLE II
SUMMARY OF EXISTING PDR WITH ACTIVITY MATCHING

Category	Matching scheme	Typical papers	Advantages	Disadvantages
W/ a prior map	Nearest object	[90]	• Easy implementation. • Applicable place: activity-related landmarks with the same attributes cannot be too close.	• High requirements for PDR accuracy. • Prone to mismatch. • Prior map dependent.
	Hidden Markov model	[91], [93], [94]	• Easy implementation. • Better robustness than the nearest point matching.	• Prone to mismatch in complex scenarios. • Prior map dependent.
	Geometric matching	[96]–[99]	• Easy implementation. • Better robustness than the nearest point matching.	• Certain requirements for PDR accuracy. • Prone to mismatch in complex scenarios. • Prior map dependent.
Activity SLAM	Nearest object or similarity	[100]–[102]	• Easy implementation. • Prior map independent. • Applicable place: activity-related landmarks with the same attributes cannot be too close.	• High requirements for PDR accuracy. • Prone to mismatch. • Needs to revisit the same landmark.
	Multiple hypothesis tracking	[104]–[106], [109]–[112]	• Better robustness and can recover from the mismatch. • Prior map independent.	• High computational load. • Needs to revisit the same landmark.

a hybrid filter combining deep learning and a Bayesian filter for the speed estimation. It is robust even in highly dynamic situations. Klein and Asraf [120] formed a deep learning framework with an activity recognition model to regress the step length. This method can recognize the smartphones location. Additionally, the framework considers regression for both fixed and varying time windows. Asraf et al. [121] introduced the PDRNet, wherein a CNN-based smartphone location recognition network and ResNet [122] are combined to regress the change in distance and heading. Wang et al. [123] proposed a pose-invariant inertial odometry. A random orientation initialization is leveraged in the training to regress the velocity. It can release the dependence on the smartphone orientation.

Furthermore, researchers utilized data-driven approaches to regress displacement vectors. Yan et al. [124] presented robust IMU double integration (RIDI), wherein SVM is used to classify the phone placement. Corrections of linear accelerations are estimated using regressed velocity vectors obtained by SVR. Then, the corrected linear acceleration is utilized to estimate the pedestrian position. Herath et al. [125] presented the robust neural inertial navigation (RoNIN) that estimates horizontal positions and heading direction using a sequence of smartphone IMU measurements. RoNIN can be achieved via three network architectures: ResNet, LSTM, and TCNs [126]. Furthermore, the RoNIN dataset, which includes different devices and placements, is released. However, the positioning performance of RoNIN is heavily affected by the orientation. Aimed at this problem, tight learned inertial odometry (TLIO) was proposed [127]. It defines a local measurement to update the state in a stochastic cloning extended Kalman filter. Sun et al. [128] presented inertial deep orientation-estimation and localization (IDOL) to solve the orientation issue by training a neural network model using IMU and magnetometer data. However, its accuracy can degrade in new scenes. Therefore, Wang et al. [129] directly integrated the learned-based inertial odometry with the magnetometer measurement to restrain the heading drift using the factor graph. Huang et al. [130] proposed an indoor neural INS. In this system, a network is designed to estimate the attitude, thereby reducing the impact of inaccurate attitude measurements. Subsequently, a ResNet-based network is used to regress the 3-D relative displacements.

To address the problem of insufficient training data in data-driven odometry, Liu et al. [131] introduced a dataset based on smartphone inertial measurements. This dataset comprises data spanning approximately 190 h, with a total walking distance of over 700 km. It also includes a variety of scenarios, holding modes, and users. Furthermore, a TCN is introduced to regress the speed.

To sum up, data-driven inertial navigation has indicated an advantage compared to model-based PDR. However, similar to other learning-based methods, its effectiveness heavily depends on the extent of the trained model's coverage, including the device and context. These factors are more complex in comparison to other applications, due to the variety of brand models, random smartphone placements, and associated human activities. Based on the above reviews, the summary of existing PDR with data-driven odometry is given in Table III.

C. Magnetic Fingerprinting

The naturally occurring magnetic field can also be employed to aid PDR. In magnetic-based positioning methods, the nonuniform magnetic field is like the fingerprint, built as a database with labeled positions. Then, the pedestrian position can be calculated by matching the current fingerprints measured by the smartphone with the database [133]. Furthermore, the magnetic fingerprinting can also be done in a SLAM mode to achieve the positioning.

1) Offline Fingerprint Database Construction: A training step and a positioning step are generally included in this type

TABLE III
SUMMARY OF EXISTING PDR WITH DATA-DRIVEN ODOMETRY

Category	Network architectures	Typical papers	Descriptions
Step length/speed	CNN	[115]	• Data collection: IMU and Apple ARKit data. • CNN: predicting the speed. • Extended Kalman filter: introducing the regressed speed to correct INS.
	CNN + GRU	[117]	• Data collection: Outdoor IMU and position data. • CNN: extracting the features of the IMU data. • GRU: capturing temporal dependency along walking patterns.
	CNN + Bidirectional LSTM	[118], [119]	• Data collection: IMU and motion capture system data. • CNN: extracting the features of the IMU data. • Bidirectional LSTM: learning the temporal dependencies and dynamic context.
	TCN	[131]	• Data collection: a dataset with different users, holding attitudes, motions, and scenarios. • TCN: predicting the speed.
Step length/speed and heading	Bidirectional LSTM	[113], [114]	• Data collection: IMU and motion capture system data. • Bidirectional LSTM: predicting the change in distance and heading.
	WaveNet [132]	[22]	• WaveNet: processing long continuous sensor signals to provide accurate predictions. • WaveNet: improving the training and inference speed.
	CNN + ResNet	[121]	• CNN: determining the smartphone's location. • ResNet: regressing the change in distance and heading.
	ResNet	[123]	• Data collection: IMU and Google Tango data. • ResNet: predicting the speed and heading.
Displacement vectors/velocity	SVM + SVR	[124]	• Data collection: IMU and Google Tango data. • SVM: classifying the phone placement. • SVR: predicting the velocity.
	ResNet	[127]	• Data collection: IMU and VIO data. • ResNet: predicting displacement and uncertainty. • Extended Kalman filter: integrating predictions from network and model to solve motion states and biases.
Displacement vectors and heading	ResNet, LSTM, TCN	[125]	• Data collection: IMU and Google Tango data. • Network: predicting the 2D displacement and heading.
	LSTM + Bidirectional LSTM	[128]	• Data collection: IMU and SLAM (LiDAR, camera, and IMU) data. • LSTM: regressing the orientation and uncertainty. • Bidirectional LSTM: predicting the displacement.

of method [134]. A database of magnetic features with the location is built in the training step.

Kuang et al. [135] introduced an ambient magnetic matching positioning method to correct the PDR. PDR is leveraged to offer the relative trajectory contour for a magnetic field sequence, which improves the distinguishability of magnetic fingerprints. Also, a Gauss–Newton iterative is proposed to match the measured sequence with the database. It can improve the positioning performance and lower the computational load. In [136], PDR is fused with the geomagnetic positioning using a genetic-particle filter. Five geomagnetic features are extracted to specify the fingerprint, enhancing the positioning performance of geomagnetic matching. To solve the issue of sample impoverishment and weight degradation in the particle filter, Shi et al. [137] used the firefly algorithm to optimize the particle filter, fusing PDR and geomagnetic matching. The positioning accuracy is improved by 120% compared to the traditional particle filter. Shao et al. [138] proposed an indoor adaptive positioning method based on geomagnetic and PDR. To improve adaptability in diverse environments, a combined fingerprint accuracy indicator is proposed. Subsequently, the high-accuracy relative displacement in PDR is fully utilized for compensation in an adaptive extended Kalman filter.

Moreover, RF signals are normally added to enhance further the performance of integration of PDR and magnetic matching. Ban et al. [139] fused Wi-Fi with PDR and magnetic fingerprints. GMM is employed to represent the fingerprint and reduce computational burden. Li et al. [140] introduced a real-time smartphone-based indoor navigation, in which the corresponding software can handle DR, Wi-Fi positioning, and magnetic matching. The DTW [141] is applied for profile matching. Li et al. [142] proposed hybrid pedestrian navigation using PDR, magnetic matching, and Wi-Fi based on comparing various schemes. It concludes that the integration of PDR, Wi-Fi, and magnetic matching can be less influenced by the environment and motion. Guo et al. [143] introduced a multimode fusion localization called WiMag. PDR, Wi-Fi positioning, and magnetic matching are fused using a particle filter framework. The 3-D magnetic vectors along the moving path are built to improve space discernibility. Chen et al. [144] proposed an indoor positioning method based on PDR, Wi-Fi, and magnetic matching. An enhanced DTW is suggested to improve the performance of magnetic matching. In addition, a robust extended Kalman filter is introduced for state estimation. Wang et al. [145] presented an adaptive extended Kalman filter-based method to integrate PDR, magnetic matching, and Wi-Fi. A matching suitability model is constructed to evaluate the magnetic matching, and the fusion strategy can be adjusted accordingly.

2) Magnetic SLAM: Magnetic fingerprinting based on offline database construction has been frequently used to achieve positioning. However, it still has some drawbacks [146], such as the complexity of recalibration and limited regression suitability. Therefore, some researchers have developed SLAM-based methods for magnetic positioning.

Robertson et al. [147] presented the MagSLAM based on the step measurements and local magnetic field intensity. A particle filter is used to achieve the SLAM to estimate the location and build the local map of the magnetic field strength. Although MagSLAM is conducted using foot-mounted sensors, it forms a novel magnetic-based SLAM for indoor positioning. Gao and Harle [146] proposed a SLAM-based PDR approach using magnetic measurements for smartphones. A sequence-matching scheme of magnetic signals is established to achieve robust localization. DTW is used for matching, and a graph-based SLAM smooths the trajectory. Gao and Harle [148] extended their research to estimate the pedestrian trajectory posthoc using SLAM and particle filter with the aid of building floorplan. Magnetic loop closures and straight-line constraints are incorporated to ensure robust trajectory recovery. Wang et al. [149] proposed a keyframe-based graph SLAM, combining geomagnetic measurements and motion patterns to achieve reliable loop closure. Furthermore, the localization with a prior geomagnetic map is also discussed. Wang et al. [150] developed an indoor self-localization method to collect magnetic fingerprints online for future calibration usage. Magnetic fingerprints and indoor landmarks are combined to calibrate PDR error. Cui et al. [151] proposed a hybrid SLAM method that combines inertial and magnetic fields. In this method, an inertial-based map is constructed to represent passable areas, which helps reduce positioning errors from inertial sensors. Following this, a magnetic field map is created to describe the environmental features of these passable areas. This combination is designed to avoid errors due to regional feature homogenization.

To sum up, magnetic fingerprinting is an effective way to suppress PDR errors without additional infrastructure. The training process is time-consuming in classical methods, and repeated calibration is often needed due to temporal or spatial instability. Magnetic SLAM is an alternative manner to solve these issues. However, it requires the accuracy of PDR, and the loop closure needs to be triggered. Based on the above reviews, the summary of existing PDR with magnetic fingerprinting is given in Table IV.

D. Visual Perception

Recently, various communities have extensively investigated visual-inertial navigation [152], [153], [154]. In modern smartphones, the camera and IMU are included and integrated in a compact form, allowing visual perception to aid PDR. Visual perception in indoor positioning can be categorized into two types: image-based localization and VIO.

1) Image-Based Localization: Image-based localization can recover the camera pose based on the correspondence between the real-time image and feature database. Image-based localization offers drift-free locations, which can be used to calibrate PDR.

Dong et al. [155] proposed an indoor navigation system by building a 3-D model of an indoor environment from crowdsourced 2-D images, using SFM [156]. In model building, PDR and images taken on the way are utilized to obtain the user trajectory. Then, Wi-Fi fingerprints can be geo-referenced and attached to the point cloud, leading to a sensor-enriched model. Image-based localization is adopted in indoor navigation, and density-based model partitioning and fingerprint-based partition selection are combined to enable fast localization. Dong et al. [157] extended their research by utilizing pressure data from a barometer to detect trajectories between floors. Meanwhile, the points of interest information and their locations are calculated for navigation. Zhou et al. [158] introduced an image-based localization-aided pedestrian trajectory estimation. A robust image registration strategy is designed to avoid the loss of correct 2-D-to-3-D matches in traditional methods. To avoid cumbersome computing, Shu et al. [159] formed an efficient MEMS-aided image-based localization for smartphones. The scalability of PDR is fully explored to speed up the pose determination. Chen et al. [160] introduced ReLoc-PDR, a method that combines PDR and visual relocalization using graph optimization to reduce drift. Additionally, the visual relocalization process employs learned global descriptors for image retrieval and learned local features for matching.

To sum up, one premise of image-based localization is constructing an image database. It typically has specific requirements for the memory space in various large-scale scenes. Moreover, real-time matching is generally time-consuming. An initial guess of position derived by other positioning methods can be used to speed up the matching.

2) Visual-Inertial Odometry: VIO is frequently used to achieve state estimation for robots. In smartphone-based VIO,

TABLE IV
SUMMARY OF EXISTING PDR WITH MAGNETIC FINGERPRINTING

Category	Fusion methods	Typical papers	Descriptions
Offline fingerprint database construction	(Extended) Kalman filter	[135]	• Combining magnetic field sequence with the measured trajectory contour to improve the distinguishability. • A Gauss-Newton iterative for matching.
		[140], [142]	• A hybrid algorithm using PDR, magnetic matching, and Wi-Fi fingerprinting.
		[144]	• An enhanced dynamic time warping for matching. • An innovation sequence covariance estimation for robust estimation.
		[145]	• A magnetic matching suitability model to adjust the fusion strategy.
		[138]	• A combined fingerprint accuracy indicator to improve the adaptability. • Utilizing relative displacements from PDR to adjust the stochastic model.
	Particle filter	[136]	• Genetic mutation to solve the particle degradation.
		[137]	• Adaptive optimization firefly algorithm to solve the sample impoverishment and weight degradation.
		[139]	• Utilizing GMM to represent the fingerprints to reduce the computing effort.
		[143]	• A sequence of magnetic vector for improving the discernibility.
Magnetic SLAM	Particle filter	[147]	• Hierarchical map representation composed of grids. • FastSLAM framework.
		[148]	• Post-hoc SLAM. • Magnetic loop closures and straight-line constraints in the filter.
		[151]	• Combining the inertial-based map and magnetic field map for complementation.
	Graph optimization	[146]	• Sequence-based magnetic loop closure. • Utilizing the trajectory from magnetic SLAM for building a signal map.
		[149]	• Keyframe based SLAM. • Geomagnetic field with motion pattern for loop closure.

inertial measurements are not formed as the classical PDR but as inertial navigation or preintegration [161], [162]. However, the computational manner of the pose in VIO is based on the reckoning equation. Moreover, although visual perception provides high-accuracy localization information in VIO, it can easily fail in dynamic and featureless scenes. Thus, it cannot be used as a centric source for obtaining the position. When visual perception fails, inertial navigation will be employed to provide a continuous solution. Therefore, we regard smartphone-based VIO as a unique form of PDR-centric positioning in this article.

At present, VIO using mobile devices has drawn notable commercial and scientific interest. Recent examples in commercial applications are the ARCore by Google and ARKit by Apple. Also, Google Tango tablet device and Microsoft HoloLens augmented reality glasses have VIO built, enabling the precise real-time tracking of human ego-motion.

To make up for the gap in the lack of the pedestrian VIO dataset, Cortés et al. [163] developed authentic dataset for visual-inertial odometry (ADVIO), a real-world benchmark for VIO. This benchmark provides a comprehensive range of raw data from Google Pixel Android phones and iPhones, accompanied by high-quality ground-truth tracks. Porzi et al. [164] described a visual-inertial tracking approach using an Android smartphone. An extended Kalman filter-based sensor fusion is utilized for ego-motion estimation. Li et al. [165] suggested an extended Kalman filter-based VIO for motion tracking on a smartphone, which accounts for the effects of rolling shutter distortion. To avoid the loss of accuracy when a camera meets with large accelerations, Li and Mourikis [166] employed inertial measurements to model the camera motion, which removes the need for low-dimensional motion parameterizations. Solin et al. [167] developed probabilistic inertial-visual odometry (PIVO) using smartphone built-in low-cost IMU sensors and the monocular camera. The advantage of coupling inertial sources is fully exploited, and more robustness can be achieved in occlusion and feature-poor environments. Qin et al. [43] formulated VINS-Mobile using iPhone devices, and graph optimization is utilized for state estimation. Chen et al. [168] introduced robust neural inertial navigation aided visual-inertial odometry (RNIN-VIO), a method that employs a tightly coupled extended Kalman filter framework. In this framework, neural inertial navigation is used to aid VIO. This approach can achieve superior robustness and accuracy compared to traditional VIO methods. The calibration effect of camera intrinsic parameters is a critical factor affecting the accuracy of VIO. Modern smartphones typically use optical image stabilization to reduce image blurs, leading to varying camera intrinsic parameters. Jin et al. [169] investigated an optimization-based VIO that can estimate camera intrinsic parameters to improve positioning accuracy in real-world applications.

Moreover, researchers have adopted additional constraints to improve the positioning accuracy of smartphone-based VIO. Liu et al. [170] developed a collaborative visual-inertial SLAM for multiple smartphones. Each smartphone runs a VIO, and the measurements are shared in the server to optimize the map. It can enhance the accuracy of each agent pose estimation. Dong et al. [171] proposed a pedestrian gait information-aided visual-inertial SLAM via smartphones. Step length and step velocity are employed to improve the accuracy of the SLAM system. Furthermore, some specific signs can also be combined with VIO for indoor positioning. Fusco and Coughlan [172] employed the camera to recognize barcode-like signs, and the relative pose to the sign can be obtained. With the aid of the indoor map, the absolute position of the pedestrian is obtained to modify VIO.

To sum up, VIO is a frequently used approach to achieving accurate positioning in unknown environments, but it generally occupies a large amount of computing resources. Moreover, smartphone-based VIO has put forward a demand for phone placements. This means that VIO cannot be used when the smartphone is in a pocket or bag.

Based on the above reviews, the summary of existing PDR with visual perception is indicated in Table V.

E. Performance Comparison

In this section, we introduce the accuracy of some current infrastructure-free PDR-centric indoor positioning solutions. The positioning errors of these solutions are typically assessed using several key indicators: APE, RMSE, ATE, RTE [173], and the error as a percentage of the total distance traveled (% $\times$ Distance).

The positioning errors of some representatives are shown in Table VI. It can be observed that activity matching yields meter-level positioning errors, given that the locations associated with these activities are typically coarse. Data-driven odometry approaches are susceptible to error accumulation, resulting in larger positioning errors than other methods. Among infrastructure-free methods, magnetic fingerprinting and visual perception demonstrate superior positioning performance, achieving accuracy at the decimeter level.

F. Discussion

Based on the above reviews, this section provides a detailed discussion on the advantages, disadvantages, and applicability of each method in infrastructure-free PDR-centric indoor positioning methods.

1) Activity Matching: PDR with activity matching methods generally rely only on IMUs in smartphones. This significantly reduces the need for additional hardware and power consumption. However, HAR presents a huge challenge, particularly for smartphone users. Smartphones can be held in various modes, including reading, swinging, and calling, and each individual has unique activity habits. Moreover, in expansive spaces like mega malls, users often take irregular routes, resulting in numerous interferences. These factors make it difficult to accurately detect human activities, thus limiting its applicability in public navigation applications.

In conclusion, PDR with activity matching introduces certain requirements for both the user and the environment. First, it is preferable for the mobile devices used to be fixed on the users. This can significantly mitigate the impact of uncertain activities. Second, the environment needs to have obvious geometric features, such as corridors, stairs, and corners to constrain the users' movement. This can help avoid the influence of random walking.

2) Data-Driven Odometry: Data-driven inertial navigation methods offer the potential to calculate more accurate changes in displacement and heading using low-cost IMUs. These methods can adapt to different users and smartphone holding modes, a challenge that has been proven difficult in traditional model-based PDR. However, data-driven methods require substantial data for training. Meanwhile, training typically requires a high-performance computer and a GPU, which can constrain these methods due to hardware limitations. While there are some publicly available datasets and models, they often suffer from low coverage. Moreover, overfitting poses a huge challenge, especially evident due to the high-level and time-varying noise present in inertial measurements. It is important to note that the data-driven odometry still faces the problem of drift due to the lack of absolute positioning correction.

In conclusion, data-driven odometry is typically used to maintain positioning performance when an absolute positioning solution is unavailable. It is better suited for scenarios in which the smartphone is held in various modes for performing DR. At present, it is generally used in positioning applications involving a limited range of known users. When more users are involved, more training data will be required.

3) Magnetic Fingerprinting: The naturally occurring magnetic field provides a commonly used solution to support PDR. These methods employ an IMU and a magnetometer, which are common sensor configurations in modern smartphones. Unlike activity matching and data-driven odometry, magnetic fingerprinting does not require the user's motion to adhere to any specific rules. This flexibility makes it applicable to a broader range of scenarios and users. However, magnetic interference consistently presents an issue that affects the performance of magnetic fingerprinting. At the same time, it is challenging for magnetic fingerprinting to determine the user's floor level due to the similarity of magnetic field strength in the vertical direction.

TABLE V
SUMMARY OF EXISTING PDR WITH VISUAL PERCEPTION

Category	Targeted issues	Typical papers	Descriptions
Image-based localization	3D model coverage	[155], [157]	• Combining PDR and images to obtain user trajectories. • Utilizing these trajectories to build Wi-Fi database.
	Image registration	[158]	• A fused matching scheme to obtain the high-accuracy image pose.
	Practicality on smartphones	[159]	• A rough pose from MEMS for a possible search space.
	Vision-challenging environments	[160]	• Utilizing learned global descriptors for image retrieval and learned local feature matching. • Incorporating the Tukey kernel to mitigate the impact of abnormal visual observations. • Graph optimization-based sensor fusion.
Visual-inertial odometry	VIO Dataset for smartphones	[163]	• A test rig with an iPhone, a Google Pixel, Android phone, and a Google Tango device. • RGB video camera, accelerometer, gyroscope, magnetometer, platform-provided geographic coordinates, and barometer are included.
	Mobile implementations	[164]	• Extended Kalman filter-based sensor fusion.
		[43]	• Graph optimization-based sensor fusion.
	Vision-challenging environments	[167], [168], [171]	• Occlusion and feature-poor environments.
	Smartphone camera errors	[165], [166]	• Rolling shutter distortion.
		[169]	• Camera intrinsic parameters online estimation.
	Drift correction	[170]	• Collaborative SLAM for joint optimization.
		[172]	• Sign recognition to obtain absolute corrections.

In conclusion, magnetic fingerprinting requires a 2-D environment where the magnetic distribution exhibits a certain degree of uniqueness and differentiation. This characteristic enables the magnetic field to be distinguished for positioning purposes. Furthermore, it is essential for the environment to maintain a relatively stable magnetic field.

4) Visual Perception: PDR aided by visual perception can provide high-accuracy positioning results in infrastructure-free PDR-centric indoor positioning. By utilizing the camera on a user's device to capture and analyze environmental features, these systems not only provide precise location tracking, but they also offer a semantic understanding of the surrounding space, thereby enhancing the user's navigational experience. However, these systems are sensitive to light conditions, as poor illumination can significantly degrade the performance of visual algorithms. The presence of dynamic objects in the environment can also introduce additional challenges for consistent feature tracking. Furthermore, image processing and computer vision algorithms typically demand high computational resources, which may lead to faster battery consumption on the device.

In conclusion, visual perception imposes high requirements on application scenarios. The lighting conditions need to be ensured, and the features need to be sufficiently rich. Moreover, it is more suitable for scenarios where pedestrian traffic is minimal, allowing for uninterrupted capture and processing of visual data.

IV. INFRASTRUCTURE-DEPENDENT PDR-CENTRIC INDOOR POSITIONING

It is noticed that pure infrastructure-free PDR-centric indoor positioning approaches restrain the error accumulation in three perspectives: more precise displacements, prior map or database, and loop closure. They are all based on underlying characteristics of sensor data to suppress PDR drift, including behavioral, kinematic, magnetic, and visual features. This positioning method does not require the preliminary deployment of extra infrastructure but makes a demand on the prior information and actual environment. For example, on the one hand, if the measured data cannot match the prior data, map-aided and data-driven methods may fail. On the other hand, if the feature in the actual environment is sparse, this kind of approach cannot work. Therefore, researchers have also extensively studied indoor positioning using infrastructure to aid PDR, as shown in Fig. 4. Comparative aspects of infrastructure-dependent indoor positioning are indicated in Fig. 5. In general, the approximate localization accuracy ranges for PDR aided by different technologies can be summarized as follows: 2.0~5.0 m for Wi-Fi (more accurate using RTT), 1.0~2.0 m for BLE, less than 0.5 m for UWB, less than 0.5 m for VLP, and less than 1.0 m for ultrasonic.

A. Radio Frequency

RF technique has been widely utilized in indoor positioning due to its widespread availability in modern cities. Frequently

TABLE VI
POSITIONING ERRORS OF SOME REPRESENTATIVES

Category	Typical papers	Descriptions	Experimental setups	Errors
Activity matching	[91]	Sequence-based map matching	• Test site 1: office building (2750 m^2). • Test site 2: shopping mall (4800 m^2). • Device: Samsung Galaxy S III. • Ground truth: markers.	APE: 0.9∼1.9 m
	[100]	Similarity-based Activity SLAM	• Test site: office building (1600 m^2). • Device: HTC Desire, HTC Nexus One, and Samsung Galaxy S.	APE: <7.0 m
Data-driven odometry	[113]	IONet	Dataset: RONIN dataset seen.	• ATE: 31.1 m. • RTE: 24.6 m.
	[124]	RIDI		• ATE: 17.1 m. • RTE: 17.5 m.
	[125]	Resnet-based RONIN		• ATE: 3.5 m. • RTE: 2.7 m.
Magnetic fingerprinting	[137]	Fingerprint-based map matching	• Test site: office building (450 m^2). • Device: iPhone 8.	APE: <0.5 m
	[147]	MagSLAM (Particle filter)	• Test site: rectangular room (40 m^2). • Device: Xsens MTx and Xsens MTw. • Ground truth: motion capture system.	APE: 0.1∼0.2 m
	[149]	Graph-based magnetic SLAM	• Test site 1: office building (1100 m^2). • Test site 2: museum (5000 m^2). • Device: Google Nexus 5. • Ground truth: manually marked.	APE: 0.4∼0.6 m
Visual perception	[158]	Image-based localization	• Test site: office building. • Device: Xiaomi2 and Lenovo ThinkPad X240 laptop. • Ground truth: reconstructed poses using the structure from motion (SfM).	APE: 0.6 m
	[167]	PIVO	• Site: Shopping mall. • Device: iPhone 6.	0.23% × Distance

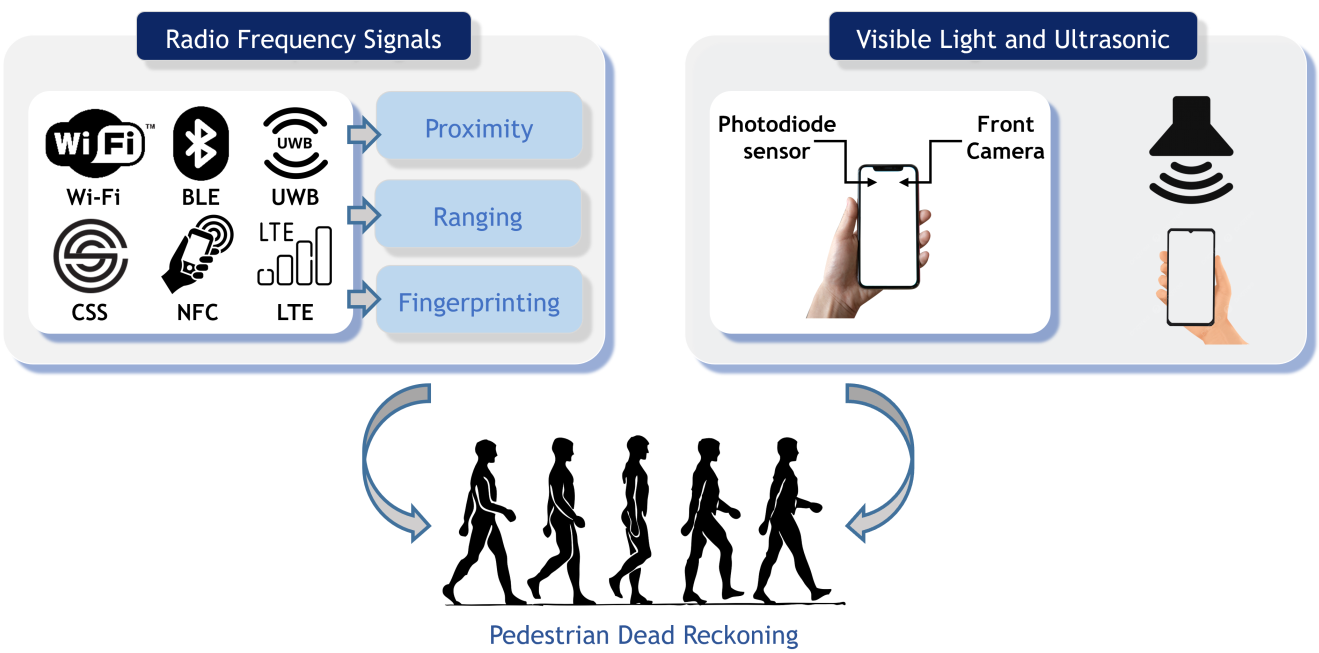

Fig. 4. Infrastructure-dependent PDR-centric indoor positioning. RF signals (e.g., Wi-Fi, BLE, UWB, etc.), VLC, and ultrasonic are normally used to calibrate PDR errors. They require the prior deployment and calibration of external devices to achieve localization.

used RF techniques for aiding PDR include Wi-Fi, BLE, and UWB. This section will discuss PDR aided by the aforementioned RF techniques.

1) Wi-Fi: Wi-Fi is a wireless communication technology that can be used for indoor positioning by connecting with widespread Wi-Fi APs in indoor scenarios. The most common

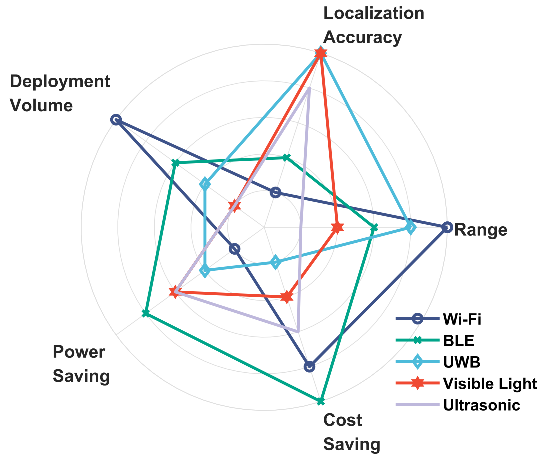

Fig. 5. Comparative aspects of infrastructure-dependent indoor positioning (the corresponding ability is enhanced from the inner to the outer circle).

Wi-Fi-aided PDR indoor positioning methods can be classified into ranging-based and fingerprinting-based.

The former refers to using range-based observation between the mobile device and Wi-Fi APs to estimate the user's position. According to the way to obtain ranging measurements, existing Wi-Fi ranging is composed of RSS-based and RTT-based methods [174]. First, the smartphone can receive the signal strength from surrounding APs. Then, the distance between the device and AP can be estimated using the LNSM. RSS-based approaches have been widely used in indoor positioning due to low cost and simple hardware [175]. Multilateration is commonly utilized to determine a position by using RSS. Zhuang et al. [176] proposed a method for indoor pedestrian navigation using INS, PDR, and Wi-Fi for handheld devices. The forward speed derived from PDR and NHC is used to limit the error of INS. Subsequently, the Wi-Fi position, based on multilateration, is employed to provide absolute positioning correction. Poulose et al. [177] achieved an average localization accuracy of 1.6 m by combining Wi-Fi localization and PDR. El-Naggar et al. [178] developed an indoor positioning system based on Wi-Fi RSS trilateration and INS in simulated environments. The process begins with the Wi-Fi positioning system calibrating the positions of the APs. Following this, a trilateration method is utilized to obtain the position measurement. This measurement is then combined with INS to determine the user's position.

However, the narrow indoor environment easily causes signal damping and reflection, which makes it challenging to achieve reliable positioning. On the other hand, Wi-Fi RTT, an FTM included in the Wi-Fi IEEE 802.11-2016 standard, is relatively reliable and supports meter-level ranging accuracy [179], [180]. It has been fully exploited as an absolute positioning to correct PDR errors. Filter-based methods are frequently used to perform sensor fusion. Yu et al. [181] designed a robust integrated localization based on an unscented Kalman filter using Wi-Fi RTT and PDR. The proposed Wi-Fi RTT ranging model considers the effect of the clock deviation, NLOS, and multipath propagation, achieving more precise and stable localization. Liu et al. [182] introduced adaptive filtering that includes a set of extended Kalman filters and outlier detection to improve the positioning performance of Wi-Fi RTT. Then, a federated filter based on observability is designed to integrate Wi-Fi RTT and PDR. Choi and Choi [183] suggested a calibration-free positioning method via an extended Kalman filter to fuse Wi-Fi range and PDR. An online parameter calibration approach is proposed, which considers parameters from RSS-based ranging, RTT-based ranging, and PDR models. It can avoid the time-consuming calibration process. To further improve state estimation accuracy, Guo et al. [184] presented a factor graph-based fusion method that includes the data-driven PDR, Wi-Fi RTT, and RSS ranging data. It can achieve better positioning accuracy than filter-based approaches. Moreover, ranging-based methods typically require at least three ranging data for positioning. Wu et al. [185] proposed an extended Kalman filter-based indoor positioning with only one single Wi-Fi AP and PDR. It fuses RSS and RTT ranges in a tightly coupled scheme.

Like magnetic fingerprinting, Wi-Fi signals can also be used in fingerprinting mode for indoor positioning. It consists of the training and positioning processes [186], [187]. The scenario needs to be divided into several grids in the training process. Wi-Fi signal strength at each grid is collected to form a fingerprint database. In the positioning process, the pedestrian position can be estimated by matching the measured signal strength with the database. Filter-based approaches are typically employed to integrate Wi-Fi fingerprinting and PDR. Kothari et al. [188] combined Wi-Fi fingerprinting with PDR via a particle filter to obtain continuous pose estimation. Radu and Marina [30] developed HiMLoc, where the PDR and Wi-Fi fingerprinting are fused using a particle filter. Moreover, in some places, the crowd-sourced Wi-Fi fingerprint is associated with a weight to be fully utilized. Hilsenbeck et al. [189] presented a particle filter formulation to integrate PDR and Wi-Fi fingerprinting. It requires fewer particles than traditional particle filter-based methods while maintaining robust estimation. Zou et al. [190] proposed an indoor positioning method based on a particle filter for large-scale indoor environments. Wi-Fi fingerprinting and iBeacon are combined to reduce the PDR drift, improving performance in a poor Wi-Fi coverage area. The Kalman filter and its variants are also utilized to perform the fusion, except for the particle filter. Deng et al. [191] introduced an extended Kalman filter-based fusion framework. The measurement model is based on kernel density estimation, enabling adaptive measurement noise estimation. Zhou et al. [192] proposed an indoor positioning method based on Wi-Fi fingerprinting and inertial odometry, using an extended Kalman filter. A Wi-Fi fingerprint data augmentation method is introduced to enhance accuracy and reduce complexity. Moreover, a regression network is designed to improve the robustness of Wi-Fi-based positioning. Chen et al. [193] integrated Wi-Fi fingerprinting with PDR using an unscented Kalman filter framework. An improved K-means clustering algorithm is proposed to improve the real-time performance in Wi-Fi fingerprinting. Li et al. [194] employed an adaptive and robust filter to integrate Wi-Fi fingerprinting and PDR. It can adapt to different path environments and motion states to improve the reliability of the state estimation. Moreover, Li et al. [195] proposed a Wi-Fi/PDR integration based on a constrained Kalman filter, which can restrain the effect of gross errors. To suppress the influence of nonlinearity in filter-based methods, Yu et al. [196] introduced a neural network-based method for integrating Wi-Fi fingerprinting and PDR. The LSTM is applied to correct the localization, and the backpropagation neural network is employed to improve the extended Kalman filter fusion.

The positions of APs need to be known in ranging-based methods. However, it is often unavailable. Similarly, the fingerprinting database must be periodically updated to ensure its accuracy, which is expensive and time-consuming. Hence, researchers have investigated the Wi-Fi SLAM [197], [198], [199], [200] to achieve the simultaneous state estimation of pedestrians and landmarks, which can avoid the cumbersome calibration effort.

Based on the above reviews, the summary of existing PDR with Wi-Fi is indicated in Table VII.

2) BLE: The BLE-based indoor positioning has drawn much attention recently due to its low power consumption, low cost, and small volume. Like the Wi-Fi-aided PDR, ranging and fingerprinting can also be applied to BLE to obtain the position [201].

From the range-based methods perspective, the fusion can be classified into loosely and tightly coupled integration. In the former, the user's position is obtained based on multilateration. Then, the position is integrated with PDR. Röbesaat et al. [202] developed a Kalman filter-based fusion via BLE-based multilateration to restrain PDR error. The environmental context information is considered to improve positioning accuracy. Aimed at the high RSS variation and long scanning interval in a dense Bluetooth environment, Huang et al. [203] introduced a Kalman filter-based hybrid fusion approach, wherein two positioning phases are included to deal with BLE and PDR. Dinh et al. [204] designed a geometric-based method to improve the accuracy of BLE-based multilateration. The improved multilateration and PDR results are fused to calculate pedestrian position. Subramanian et al. [205] proposed a particle filter-based localization. BLE positioning results based on multilateration and PDR are combined to localize the user. Qiu et al. [206] introduced a BLE-based collaborative indoor positioning method. A particle filter model is formulated to integrate PDR, adaptive multilateration-based results, and mobile encountering. In the tightly coupled mode, the ranging data are directly employed for fusion. Chen et al. [207] used iBeacon, a BLE-based technology developed by Apple, to suppress PDR drift. An extended Kalman filter is used for the fusion, which achieves a lightweight positioning solution. Guo et al. [208] developed an indoor positioning system that used a multimodule BLE transmitter and associated software. Employing a hybrid channel path loss model and multiple RSS values, a fine-grained BLE ranging measurement can be achieved. Subsequently, a robust adaptive Kalman filter is designed to fuse the data-driven pedestrian walking velocity with BLE ranging [208]. Wang et al. [209] presented a tightly coupled integration of PDR and BLE based on a combination of filter and optimizer. The RSS-based ranging information is fused with PDR using a particle filter in a tightly coupled manner. Meanwhile, a graph optimization model is leveraged to optimize the user's heading and step length.

For fingerprinting, Riady and Kusuma [210] proposed a hybrid positioning method using BLE fingerprinting and PDR. A machine learning-based method is employed, and it can achieve better accuracy than the Kalman filter. Chen et al. [211] used a particle filter to integrate data-driven inertial navigation and BLE-based positioning results. Both multilateration and fingerprinting are involved, and a threshold of RSS is set to determine the mode of BLE-based localization. Dinh et al. [212] proposed an improved BLE RSS-based ranging estimation to obtain an accurate initial position. Then, a lightweight and reliable BLE fingerprinting database is used to correct the PDR error. Gong et al. [213] proposed a method of dynamic radio fingerprinting for spatial context recognition, which can enhance the accuracy of both floor and region recognition.

Based on the above reviews, the summary of existing PDR with BLE is indicated in Table VIII.

3) UWB: UWB is an emerging RF technology that can be leveraged for positioning. The standard UWB system consists of anchors and tags. During the positioning process, UWB anchors are deployed in fixed positions throughout the indoor space. They detect and exchange information with the tracking tag to obtain the distance. With the distance information, the tag's position can be determined based on the multilateration. Compared with Wi-Fi and BLE, UWB can provide centimeter-level position estimates in LOS scenes [214], [215], attracting industry and academia's attention.

Recently, many smartphone manufacturers have introduced UWB modules into mobile devices for nearby features and proximity finding [216]. Among major players, Apple began incorporating UWB into its product for spatial awareness with the release of the iPhone 11. Apple also implemented UWB into its smartwatches and IoT devices, such as HomePod and AirTag. Other companies like Samsung, Google, and Xiaomi have followed suit and adopted UWB in some of their newly released intelligent terminals.

Moreover, UWB can be fused with PDR to offer a better indoor positioning solution. Lee et al. [217] combined UWB and PDR using a Kalman filter framework. In this article, UWB is not built into the smartphone but is attached to the smartphone. First, UWB is employed to obtain a deep learning-based speed estimation and calibrate the tilt effect of smartphones. Then, data-driven PDR and UWB are integrated to calculate the position. Although UWB can achieve accurate positioning, it refers to the LOS area. In indoor space, the UWB signal is easily blocked by surrounding objects, leading to seriously deteriorated accuracy due to the NLOS [218]. Li et al. [219] proposed tightly coupled integration based on a robust Kalman filter for the fusion of PDR and UWB. The Mahalanobis distance from the observation to the prior distribution is used to restrain the influence of abnormal values. Li et al. [220] developed an incremental smoothing approach via the Tukey kernel function to combine PDR and UWB. It can achieve stronger robustness than the robust extended Kalman filter-based method.

In traditional UWB-based positioning, multilateration is the most common method. However, this method typically requires at least three anchors, whose positions must be known

TABLE VII
SUMMARY OF EXISTING PDR WITH Wi-Fi

Category	Schemes	Fusion methods	Typical papers	Descriptions
Ranging	Multilateration	(Extended) Kalman filter	[176]	• WiFi positions with small variances are selected as observations.
			[177]	• Wi-Fi signal fluctuations and PDR drift can be restrained by integration.
			[178]	• Calibration and positioning phases were included in Wi-Fi positioning system.
	Tightly coupled integration	(Extended) Kalman filter	[182]	• Adaptive filter to reduce the Wi-Fi RTT error. • Federated filter to combine PDR and Wi-Fi RTT.
			[183]	• Wi-Fi and PDR parameters online calibration.
			[185]	• Positioning with one single Wi-Fi AP.
		Unscented Kalman filter	[181]	• A real-time ranging model to reduce the error caused by clock deviation, NLOS, and multipath.
		Graph optimization	[184]	• Combining data-driven PDR, Wi-Fi RTT, and RSS ranging. • Better accuracy than filter.
Fingerprinting	/	Particle filter	[30]	• Dynamic weight assignment for the fusion given that different places have different accuracy using Wi-Fi.
			[188]	• Robot-based Wi-Fi data collection for database construction.
			[189]	• Graph-based representation of the indoor space for complexity reduction.
			[190]	• iBeacon is added to improve the accuracy in large-scale indoor environments with poor Wi-Fi coverage.
		(Extended) Kalman filter	[191], [194], [195]	• Adaptive and robust filter for noise statistics estimation and gross errors suppression.
			[192]	• A Wi-Fi fingerprint data augmentation to improve the accuracy and reduce the complexity. • A convolutional denoising autoencoder to improve the robustness.
			[196]	• Machine learning-based fusion for nonlinear errors correction.
		Unscented Kalman filter	[193]	• An improved K-means clustering method to reduce fingerprint database search time.

in advance. This increases the reliance on external infrastructure and leads to a time-consuming calibration process. Tian et al. [221] proposed an INS and UWB integrated pedestrian tracking system to solve the above issues using only one UWB anchor with an unknown position. The position of the UWB anchor can be determined at the initial stage with the aid of PDR. Then, the ranging information from one anchor is solely leveraged to provide the tracking information. Tian et al. [222] extended their research with an adaptive UWB ranging uncertainty model and PDR based on a particle filter framework. It can reduce errors of UWB measurements to improve positioning accuracy.

4) Other RF: Some other RF technologies have also been exploited to aid smartphone-based PDR, such as the CSS, NFC, LTE, and 5G.

CSS is a long-range RF technology with high reliability and low power consumption. Lee et al. [223] presented a pedestrian localization system based on CSS and PDR. Positions of the pedestrian and beacons can be simultaneously estimated using a SLAM method. NFC is a wireless technology that enables devices to exchange data at a close distance. Edwan et al. [224] utilized the NFC to compensate for PDR drift. The NFC module is installed in the shoe, and it can communicate with the NFC passive tags installed on the ground to obtain absolute correction. LTE is a technology for wireless broadband communication for mobile devices with high band and a frame and synchronization structure, which can be used for positioning purposes [225]. Mirowski et al. [226] introduced a Signal-SLAM. Multiple RF signals, including 4G LTE and NFC, are integrated with PDR based on a modified GraphSLAM optimization method. The user positions can be recovered, and RF signal maps in buildings can be automatically generated and updated. Traini et al. [227] proposed a dual-step fusion process. RF localization is initially conducted through pattern matching, utilizing LTE, Wi-Fi, BLE, and magnetometer data. Then, the RF output is fused with PDR to derive position. Shoushtari et al. [228] introduced a 5G-aided data-driven inertial navigation for indoor positioning. The DNN-based

TABLE VIII
SUMMARY OF EXISTING PDR WITH BLE

Category	Schemes	Fusion methods	Typical papers	Descriptions
Ranging	Multilateration	(Extended) Kalman filter	[202]	• Environmental context information to rectify PDR and multilateration.
			[204]	• Choose reliable RSS range based on the estimated uncertainty. • A geometric-based method to improve the accuracy of BLE-based multilateration.
		Particle filter	[205]	• An uninterrupted positioning service.
			[206]	• Adaptive ranging to adjust the parameters of signal propagation. • PDR, adaptive multilateration-based results, and mobile encountering are combined.
			[211]	• Data-driven PDR and BLE multilateration are combined.
	Tightly coupled integration	(Extended) Kalman filter	[207]	• An efficient calibration range as extra constraints. • Executed in resource-limited smartphone.
			[208]	• A hybrid channel path loss model and multiple RSS values to obtain fine-grained BLE ranges. • Data-driven walking velocity and BLE ranging.
		Particle filter and graph optimization	[209]	• Gaussian-based distance model to reduce the influence of inaccurate data. • Map information and a back strategy to improve the positioning accuracy.
Fingerprinting	/	Machine learning	[210]	• Artificial Neural Network and SVR for the fusion.
		Particle filter	[211]	• Data-driven PDR and BLE fingerprinting are combined.
			[212]	• An improved BLE ranging estimation for accurate initial positioning. • A lightweight radio map to correct PDR errors.
		Unscented Kalman filter	[213]	• A dynamic fingerprinting sparse features-based floor detection to achieve the floor positioning. • A fingerprinting region recognition to reduce the influence of wrong match.

odometry is fused with absolute positions obtained from the 5G uplink time difference of arrival positioning. The results show that indoor positioning on a commercial smartphone is feasible, even in heterogeneous 5G-positioning service areas.

Based on the above reviews, the summary of existing PDR with other RF signals is shown in Table IX.

B. Visible Light Positioning

Ubiquitous RF signals have become a mature and frequently used method for indoor positioning. However, RF-based indoor positioning is easily subject to electromagnetic interference and spectrum crowds [229], [230], leading researchers to look for new solutions. VLC, which leverages ordinary LED lights to transmit data, has become a promising alternative for indoor positioning. Similar to RF-based positioning, VLP can adopt proximity, fingerprinting, and triangulation to calculate the user's position [231], while the difference lies in how measurements are obtained. In addition, VLP can use vision analysis, in which the geometric relation between the 3-D position of the object in the real world and its 2-D position in the projection is considered to locate the user. VLP enables high-accuracy indoor positioning [232]. However, it requires the LOS of VLC for positioning. This is often unavailable in actual situations due to the sparse arrangement of LED lights. Therefore, PDR has become an effective manner to provide positioning information when VLC is unavailable. Once the smartphone can capture VLC-encoded data, VLP can be utilized to suppress PDR drift.

Current VLP approaches can be classified into two categories according to the type of receiver: photodiode-based and camera-based [233]. Xu et al. [234] proposed indoor localization using inertial and light sensors (IDyLL) based on smartphone built-in IMU and photodiode sensors. The luminary is used to assist the displacement estimation, and illumination peaks are employed to form an observation model. This model is then applied to correct PDR within a particle filter framework. Wang et al. [235] introduced the LiMag, in which a hybrid fingerprint model using the magnetic field and light intensity information is built. Then, the hybrid model and particle filter are combined to achieve real-time positioning and tracking. Wei et al. [236] investigated the integration of PDR and VLP by employing the distance

TABLE IX
SUMMARY OF EXISTING PDR WITH OTHER RF SIGNALS

Category	Features	Typical papers	Descriptions
CSS	• Long range. • Low power consumption.	[223]	• SLAM mode: positions of the pedestrian and the beacons are simultaneously estimated.
NFC	• Short range (a distance of 4 cm or less).	[224]	• NFC tags are installed at the floor. • NFC extension cable is used to connect the NFC module in the shoe and smartphone.
LTE	• Long range. • High bandwidth.	[226]	• Multiple RF signals, including 4G LTE and NFC, are integrated with PDR. • GraphSLAM framework.
		[227]	• Potential Wi-Fi, LTE, BLE, and magnetomer are used for localization, then used to correct PDR errors.
5G	• High accuracy. • Low latency. • High bandwidth.	[228]	• DNN-based inertial navigation and uplink time difference of arrival 5G positioning are combined.

calculated via the intensity of visible light signals. An extended Kalman filter-based tightly coupled integration is formulated to achieve the state estimation. However, photodiode-based methods cannot achieve high-accuracy positioning under interference [237]. On the contrary, camera-based approaches have better robustness. Moreover, consumer smartphones are typically equipped with high-resolution cameras that feature CMOS image sensors. This can be employed to improve the positioning performance of VLP further. Wang and Zhao [238] developed an improved smartphone-based PDR aided by VLP. The smartphone camera decodes the data, and a predefined range is set to form the LED coverage. If the user is within the range, the absolute position of the LED is used to correct PDR. Huang et al. [239] proposed a hybrid indoor localization employing the VLP to suppress the PDR drift, which can achieve decimeter-level indoor location even with sparse light-source beacons. To fully utilize VLP to correct PDR, Hussain et al. [240] introduced LiDR. VLP using vision analysis is employed to calibrate PDR positions. In addition, it can also be utilized for step length estimation and heading angle calibration, which further improves positioning accuracy. Wen et al. [233] designed a proximity-PDR hybrid positioning. Step length and heading angle can also be estimated online, suppressing the influence of device heterogeneity and user diversity. Alcázar-Fernández et al. [241] introduced a VLP-PDR mobile app-based indoor positioning system, specifically for seamless museum navigation. An angle of arrival algorithm is used to determine the position relative to the smart light sources, which helps mitigate cumulative errors in PDR. Concurrently, the PDR provides positional information in the absence of VLP correction.

C. Ultrasonic Positioning

Moreover, ultrasonic signals serve as an effective means of providing absolute positioning information, offering several advantages for indoor positioning. These advantages include low system cost, reliability, scalability, high energy efficiency, and most notably, zero signal leakage between rooms [242]. Several well-known ultrasonic systems, such as Cricket, Buzz, and Dolphin, have demonstrated superior positioning accuracy, achieving better than decimeter-level accuracy in relatively optimal environments. Additionally, in response to noisy environments, Carter et al. [243] developed a robust ultrasonic positioning system. The proposed method can maintain positioning accuracy better than 35 cm in both LOS and NLOS environments. The integration of PDR and ultrasonic systems has also been extensively explored. Pérez-Bachiller et al. [244] introduced an Android application for indoor positioning, leveraging ultrasound signals and IMU. The ultrasonic positioning systems are situated in areas requiring high-accuracy positioning, while positioning in the intermediate range between ultrasonic systems is accomplished through PDR. The developed application features an interface to display estimated positioning results on Google Maps. Thio et al. [245] proposed a novel step detection method for PDR. Meanwhile, they integrated position and heading measurements from the ultrasonic system to correct accumulated errors in PDR within an EKF framework. Gualda et al. [246] introduced an indoor positioning system based on PDR, ultrasonic, and map information for smartphones and other mobile devices, achieving errors within a few decimeters in 80% of cases. Yan et al. [247] combined ultrasonic positioning with an improved PDR algorithm for smartphone-based indoor positioning. The proposed method is validated in different scenarios with different devices, providing a low-cost and high-accuracy solution.

D. Performance Comparison

The positioning errors of several existing infrastructure-dependent PDR-centric indoor positioning methods are illustrated in Table X. It can be observed that PDR methods, when supplemented with UWB, VLP, and ultrasonic, are capable of achieving accuracy at the decimeter level. Additionally, it is evident that the size of the test site for these methods is generally smaller than that for infrastructure-free solutions. This suggests that such approaches impose specific demands on application scenarios, and the coverage of external devices must be considered as a priority.

E. Discussion

Based on the above reviews, this section provides a detailed discussion on the advantages, disadvantages, and applicability of each method in infrastructure-dependent PDR-centric indoor positioning methods.

1) Wi-Fi: Wi-Fi routers are currently widely deployed in indoor environments. Users can utilize existing devices for positioning without the need for additional installations or smartphone hardware upgrades. PDR and Wi-Fi fingerprinting can provide meter-level positioning accuracy. However, they typically require a substantial amount of database construction and regular updates. The introduction of Wi-Fi RTT can offer a more accurate positioning solution. However, these types of devices have not been widely deployed. Additionally, Wi-Fi RTT is susceptible to NLOS and multipath effects.

In conclusion, PDR aided by Wi-Fi is more suitable for large-scale environments where the need for high-accuracy positioning is not critical. The use of Wi-Fi RTT is typically applicable to a limited range of scenarios that require more accurate positioning, and it generally proves effective in relatively open spaces.

2) BLE: BLE is also widely distributed in indoor scenarios and can be used directly with existing smartphone hardware. It offers the advantages of both low power consumption and cost. The integration of PDR and BLE can provide meter-level positioning results. However, its range is relatively limited, and its signal can be easily influenced by environmental factors.

In conclusion, this method is applicable in situations where there is a need for low-cost and low-consumption solutions with meter-level positioning performance.

3) UWB: Compared to Wi-Fi and BLE, the integration of PDR and UWB can achieve a more accurate positioning solution. Additionally, it is more robust against signal interference. However, not all smartphones are equipped with UWB. Furthermore, the availability of existing UWB systems is generally limited due to their relatively high cost. These factors collectively limit its application.

In conclusion, this method is more suitable for situations where positioning accuracy is the top priority. Moreover, the use of specific smartphones that support UWB is required, which currently affects its universality.

4) VLP: VLP can provide a high-accuracy positioning solution to correct PDR. VLP can be facilitated using a smartphone's built-in photodiode and camera, significantly reducing the need for additional sensors in smartphones. Moreover, the use of visible light can avoid interference with other RF signals and is robust to electromagnetic interference. However, the range of VLP is shorter compared to RF signals, necessitating a dense deployment for its application. It also requires that the photodiode and camera are not obstructed, which imposes limitations on how smartphones can be held. Additionally, the lighting conditions are a key factor that needs to be considered.

In conclusion, this method is best suited for environments that require high-accuracy positioning. The deployment of LED lights should be dense, and the user needs to hold the smartphone to ensure optimal reception of light.

5) Ultrasonic Positioning: PDR aided by ultrasonic positioning can be implemented using a smartphone's microphone and IMU. This approach also reduces the reliance on built-in sensors in smartphones. Moreover, compared to RF and visible light, ultrasonic positioning can deliver superior positioning performance at a lower cost. However, the range of ultrasonic positioning is limited, typically from several meters to tens of meters. It operates at a relatively low frequency, which makes it unsuitable for tracking high-speed objects. NLOS and multipath propagation are also key issues that affect the positioning performance.

In conclusion, this method is typically employed in scenarios that require high-accuracy and low-cost positioning. It is most effective in relatively open environments with a dense deployment of ultrasonic transmitters.

V. Comprehensive Performance Analysis

In much of the existing research, comparative analyses of algorithm performance are often conducted with a limited number of users in restricted scenarios. This approach does not fully validate the algorithm's effectiveness in real-world situations. In this section, we will outline key considerations for conducting a more comprehensive comparative analysis of the algorithm.

1) *Setups:* the devices for data collection need to be determined. It is beneficial to use multiple smartphones from different companies, such as Apple, Huawei, Samsung, and OPPO.
2) *Ground Truth:* When conducting comparative tests in a laboratory, a motion capture system can be used to provide the ground truth. However, for large-scale scenarios, the ground truth can be established in two ways. One way is to use stickers on the ground that are calibrated in advance. Alternatively, a high-accuracy autonomous positioning system, such as a visual or LiDAR system, can be used to provide the ground truth.
3) *Sites and Users:* Multiple scenarios should be selected, such as office buildings, shopping malls, and metro stations, to serve as test sites. Users of different ages and genders need to be selected to carry these mobile devices in various holding modes (swing, texting, pocket, etc.) to test the algorithm.
4) *Evaluation Metrics:* Multiple performance metrics need to be used to evaluate the algorithm, which includes the following [248], [249].
   (a) *Accuracy:* The geometric error between the estimated and actual positions.
   (b) *Precision:* The success rate of position estimations in relation to a predefined level of accuracy.
   (c) *Stability:* The system's performance under varying environmental and temporal conditions. A system exhibits high stability if its performance does not significantly degrade due to changes in the environment or the passage of time.
   (d) *Robustness:* The system's ability to resist noise and interference. In an indoor environment, various factors such as walls, furniture, and human bodies can affect external signals, introducing noise and interference.
   (e) *Real-Time Performance:* The operating speed in performing positioning and delivering results. In certain applications, like the emergency

TABLE X
POSITIONING ERRORS OF SOME REPRESENTATIVES

Category	Typical papers	Descriptions	Experimental setups	Errors
Wi-Fi	[181]	PDR and Wi-Fi RTT	• Test site 1: rectangular room (4800 m^2) and long corridor (45 m). • Test site 2: shopping mall. • Device: Google Pixel 3 and Wi-Fi AP using an Intel 8260 Wireless card. • Ground truth: markers.	APE: <2.0 m
	[195]	PDR and Wi-Fi fingerprinting	• Test site: office building. • Device: Samsung Galaxy Note 3 and D-LINK wireless routers (DIR-600NB).	RMSE: 3.0 m
BLE	[204]	PDR and BLE multilateration	• Test site: indoor scene with medium open space and small hall space (350 m^2). • Device: iPhone SE and Estimote Beacons. • Ground truth: predefined route.	APE: 1.1∼1.6 m
	[207]	PDR and BLE tightly coupled integration	• Test site 1: research lab (308 m^2). • Test site 2: empty hall (425 m^2). • Device: Google Nexus 5 and Estimote Beacons. • Ground truth: manually marked.	APE: 1.3∼1.4 m
	[212]	PDR and BLE fingerprinting	• Test site: office building (375 m^2). • Device: iPhone SE and Estimote Beacons. • Ground truth: predefined route.	APE: 0.8 m
UWB	[217]	PDR and UWB	• Test site: office building. • Device: Samsung Galaxy S7 and Decawave DWM1001.	APE: 0.2 m
VLP	[236]	PDR and photodiode-based VLP	• Test site: indoor scene (8 m^2). • Device: Samsung Galaxy Note 10+ and HUWEI P30 Pro. • Ground truth: predefined route.	APE: 0.2 m
	[240]	PDR and camera-based VLP (vision analysis)	• Test site: laboratory (450 m^2). • Device: Huawei P30 Pro.	APE: <0.7 m
	[233]	PDR and camera-based VLP (proximity)	• Test site: rectangular room (72 m^2). • Device: Huawei Mate 10 Pro.	APE: <0.5 m
Ultrasonic	[245]	PDR and ultrasonic	• Test site: office room (150 m^2). • Device: Samsung Galaxy S9 and Forkbeard positioning system. • Ground truth: motion capture system.	APE: <1.0 m

response, real-time performance is of utmost importance.

(f) *Scalability:* Whether a system can handle a larger environment or more users. A highly scalable system can accommodate a wider coverage area and more users without compromising performance.

(g) *Cost:* The resources needed to deploy and maintain the system, which includes hardware, software, and human resources.

VI. Challenges and Future Trends

In this section, we first present the challenges of current PDR-centric indoor positioning and then conclude the future research trends.

A. Challenges

Unlike other indoor positioning for robots and pedestrians with wearable devices, smartphone-based indoor positioning is often noncustomizable, which is mainly reflected as follows.

1) A variety of high-performance navigation sensors are available on the market at an acceptable cost for both consumers and researchers. Robots and pedestrians can be equipped with sensor setups that are tailored for specific positioning needs. However, smartphone sensors are assembled by manufacturers. Given the cost and volume, the performance of these built-in sensors is compromised. Moreover, only part of them can be used for positioning. Although researchers can combine external sensors with the smartphone for positioning, this approach is constrained by the impracticality of expecting pedestrians to carry these additional devices in their daily lives.

2) Robots and wearable devices applied for indoor positioning are often aimed at specific situations, such as warehouse logistics, routing inspection, and disaster rescue. Scenarios in these situations are relatively fixed. Accurate and reliable indoor positioning can be achieved with some customized infrastructures. For instance, users can construct a local high-accuracy wireless network or employ some feature landmarks in the restricted space to offer location references. However, pedestrians can hold their smartphones in various public places, such as metro stations, shopping malls,

and even some outdoor sites with poor GNSS signals. In these situations, it is unrealistic to build accurate reference information due to the high cost and different regulations.

In summary, smartphone-based indoor positioning aims to provide continuous and reliable location solutions across various uncontrolled environments using limited resources. These constraints have presented huge challenges to the existing PDR-centric indoor positioning algorithms. This article presents some of the challenges:

1) Pedestrian and Smartphone Diversity: PDR is a person-sensitive positioning method. Many factors, including heights, weights, ages, genders, leg lengths, dressings, and personal habits, affect step length estimation. In current approaches, the step length is estimated based on either a fixed-parameter model or an adaptive scheme with online calibration. However, both methods suffer from unpredictable human motions, resulting in degraded performance.

Furthermore, the smartphone-based indoor positioning aims to enable pedestrians to navigate with their own smartphones. However, there are multiple generations of smartphones from various manufacturers. Even if smartphones have the same brand and model, the performance of built-in sensors differs. Most researchers have collected data for validating their algorithms via a few phones with known error properties. It is difficult to form a unified scheme to cover all smartphones for indoor positioning.

2) Smartphone Arbitrary Placements: In contrast to many navigation applications where sensors are affixed to the body, smartphone-based indoor positioning does not secure sensors in this manner. Consequently, there is a discrepancy in spatial awareness between pedestrians and their phones. For example, smartphones can be in the hand, pocket, and bag with multiple placements. It can cause different headings between the pedestrian and smartphone. If the heading misalignment is not compensated, PDR will fail. In most existing research, the misalignment is assumed constant. It is unrealistic as the pedestrian cannot hold a pose long. Researchers also developed other approaches to estimate the pedestrian heading online, but how to ensure the estimation accuracy has always been a challenging issue. In addition, smartphone placement and switching will also affect indoor positioning corrections, such as activity-based and vision-based methods.

3) Environmental Complexity: Environmental complexity in indoor scenes is mainly reflected in the diverse internal structures and unpredictable movable obstruction. The former indicates that different places have different construction features. It can lead to different motion patterns and error representations. For example, people cannot walk in the office like in the mall due to different space usage and floor types. At the same time, the signal transmission might be worse in the office as it is not that open in malls. The latter lies in that there are typically many people in public places. On the one hand, the movement of a person is restricted by other people. On the other hand, the moving people can affect the signal transmission and feature extraction. The above two perspectives degrade the performance of PDR and other aiding positioning manners. Existing approaches are designed for some specific scenarios. The effect of movable obstruction is seldom discussed.

4) Initial Positioning: No matter whether PDR or other forms of DR, it is critical to obtain the initial absolute position for the following estimation. When a person enters a building from outside, it is feasible to regard the location where the GNSS signal is lost as the initial position in indoor scenarios. However, when a person wants to launch the positioning service when he is already in an indoor space, acquiring an initial position needs external infrastructure. Therefore, how to determine an accurate initial absolute position even with polluted external information is critical.

5) Limited Configurations: With the rapid development of mobile phone hardware, more complex indoor positioning algorithms can be utilized to obtain accurate locations, such as optimization-based and learning-based methods. Meanwhile, richer sensor configurations can be achieved to provide multidimensional positioning information. Although these ways can achieve good performance, they have put forward high requirements for phone configuration and taken up many computing resources. However, many mobile phones have limited configurations. In addition, the primary purpose of smartphones is for personal time, social contact, etc. The indoor positioning function should avoid consuming many resources, ensuring the regular running of other applications. Therefore, building an accurate indoor positioning with limited smartphone configurations and controllable resources is an essential problem.

In conclusion, there are still some problems to be solved in smartphone-based PDR-centric indoor positioning approaches. This article proposes potential solutions for these challenges. By targeting the diversity and arbitrary placements, the application of AI remains a viable solution. Enhancing the generalization capability and context prediction of AI model can significantly enhance its practical applicability. Moreover, given that a single sensor can operate in various modes to achieve positioning, incorporating multiple positioning algorithms into the system to facilitate multimodal solutions becomes crucial. The integration of redundant data can secure the positioning solution and achieve robust initial positioning using limited configurations. This approach can significantly improve the performance of the indoor positioning system.

B. Future Research Trends

PDR-centric indoor positioning still holds vast potential for future development. This article concludes some of the future research trends.

1) Plug-and-Play PDR-Centric Indoor Positioning: In outdoor environments, GNSS is mainly used to provide positioning information. User locations are determined through multilateration using satellite data, which is less affected by pedestrian and smartphone-related factors. Although the positioning accuracy of GNSS is severely influenced by the environment, the primary interference comes from stationary buildings. GNSS errors can be modeled with the map to improve positioning accuracy. Therefore, the outdoor scenarios with the usage of GNSS have a relatively low demand for plug-and-play positioning.

However, due to the lack of GNSS, indoor positioning needs to combine any available information to calculate the position. This necessitates considering the influences from pedestrians, smartphones, and the environment collectively. PDR-centric indoor positioning with smartphones should have a plug-and-play capacity. First, the indoor positioning algorithm needs to enable continuous and usable solutions with mainstream smartphone sensors. Meanwhile, it can be integrated with any new information when extended sensing devices are available. Finally, sensor fusion must be capable of integrating various types of information. It can be resilient against unpredictable interference from dynamic and unknown objects, thereby formulating a reliable estimate with rapid reconfiguration. These capabilities can be achieved by building a local, generic positioning engine that includes three main modules: sensor, algorithm, and fusion. The sensor module is responsible for ensuring data compatibility and conducting adaptive error modeling. The algorithm module incorporates methods such as DR, fingerprinting, and multilateration, among others. The appropriate algorithm will be selected based on the availability and quality of the data. The fusion module contains both loosely coupled and tightly coupled integration modes and robust estimation methods.

2) Hybrid Computing-Based PDR-Centric Indoor Positioning: Taking advantage of available information and using sophisticated estimation methods have become dominant trends in improving positioning accuracy. State estimation methods using optimization or machine learning have become increasingly popular in recent years. These emerging approaches have been widely utilized in autonomous vehicles, mobile robots, unmanned aerial vehicles, etc.

Professional equipment is used to perform the calculation among the systems mentioned above. However, smartphones cannot employ additional computing units, which limits the applications of some advanced algorithms. One viable way is to simplify the algorithm, achieved at the expense of accuracy. In addition, a high-performance cloud computing platform can be utilized to help execute some complicated operations. The data can be transmitted via a 5G network, potentially leading to increased power consumption. Therefore, hybrid computing can be exploited in PDR-centric indoor positioning to solve these problems. A dynamic management strategy is required to distribute tasks between local and cloud computing. Lightweight algorithms can be executed on the local positioning engine, while more complex methods, such as feature extraction, learning-based methods, and optimization techniques, can be deployed on the cloud. This approach caters to the needs of high-performance positioning applications.

VII. Conclusion

This article reviews the PDR-centric indoor positioning techniques with smartphones. It categorizes existing studies into two groups based on the involvement of additional physical hardware in the environment. The activity matching, data-driven odometry, magnetic fingerprinting, and visual perception are reviewed and compared in infrastructure-free PDR-centric indoor positioning. Furthermore, infrastructure-dependent PDR-centric indoor positioning approaches discuss PDR assisted by RF signals, visible light, and ultrasonic. Key factors for a comprehensive performance analysis are offered. Finally, the challenges and future research trends are given.

This article can provide a comprehensive understanding for readers about integrations based on PDR and other information. It can help readers quickly get information and provide guidance for developing progressive smartphone-based PDR-centric indoor positioning techniques.

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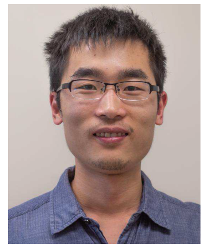

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