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A Survey of the Research Status of Pedestrian Dead Reckoning Systems Based on Inertial Sensors

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Abstract: With the development of micro-electromechanical systems (MEMS), miniaturized, low-power and low-cost inertial measurement units (IMUs) have been widely integrated into mobile terminals and smart wearable devices. This provides the prospect of a broad application for the inertial sensor-based pedestrian dead-reckoning (IPDR) systems. Especially for indoor navigation and indoor positioning, the IPDR systems have many unique advantages that other methods do not have. At present, a large number of technologies and methods for IPDR systems are proposed. In this paper, we have analyzed and outlined the IPDR systems based on about 80 documents in the field of IPDR in recent years. The article is structured in the form of an introduction-elucidation-conclusion framework. First, we proposed a general framework to explore the structure of an IPDR system. Then, according to this framework, the IPDR system was divided into six relatively independent sub-problems, which were discussed and summarized separately. Finally, we proposed a graph structure of IPDR systems, and a sub-directed graph, formed by selecting a combined path from the start node to the end node, skillfully constitutes a technical route of one specific IPDR system. At the end of the article, we summarized some key issues that need to be resolved before the IPDR systems are widely used.

Keywords: Inertial measurement unit (IMU), pedestrian dead-reckoning, indoor navigation, technical route, general framework.

1 Introduction

Pedestrian positioning information plays an increasingly important role in human works and lives and greatly improves the efficiency of human activities. With the progress of society and the development of science and technology, people′s demands for navigation and positioning are also growing. In the outdoor environment, the global navigation satellite system (GNSS) is widely used in outdoor positioning and navigation due to its wide coverage and high positioning accuracy. However, GNSS will not be able to work at locations where the satellite signals are blocked, such as indoor environments, around high buildings, dense forests, underground mines, underground parking lots, underwater and so forth. Therefore, other positioning methods are needed to make up for this lack of GNSS. Many human activities are carried out indoors, and the demands for indoor positioning are also growing stronger. However, there are currently no standard indoor positioning technologies which are widely used in the world like GNSS. Every indoor positioning method proposed at present has its inherent advantages and disadvantages, and is not universally applicable. Zheng et al.[1] divides the current indoor positioning technology into two categories: infrastructure-based approaches and infrastructure-free approaches.

The infrastructure-based approaches refer to the techniques for deducing the indoor location by sensing the signal of the devices arranged in advance in the indoor environment. These devices include many available communicational technical facilities such as wireless fidelity (Wifi), Bluetooth, wireless sensor networks (WSN), ultra wide band (UWB), infrared[2] and visual facilities[3, 4]. A big drawback of these methods is that the layout cost is proportional to the indoor area. At the same time, these devices are not arranged in advance in many indoor environments, obstructing wide promotion and application.

The infrastructure-free approaches refer to the positioning methods that do not need to receive signals from devices arranged in the environment in advance. Among these strategies, the typical methods are pedestrian dead-reckoning algorithms which make use of the motion information measured by the inertial sensors mounted on the pedestrians′ bodies to estimate the positions relative to the starting point. These approaches are hardly constrained by any environments, meanwhile the layout costs are only proportional to the number of users, thus the infrastructure-free approaches are generally cheaper than the infrastructure-based approaches. Nevertheless, subject to the accuracy, drift and deviation errors of inertial sensors, the continuous working time and application environments of these methods are greatly limited. Based on this, many researchers proposed a variety of error-

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compensation methods, so that the final accuracy will be significantly improved.

In this paper, we make an overview of the inertial sensor-based pedestrian dead-reckoning (IPDR) systems by decoupling the IPDR systems into several independent sub-problems of which the technical solutions are separately discussed and summarized. As a result, we propose a general framework of IPDR systems and regard a specific IPDR system as a combination of techniques for each sub-problem. This is a difference or innovation of this article compared to other IPDR reviews such as [2, 5–7].

This paper is arranged in the form of an introduction-elucidation-conclusion framework. The remainder of this paper is organized as follows: In Section 2, a general framework for understanding the IPDR system is proposed. The methods used by each sub-problem are separately elaborated and compared in Section 3. The current technical routes of the main research methods of IPDR systems are portrayed by a directed graph in Section 4. Finally, the conclusions are presented in Section 5.

2 General framework of IPDRs

Through all of the cited literature in this paper, it can be seen that the main focus of the IPDR systems was how to suppress and reduce the drifts and deviation errors caused by inertial sensors. Taking full account of and utilizing the external constraints of the motion characteristics of the human body and the environments of activities, and deepening the deep-seated information of the sensor output signals are the keys to error control. The body is the creator of the human movements. Therefore, the body′s own constraints should be considered and analyzed first. In the process of human body movement, the motion characteristics of different parts of the body are not the same. For example, during the movements of lower extremities, the soles of the feet periodically contact with the ground during which the speeds are considered to be zero, and the legs can be viewed as two periodic inverted pendulum models. More precise knowledge of human motion information will provide more reliable prior knowledge for error correction. For examples, in the foot-mounted IPDR systems, zero-rate and zero-angle velocity observations are obtained by measuring the stance-phase period of each step, then the zero-velocity update (ZUPT) and the zero-angle rate update (ZARU) are performed to limit the errors within a short period of time. In the IPDR systems based on the waist or leg-mounted sensors, the step-by-step measurement information is used to establish mathematical models to directly estimate the steps′ sizes and headings. Furthermore, in order to obtain accurate gait classification under complex motion conditions, it is optional to classify movements with classification algorithms or create more complex models such as hidden Markov models (HMM). Considering the environmental factors, the analysis and acquisition of map and magnetic field information are extremely important.

The filtering algorithms which integrate all observation information are the core of the IPDR systems. The commonly used filtering algorithms include extended Kalman filters (EKF), complementary filters (CF), particle filters and so forth. On this basis, it is also necessary to determine whether the trajectory estimations are directly obtained by integrating the sensor measurement data – inertial navigation systems (INSs) or by using the outputs of the sizes and headings of the steps – step and heading systems (SHSs). In addition, the uses of particle filters in conjunction with the outputs of INSs or SHSs for dead reckoning are the choice of many in the literature when computational capabilities permit and detailed maps are available. Fig. 1 shows the general framework of the IPDR systems proposed in this paper based on the cited literature.

An IPDR system usually needs to consider the following issues. First, what kinds of sensors are considered to constitute the measurement units? The commonly used measurement unit is combined by accelerometers and gyroscopes. Second, where are the measurement units fixed to the body? Third, is the motion classification considered in the system? Fourth, what gait classification and gait detection methods are considered? Fifth, is it necessary to use the environment factors? Sixth, what kind of trajectory estimation strategy is considered, e.g., INS or SHS? In addition, will the particle filters be adopted? This article will analyze and summarize these sub-questions separately.

3 Sub-problems analysis

3.1 Sensor types and layouts

The different choices of sensor types and layout methods will lead to great differences in algorithm design. Different combinations of sensors determine different dimensions of motion data perception. Simple sensor combinations reduce the hardware model complexity, and correspondingly require more complex algorithm designs to achieve the same accuracy. Similarly, complex sensor combinations increase the hardware model complexity, but the algorithm complexity can be lower while obtaining the same accuracy. How to achieve a balance between these two complexities is one of the factors that needs to be considered. In the process of walking, the movement characteristics of different parts of the lower limbs are different, and the designs of the algorithms corresponding to different layout methods are also different.

1) Types

A classical inertial measurement unit consists of a triaxial accelerometer and a triaxial gyroscope. Sometimes, a triaxial magnetometer is also integrated into the inertial measurement unit, because the magnetometer can output high-precision heading information under uniform

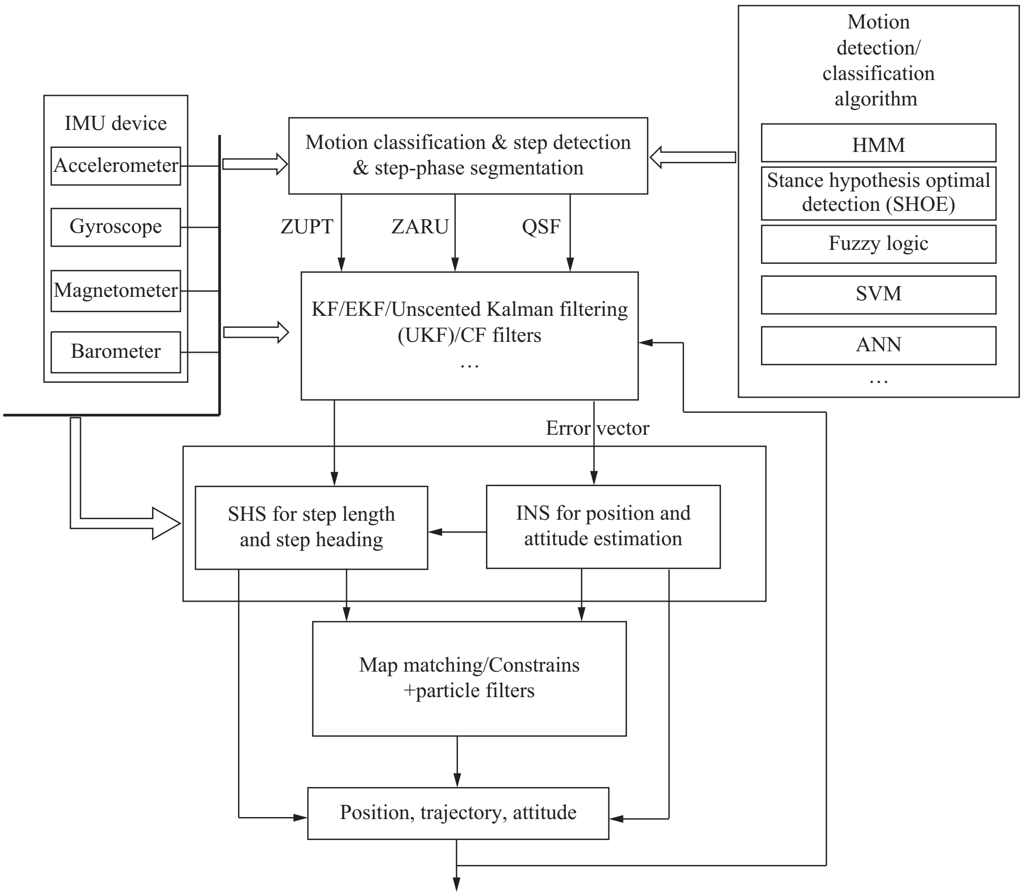


Fig. 1 Framework of IMU-based PDR systems

and undisturbed geomagnetic conditions. However, due to the large number of uncertain magnetic field disturbances in the human activity environment, especially in the indoor environment where there are serious magnetic field disturbances, the output of the magnetometer may seriously deviate from the true geomagnetic field direction, resulting in the magnetometer's data being unreliable for azimuth estimation. This is one of the reasons why some IPDR researchers directly abandon or selectively use the magnetometers in their algorithms.

In addition, some researchers also use other sensors to assist inertial measurement units to achieve the specific purpose of motion detection, such as using a pressure gauge fixed to the sole[8] for measuring the foot's zero-rate point by sensing the pressure of the sole of the foot, measuring the height variation of the human body with a barometer[9], and some other used sensors like radar[10] or ultrasonic[11]. These aids can indeed reduce the difficulty of the algorithm and improve the accuracy of the motion detection, but this will make the system more complex. The scope of this review is limited to the pure inertial measurement unit (IMU)-based pedestrian dead-reckoning (PDR) systems.

2) Layouts

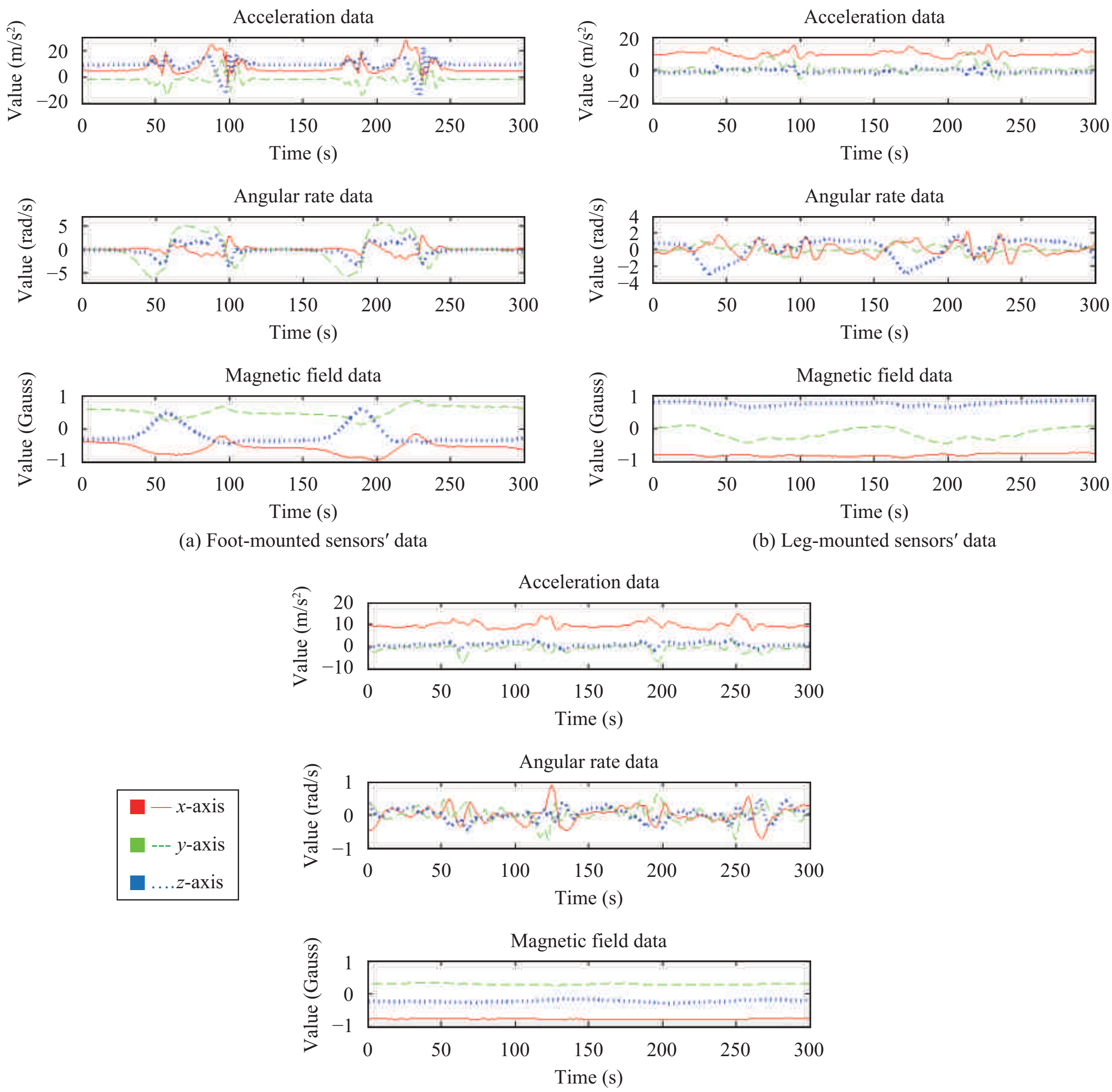
The movement parameters of the human lower limbs are the most relevant to the pedestrian trajectory, because the final trajectory is determined by the distance and direction of each step. Therefore, it is a natural idea to extrapolate the trajectory of a pedestrian through the accurate perceptions of the data of the lower extremities. The main parts of the lower limbs of the human body include the foot, calf, thigh and waist.

Since a PDR system based on shoe-mounted inertial sensors was proposed by Foxlin in 2005[12], a large number of foot-mounted IMU-based algorithms for IPDR systems have been proposed. The advantage of tying the sensors to the foot is that it directly senses the movement of the foot. If the trajectory of the foot can be found, the trajectory of the body can also be determined. The most important point of this method is that the feet are in contact with the ground periodically and alternately during walking, and during the small period of time when the feet are on the ground, the speed and displacement of the feet can be considered as zero – called zero velocity point (or stance phase), meanwhile the foot posture can also be considered as constant. With this constraint, the estimated error can be corrected at each step to achieve more accurate trajectory estimation. But the movement of the foot is the most drastic one compared to the other parts of lower limbs, and with the speed of the movement increasing, the severe shaking will bring a lot of errors.

There are no clear zero-rate points when the sensors are tied to the leg (thigh or calf), which means the zero rate constraints are lost and cannot be used to correct the motion parameters like the foot-mounted methods. However, during the walking process, the periodic changes of the leg posture can still be used for step detection. At the same time, the method of tying the sensors to the leg is more convenient, easier to fix, and less violent than the foot-mounted method, which facilitates the use of a portable device or a wearable device for pedestrian trajectory estimation.

Among the movements of lower limbs, the waist is more stable than the thighs, calves and feet, which gives the measurement units tied to the waist a more stable measurement environment. This is an advantage for posture estimation[13]. However there are still no clear constraints on the waist to correct the measurement parameters in real time. Although the waist has the highest point during walking, and the vertical velocity is zero at this point, the duration of this point is very short and can be considered as instantaneous, so it is still difficult to consider the zero vertical velocity point of waist as a constraint point.

Fig. 2 shows the data outputs when the sensors are attached to the feet, legs, and waist. It can be seen that the characteristics of the data output by sensors at various locations are different in the same motion state. It also can be seen that the foot-mounted data has the strongest periodicity and regularity, and the zero point and non-zero point are clear which is a benefit for the gait division and the performance of the ZUPT and ZARU. So, the foot-mounted way is the most adopted method and also the most accurate solution amongst these different sensor layouts.



(a) Foot-mounted sensors' data (b) Leg-mounted sensors' data

(c) Waist-mounted sensors' data

Fig. 2 Output data from sensors tied to different places while walking

3.2 Motion types and classification algorithms

People will encounter different situations while walking, and the types of activities will also change, accordingly the model parameters will also not be the same. The fixed model parameters are usually only useful for a single state of motion and will no longer be suitable for the complex and mixed athletic situations. Adjusting the model parameters adaptively according to the type of motion is a method used by some researchers to solve the motion trajectory estimation under this situations.

1) Motion types

The most common pedestrian movements are walking and running[14, 15]. Based on this, some of the literature considers other types of motion, such as upstairs, downstairs[16–18], side stepping[19], standing[17, 20], etc. Considering some more detailed cases, Edel and Köppe[21] considered walking and running forward, backward and sideways, respectively. Edel and Köppe[22] established a database of 14 different daily activities, which, besides walking and running, also includes jumping, falling, etc. Running was divided into the activities of running, sprinting, jogging, while crouching and climbing were also considered in the literature[23]. Beaufils et al.[24] further divided walking into slow walking, normal walking and quick walking. Uphill and downhill activities were considered in [25], while Elhoushi et al.[26] considered the use of escalators, elevators, and standing and walking on mobile channels.

Due to the differences in environment, region, country and so on, the types of human activities vary widely, and it is impossible to cover and classify all types of human movements. However, by classifying some common types of activities, more prior knowledge was obtained for PDR systems, thus creating a potential for higher trajectory estimation accuracy.

2) Classification algorithms

a) Feature extraction

Before the classification is performed, the features of the input data need to be extracted first. The original output data of the inertial measurement units generally include triaxial acceleration, triaxial angular velocity, and triaxial magnetic field strength. A single frame of output data can only represent one feature dimension. In order to obtain more data features, it is necessary to analyze other characteristics of the output data. As described in [16], commonly used statistical features include: mean, standard deviation, variance, mean absolute deviation, root mean square (RMS), interquartile range, correlation coefficient, etc. Zhang et al.[18] divided the data features into time domain features and frequency domain features. The time domain features include the mean, maximum, minimum, variance, and energy of acceleration and angular velocity; the frequency domain feature is the Fourier transformation of statistical features in the time domain. Elhoushi et al.[26] gave more detailed feature types of inertial sensors output data, including: 10 statistical features, 6 energy and module characteristics, 2 time domain features, 6 frequencies domain features and 2 other features.

Intuitively, the more characteristic dimensions there are, the better the separability of the data can be, but the larger the data dimensions are, the greater the required calculations are. Therefore, when many features are used, it is necessary to reduce the dimensions of the features. This will undoubtedly increase the time complexity of the algorithm. How to choose between feature dimensions and algorithm efficiency is one of the factors that needs to be considered in the classification of movements.

b) Classification models

After the feature is extracted, the next step is to use the features to train a specific machine learning model for motion classification. There are many methods for pattern classifications. In the references given in this article, the main classification methods and their abbreviations are as follows:

PNN – Probabilistic neural network classifier[16].

SVM – Support vector machine classifier[15, 18].

MLP – Muti-layer perceptron[18].

DT – Decision trees[20, 26].

HMM – Hiden Markov model[17].

BA – Boosting algorithms[24].

BLSTM-RNN – Bidirectional long short-term memory recurrent neural networks[21].

Table 1 shows some representative citations and their performance in motion classification.

Of course, not all PDR algorithms need to classify the motions, because adding the motion classification step will undoubtedly increase the complexity of the algorithms. Differences in the lectotype, number, and location of sensors may cause the trained models not to perform well.

However, without considering other aids, in order to achieve the trajectory estimation under complex environments and mixed motions, it can indeed increase the accuracy of the estimations by adding motion classification algorithms[15, 21]. In the case where the precision of the inertial sensors cannot be significantly improved, the more prior knowledge about the movements there is, the better the accuracies of the algorithms will be. Without any prior identifications and classifications for the motions, there is currently not such a robust algorithm that uses only micro inertial sensors and does not rely on other aids to accurately estimate the trajectories for any motions. Therefore, it is a good choice to accurately classify and recognize the motions in real time to achieve more accurate trajectory estimations under complex motion conditions.

3.3 Gait division strategies and methods

Gaits are basic features of the movements of human

Table 1 Motion classification methods

Reference	Sensors	Features	Classifiers	Motion classes	Accuracy
[21]	3D-gyroscope 3D-accelerometer 3D-magnetometer	Normalized data	BLSTM-RNN	Forward, backward, sideways respectively for running and walking	98.5%
[27]	3D-accelerometer	Standard deviation; peak value of the discrete Fourier transform; amplitude of the medio-lateral acceleration	Linear discriminant analysis (LDA) classifiers	Walk stand, upstairs, downstairs	83.20%(280 m combined walking) 82.87%(2 350 m combined walking)
[18]	3D-gyroscope 3D-accelerometer	Mean value; maximum; minimum; variance; energy	SVM or MLP	Walking, running, upstairs, downstairs	98.7%(max) 87.9%(max) 92.9%(max) 88.4%(max)
[26]	3D-gyroscope 3D-accelerometer 3D-magnetometer Barometer	10-statistical features; 6-energy, power, and magnitude; 2-time-domain; 6-frequency-domain; 2-other features	DT	Stationary versus standing on moving walkway	97.2% 84.2%
				Walking versus walking on moving walkway	90.2% 73.1%
				Elevator versus escalator standing	96.2% 94.1%
				Stairs versus escalator walking	90.2% 78.3%
[15]	3D-gyroscope 3D-accelerometer (on foot)	Amplitudes of fast Fourier transformation (FFT) of the gait data	SVM	Walking, running	Unclear
[17]	3D-gyroscope 3D-accelerometer (on chest)	Mean; variance; slope; curvature	HMM	Standing, walking, running, going downstairs, going upstairs	98% 90% 96% 90% 91%
[20]	3D-gyroscope 3D-accelerometer (on pocket)	Signal norm; signal energy; signal variance; spectrogram	DT	Walking, running, standstill	Unclear
[24]	3D-gyroscope 3D-accelerometer	Maximum; mean; standard deviation; root mean square; interquartile range;fast fourier transform	BA	Normal walking, running, climbing, descending stairs	Unclear

lower limbs and are directly or indirectly related to the displacements and trajectories of human motions. It is impossible to directly integrate the original data to obtain the pedestrian's displacements under the limits of the accuracies of inertial sensors. Therefore, it is necessary to perceive and analyze the gaits information associated with lower limb movements. Among the citations of this paper, gait perception is one of the basic tasks that must be included in almost all PDR systems.

1) Gait division strategies

According to different trajectory estimation strategies and different sensor binding positions, diverse gait division strategies are proposed in distinct articles. This survey divides the gait division strategies in the quotations into two categories: abbreviated strategy and detailed strategy.

As the name implies, the abbreviated strategy is to simply divide the gaits, and usually only sense one or two key events of the gaits. For examples, the very classic strategy of dividing gaits as described in [28] is to use the measurement unit attached on the foot to divide the gait into the stance phase (the time period when the foot touches the ground) and the swing phase (time period when the foot is off the ground). Diaz et al.[29] attached the IMU to the thigh to detect the only moment when each foot landed to separate each step. Lan and Shih[30] divided one step of walking into stance, heel off ground, and heel touching ground events according to the changes in waist height, and a measurement unit attached to the waist was used to perceive the heel touching ground event.

The detailed division strategy refers to dividing the gait into three or more phases, and accurately distinguishing these phases from each other. Perry and Burnfield[31] divided one human walking step into 8 basic phases:

Phase 1 (initial contact). This phase includes the moment when the foot just touches the floor. Floor contact is usually made with the heel.

Phase 2 (loading response). The phase begins with initial floor contact and continues until the other foot is lifted for swing.

Phase 3 (mid stance). This is the first half of the single limb support interval.

Phase 4 (terminal stance). It begins with heel rise and continues until the other foot strikes the ground.

Phase 5 (pre-swing). It begins with initial contact of the opposite limb.

Phase 6 (initial swing). The foot is lifted.

Phase 7 (mid swing). The swinging limb is opposite the stance limb.

Phase 8 (terminal swing). The final phase of swing and it ends when the foot strikes the floor.

The gait classification strategies in most of the literature is based on simplifications of the above 8 gaits, resulting in many simplified gait classification strategies. The above 8 gait stages were reduced into 4 gait states in [14, 32] which include state 1: gait Phases 1 and 2, state 2 : gait Phase 3, state 3: gait Phases 4 and 5 and state 4: gait Phases 6–8. In [33], one step is divided into four gait events: foot strike (FS), flat foot (FF), heel off (HO), and toe off (TO). These four gait events correspond in connotations to the 4 states in [32]. Ruppelt et al.[34] also simplifies the above 8 basic gait stages into 4 stages, as shown in Fig. 3, which are: Loading response: Phase 2; Midstance: Phase 3; Terminal stance: Phases 4 and 5 and Swing: Phase 6–8. Ren et al.[25] divided one step into three phases, namely state 1: zero velocity interval, state 2: acceleration interval, and state 3: deceleration interval.

It is not difficult to see from the discussion of the above division strategies that, whether in the abbreviated strategy or the detailed strategy, the touching events in the time period when the foot touches the ground were all detected. This is due to the good nature of the time period when the foot is in contact with the ground. First, this time period can be seen as the end of this step and the beginning of the next step. If it only needs to achieve the purpose of step counting or distinguishing each step, detecting the true subset of this time period is enough. Secondly, during the period when the foot is completely in contact with the ground, it has zero-speed characteristics. In the algorithms that need to use this time for error correction, the accurate detection of this time period is particularly important. The purpose of many detailed detections of gait events are to get a more accurate time period when the foot completely touches the ground, such as the flat foot event described earlier, by sensing and removing the unstable time period before and after this period from the touching event. Much of the literature regarded the detection accuracies of this touching events as important indicators for evaluating the gait classification algorithms.

2) Gait division algorithms

The gait division algorithms study the methods that distinguish each event or stage in the gait division strategies. The simplest division algorithms are the threshold-based methods. If the extracted features satisfy the set thresholds, then the corresponding gait phases are determined. The threshold-based methods can be divided into the fixed threshold methods and the adaptive threshold methods.

The fixed threshold methods refer to the approaches for determining the gaits of input data using fixed determination thresholds. Zhang and Meng[35] set the thresholds for the net acceleration modulus and the angular velocity module values respectively. When both values of the input data are less than the set thresholds, it is determined that the current moment belongs to the stance phase. Tian et al.[36] used the acceleration modulus, acceleration local variance and angular velocity modulus, and the corresponding fixed thresholds to determine the zero-rate intervals of the steps. Hsu et al.[16] used only the net acceleration modulus and its set fixed threshold for gait determination. The outcomes of the fixed threshold methods are often capable of meeting the designer's requirements under the conditions where the motions are not very complicated. Therefore, a large number of documents use the fixed threshold methods to determine the gait phases, such as [29, 30, 37–45]. As early as in 2010, Skog et al.[46]. studied the three kinds of commonly used threshold detectors: the acceleration-moving variance detectors, the acceleration-amplitude detectors and the angular velocity energy detectors. They proved that all these three types of detectors can be derived from a same likelihood ratio test (LRT) framework. However, the fixed thresholds are only suitable for the

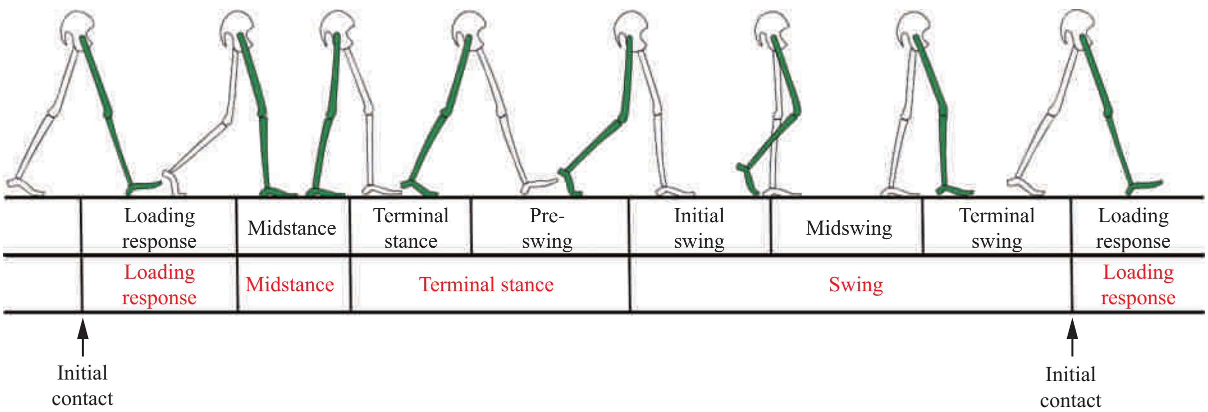


Fig. 3 Motion analysis of a typical human gait cycle (cut from [34])

single motion situations. In the case of complex and variable motions, the error rates of the fixed threshold methods will greatly increase.

The adaptive threshold methods are improvements over the fixed threshold methods, whose thresholds are no longer fixed, but adjusted adaptively according to the different motion conditions. Different thresholds are set for walking and running in [15, 23], and adaptively switched based on the results of the movement classification. Mikov et al.[47] dynamically adjusted the threshold at the current time instance based on the difference between the maximum and minimum values of the filtered acceleration in the last second and the dynamic threshold at the previous moment. The idea of dynamically setting the thresholds for gait determination is theoretically very good, but not much of the literature uses the methods which identify the types of movements first, then set the adaptive thresholds. First, the motion classification tasks will consume a certain amount of time and space, and even if some motions are identified, it is difficult to distinguish the gait phases with corresponding fixed thresholds. Secondly, the models that dynamically adjust the thresholds are rarely proposed by researchers. In addition, some non-threshold methods are proposed and the division effects are better than many threshold methods.

The non-threshold methods are the algorithms which divide the gaits not only according to the thresholds, but also mainly based on some other techniques. Using a hidden Markov model (HMM) to model the mutual transformation between gait events is the most commonly used non-threshold algorithm[25, 32–34, 48], which mainly makes use of the two properties of the gait events, i.e., periodicity and sequentiality. Periodicity means that the movements shown by the lower limbs of the human body are repeating cyclically, while sequentiality indicates that the occurrence of each gait event is strictly sequential within a gait cycle. These two properties allow us to model the real-time gait events with a finite state machine. For example, Park and Suh[14] divided the output data of the y-axis of the gyroscope into four types of segments, corresponding to the four stages of the gait, by dividing the points which continuously preserve in a range of values into a segment, and uses these segments to construct a hidden Markov model which will be trained on the predefined data set to determine which gait event each segment belongs to. The experimental results show that this method is more accurate and robust than the fixed threshold methods for detecting gaits. Similarly, Panahandeh et al.[17] used a continuous Hidden Markov Model to model the type of movement and gait at the same time, achieving the simultaneous division of movement types and gaits under the condition of mixture motions.

There are many other gait division techniques, such as Bayesian network[49], fuzzy logic[50, 51], subtraction clustering[28], peak detection[12], zero crossing method[52], etc. Taborri et al.[53] introduced and summarized the gait classification algorithms based on IMU in 2016. Interested readers can refer to this article.

There are two main purposes for gait division: one is for step counting and the other is for zero point observation. These two observations play such an important role in pedestrian trajectory estimation that the results of the gait division are called pseudo-measurements to show that they are as important as the original measurement data. Table 2 shows some common gait division methods in the literature.

3.4 Environment constraints

Normal human activities are constrained by environmental constraints. If the environmental information can be used effectively, it will provide more prior knowledge for the IPDR systems and create more favorable conditions for improving the performance. There are two kinds of main environmental information that can be used for pure IMU-based PDR systems – map information constraints and magnetic field information constraints.

1) Map information constraints

The map is an accurate description of the geospatial environment, from which it is easy to obtain the possible paths and directions of normal human activities. Abdulrahim et al.[54] extracted the straight line formed by the outline of the building's edge in the aerial image, and calculates the inclination of the straight line in the image, based on this, then calculated the angles of the other three vertical directions, forming the four main headings, and assumes that the heading of the person's walking need to be aligned with these four main headings. Based on this method, the cardinal heading aided inertial navigation (CHAIN) system is proposed by [55, 56]. However, the assumptions of the four main headings are so rough that in the case of complex passages the correction process may cause large positional errors. Therefore, Gu et al.[57] proposed eight main headings to cope with more complicated situations. Lan and Shih[30] proposed a map matching method using a floor plan to locate users based on the geometric similarity between trajectory data and maps. Gu et al.[58] defined the points of intersections of the mutually perpendicular channels in the building as an anchor, then corrected the trajectory through the anchor's constraints.

Nevertheless, in many indoor environments, there are no electronic indoor maps, limiting the use of map information to correct trajectories. Some map correction methods will not work if the initial positions cannot be determined. In addition, in the open environment, the map provides very little constraint information, and algorithms that strongly rely on environmental information to correct the trajectory will perform poorly.

2) Magnetic information constrains

Earth's surface is covered with geomagnetic fields. The undisturbed geomagnetic fields provide absolute heading

Table 2 Methods of gait phase detection

Reference	Classification	Gait phases	Sensors used	Technique details
[12]	No	Stance, swing	Gyro, acc	Fix threshold
[42, 59, 60]	No	Stance, swing	Gyro, acc	$th_{a\min} < \lvert a_k \rvert < th_{a\max} \& \sigma_{a_k^b} < th_{\sigma_a} \& \lvert \omega_k \rvert < th_{\omega\max}$
[14, 48]	No	Strike, flat, toe-off, swing	y-axis gyro	Fix threshold pre-segment + HMM estimate
[47]	No	Stance, swing	Acc	Adaptive threshold and time limits $T_n = \dfrac{T_{n-1} + \dfrac{a_{\max} - a_{\min}}{K_s}}{2} \& \begin{cases} t_k - t_{k-1} \geq 0.25 \\ t_k - t_{k-1} \leq 3.5 \end{cases}$
[43, 44, 61]	No	Stance, swing	Acc	Fix threshold of variance $\sigma_a^2 < L$
[28]	No	Stance, swing	z-axis acc	Fix threshold pretreatment + subtractive clustering
[35]	No	Stance, swing	Acc, gyro	Fix threshold $\lvert \lvert a_k \rvert - g \rvert < \lambda_a$ & $\lvert \omega_k \rvert < \lambda_G$
[15]	Walking, running	Stance, swing	Acc, gyro	Fix threshold for walking same as [33] adaptive threshold for running: $Th_{\sigma_a} = 280\overline{v}_k - 488, Th_w = 1.8\overline{v}_k - 2$ SVM+FFT classifier for gait phase detection
[23]	Walk, jog, run, sprint, crouch, climb (SVM classifier)	Stance, swing	Acc, gyro	Different motion with different threshold $\dfrac{1}{W}\sum_{k=n}^{n+W-1}\left(\dfrac{1}{\sigma_a^2}\left\lVert \sigma_k^b - g\dfrac{\overline{a}_n^b}{\lVert \overline{a}_n^b \rVert}\right\rVert^2 + \dfrac{1}{\sigma_\omega^2}\left\lVert \omega_k^b \right\rVert^2 < \gamma\right)$
[21]	Forward, backward, running, walking (BLSTM-RNN)	Stance, swing	IMU	Adaptively estimate step directly with BLSTM-RNN
[25]	Any motion	Stance, first-half of swing, second-half of swing	Speed output	A HMM model to estimate the three states of a gait
[39]	No	Stance, swing	Acc, gyro	Threshold based soft foot still signal for adaptive determination $SFS_k \triangleq \dfrac{1}{F}\sum_{i=k-F}^{k+F} C_i^1 C_i^2 C_i^3 C_i^4$

information. But, due to hard and soft magnetic interferences, headings measured by magnetometers are not available at all times. Hence, judging whether the magnetic field information is available or not is the first problem that needs to be solved before making use of the magnetometer to estimate the headings. Afzal et al.[62] specifically analyzed the magnetic field errors including three axial modulus errors and heading errors, and assumed that the good and bad magnetic fields obey different Gaussian distributions. Hence, the maximum likelihood ratio method is used to evaluate the magnetic fields. Magnetic field calibration is performed to make further improvements in [63]. The local variance of the magnetic field is used to perceive quasi-static magnetic fields (QSF) with a fixed threshold in [64]. However, in the case of huge hard magnetic or permanent magnetic interferences, when a person is at rest, it is also judged as a quasi-static magnetic field. Therefore, an error judgment test is considered in [29]. These magnetic field anomaly detection (MAD) algorithms allow magnetic field information to be selectively used in PDR systems.

3.5 Trajectory estimation strategies and methods

The trajectory estimation algorithms are the methods which estimate the trajectories of pedestrians by integrating the measurement data (IMU data), the layout information of the sensor units, the motion event observations (including movement types and gait events), and the environmental constraints. How to organically combine these acquired information to obtain the dead-reckonings is the core content of the PDR algorithm. Harle[5] divided the PDR system into two categories:

INSs (inertial navigation systems). An INS is a system that tracks position by estimating the full 3D trajectory of the sensor at any given moment.

SHSs (step-and-heading systems). An SHS is specific to pedestrians, estimating position by accruing {distance, heading} vectors representing either steps or strides.

Here, we specifically analyze how these two types of PDR systems fuse the above observation information to get the final dead reckoning, and summarize which data fusion algorithms are used in these two types of systems.

1) INSs

The basic theory of INSs is based on the following: the single integral over time of pure external acceleration can obtain the real-time speed, and the double integral gets real-time displacement. The one-time integration of the gyro output data over time can give a real-time attitude. The final trajectories can be obtained by the accumulation of the displacements and the attitudes. However, due to the effects of noise, measurement bias, and other disturbance factors, obtaining the trajectories through the triple integration will make the estimation errors proportional to the third power of time, which will bring huge errors in a very short time. Therefore, how to use the filter algorithm and the various types of information mentioned above to limit and correct the growth of errors is the core of INS systems.

First, we consider the roles of various types of information, described earlier in this article, in the INS system.

a) Zero velocity update (ZUPT) and zero-angular rate update (ZARU)

Under the assumption that the speed and angular velocity of the sole should be zero during the flat foot or stance phase period when the sole is completely in contact with the ground, once the flat foot or stance phase is identified or detected, we can observe that the velocity and the angular velocity are zero, i.e., they are zero-velocity pseudo-measurements. The zero-velocity pseudo-measurements are compared with the system output to obtain the error observation which will be compensated to the system output to limit the long-term accumulation of errors. This process is called zero-velocity update (ZUPT) and zero-angular update (ZARU). It is worth noting that ZUPT and ZARU are only for the situation where the sensors are tied to the foot. For the situations where the sensors are tied to other positions, ZUPT and ZARU cannot be used because they do not meet the hypothesis of zero-rate pseudo-measurement. Therefore, the INS systems mainly research the foot-mounted-based PDR algorithms.

Although the ZUPT and ZARU techniques can well limit the accumulation of integral errors, the final accuracies of trajectory estimation are very dependent on the precision of the flat foot phase detection. Hence, a lot of researches have been devoted to improving the accuracy of gait classification. However, as the speed of movement increases, the time during when the sole is completely in contact with the ground is very short, making the flat foot detection more difficult.

b) Heuristic heading reduction (HDR)

HDR was first proposed by Borenstein et al.[65] which is mainly based on the assumption that when the roads and the channels are straight, the human headings are changeless. If the algorithm judges that the heading is unchanged, the heading deviation can be corrected. The use of HDR can limit the constant heading drifts, especially in the case where ZARU is not available, such as in non-foot-mounted PDR systems, the headings can be confined within a certain range by HDR methods.

In the case where the direction of walking is changed slowly, the HDR easily judges the heading unchanged, on the contrary. How to solve this problem needs to be considered before using HDR algorithm.

c) Heading observation of magnetometer

Under the ideal geomagnetic conditions, the magnetometer can output the user′s absolute heading without integral options. The heading accuracy obtained from the filtered magnetometer's output is pinpoint. Therefore, many researchers also use the magnetometers outputs to compensate for the heading errors of gyros integral. However, due to the fact that the geomagnetic field is very susceptible to the hard magnetic interference of the surrounding environments, the deviations measured by magnetometers may sometimes be too large to be used. Therefore, only when the tolerable magnetic field interferences are detected, may the output of the magnetometers be integrated with the gyro integral to estimate the headings[64].

d) Data fusion filter

The most commonly used filter in the INSs is the extended Kalman filter (EKF), of course, other filters in the Kalman filter families, such as unscented Kalman filtering (UKF)[66, 67], complementary Kalman filtering (KF)[68], cubature Kalman filtering[69](CKF), are also occasionally used for filtering. Some papers also use complementary filters[61, 70]. Ashkar et al.[66] evaluated the performance of the EKF and UKF in trajectory estimation and found that the estimation accuracy of EKF and UKF is basically the same, but UKF needs more computational overhead. Therefore, the EKF performs better overall. The filtering methods are divided into direct estimation and indirect estimation. The direct estimation means that the filter directly outputs the final tracking data, and the indirect estimation means that the filter estimates the errors of the tracking data which will be compensated to the integration results. The commonly used method is the indirect estimation which estimates the state vector that contains 15 error states, including three-dimensional errors of acceleration, angular velocity, velocity, displacement, and attitude respectively. As shown in Fig. 4, a typical INS structure for estimating the error vectors using EKF is derived from the literature[48, 59].

e) Outcome of INS + EKF + ZUPT + ZARU + HDR + Compass algorithm

Abdulrahim et al.[54] specifically evaluated the performance of this framework in 2010. Their reports showed that the position errors exceeded 15% for INS + EKF + ZUPT only, were 8% for INS + EKF + ZUPT + ZARU, and 2%–10% for INS + EKF + HDR, 0.68%–5% for INS + EKF + ZUPT + Compass, and 0.38%–1.5% for INS + EKF + ZUPT + ZARU + HDR + Compass. The latest article published by Zhang et al.[48] in 2017 shows that the 3D trajectory estimation error based on this framework is from 0.207% to 0.350% and the average position error is within 1 m. This error has basically reached the user's acceptable range. However, the actual situations are much more complicated than the experimental conditions, and the types of movement are also complex and varied. It is still difficult to make the accuracies in practical applications as accurate as in the experimental environments.

2) SHS trajectory estimation strategy

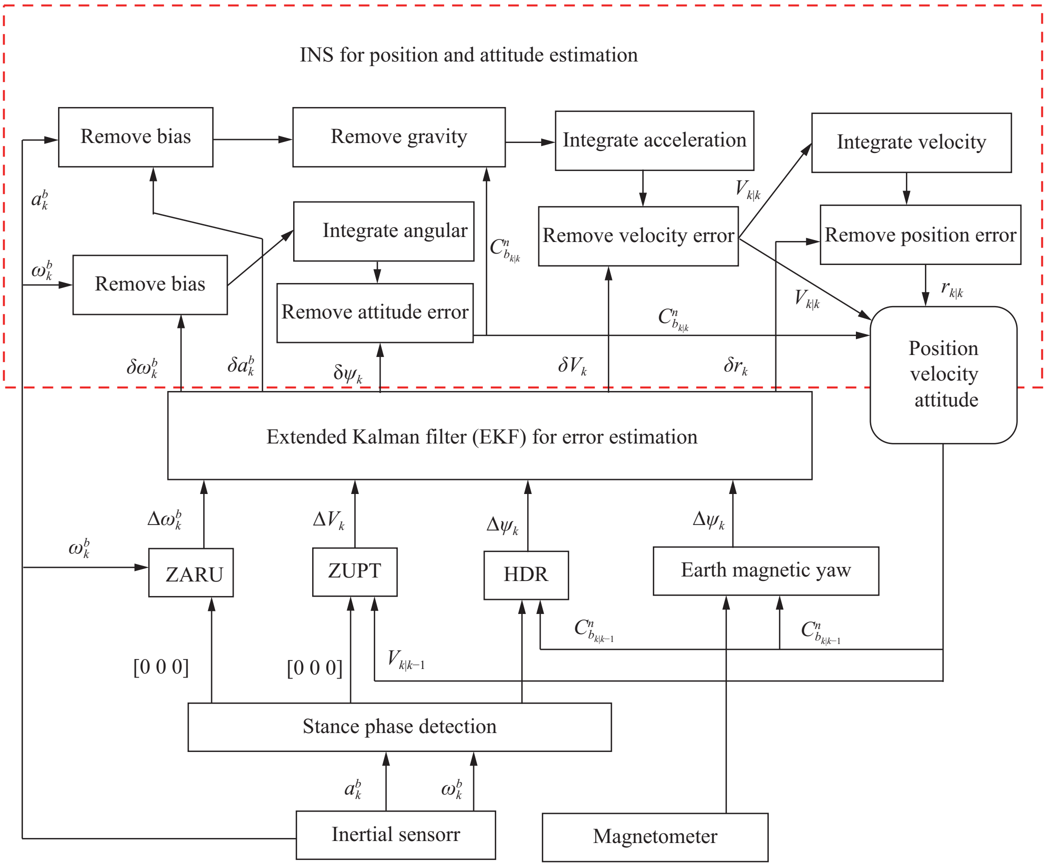


Fig. 4 INS using EKF with ZUPT, ZARU, HDR and Compass

The basic idea of step and heading systems (SHSs) is to divide the walking process into steps, and use the measurements outputs of each step to directly estimate the step size and heading, then accrue the {length, heading} vector to estimate the positions. The key issues involved in SHSs include: perceptions and divisions of steps, step sizes estimation, and step headings estimation. The step perceptions and divisions have been specifically discussed in Section 3.3. Here we summarize the step sizes estimation and headings estimation methods.

a) Step size estimation

Most non-foot-mounted PDR systems use the SHSs trajectory estimation strategies because non-foot-mounted systems do not have clear zero-rate points and cannot perform the very important ZUPTs to limit drifts. The SHSs usually use mathematical models to directly model the measured data in one step to estimate one step size. Since there are no integrals, it is a linear relationship between distance errors and time.

Table 3 summarizes some of the estimation models of the step sizes in the literature. In essence, the step sizes can be obtained by using the acceleration integrals. Therefore, there are large corresponding relationships between the acceleration characteristics and the step sizes. From Table 3, it can also be seen that the most commonly used step features are the differences between the maximum and minimum acceleration in one step. Some of the literature assumes that the human lower limb movements are similar to that of inverted pendulum models. Therefore, one step length can be estimated by using the characteristics of the leg length and height variation in one step, as shown in Table 3[13, 30]. In some models, features such as cadence and acceleration variance which reflect the severity of the movement are also used as inputs of models[21, 29]. In [71], the vectors composed by the features mentioned above are input into a trained back-propagation artificial neural network (BP-ANN) to directly estimate the step sizes, and the results show that the estimated error range is 1.7% to 2.1% which is 2% lower than that of the frequency models and nonlinear models mentioned above. Since artificial neural networks can fit almost any functions and can consider many dimensions of the input features at the same time, training a good artificial neural network model to estimate the step sizes is usually better than artificially designing a fixed mathematical model.

However, the above-mentioned mathematical models with parameters are generally obtained based on the experience in normal walking or running data, and will completely fail for some abnormal movements such as marking time. Marking time may have a large acceleration difference and a high step frequency, but no step length. If we use the model mentioned in the literature, we will get a normal step size. Problems like this have

Table 3 Methods of step length estimation in SHSs

Reference	Step length estimation	
	Parameter description	Model
[72]	K: constant coefficient $a_{\max}$: maximum acceleration $a_{\min}$: minimum acceleration	$L = K \times \sqrt[4]{a_{\max} - a_{\min}}$
[73]	K: constant coefficient $a_{\max}$: maximum acceleration $a_{\min}$: minimum acceleration a_i: acceleration sample	$L = K \times \dfrac{\dfrac{\sum_{i=1}^{N} \lVert a_i \rVert}{N} - a_{\min}}{a_{\max} - a_{\min}}$
[74]	K: constant coefficient a_i: acceleration sample	$L = K \times \sqrt[3]{\dfrac{\sum_{i=1}^{N} \lVert a_i \rVert}{N}}$
[13]	L: the length of leg h: the height chenge of step	$d = 2 \times \sqrt{2 \times Lh - h^2}$
[75]	K: constant coefficient $a_{\max}$: maximum acceleration $a_{\min}$: minimum acceleration a_k: acceleration sample	$L = K \times \dfrac{\sum_{k=1}^{N} \lVert a_k \rVert}{N} \times \sqrt[4]{a_{\max} - a_{\min}}$
[30]	L: the length of leg h: the height chenge of step	$D = 2 \times \sqrt{L^2 - (L - h^2)}$
[76]	$t_{k_{stepStart}}$: start time of the step $t_{k_{stepEnd}}$: end time of the step c_0, c_1: the constant parameters	$\Delta S_k = \dfrac{c_0 + c_1}{(t_{k_{stepEnd}} - t_{k_{stepStart}})}$
[29]	h: height f_{step}: step frequency a, b, c: calibration parameters	$l = h \times (a \times f_{step} + b) + c$
[21]	Δ_{fw}: the forward walking step length Δ_{fr}: the forward running step length Δ_{bw}: the backward walking step length $Var(a_z)$: the variance of the z-axis acceleration during a step e, f, g, h, k, m: the linear regression parameters	$\Delta_{fw} = e + f\sqrt{Var(a_z)}$ $\Delta_{fr} = g + h\sqrt{Var(a_z)}$ $\Delta_{bw} = k + m\sqrt{Var(a_z)}$
[77]	$a_{pp,t}^{step} = a_{peak,t}^{step} - a_{valley,t}^{step}$ $a_{peak,t}^{step}$ peak value of the step $a_{valley,t}^{step}$ valley value of the step β: the scale factor γ: the offset	$l_k = \begin{cases} \beta\sqrt[4]{a_{pp,t}^{step}} + \gamma, for a_{pp,t}^{step} < a_{\tau}^{step} \\ \beta \log\left(a_{pp,t}^{step}\right) + \gamma, for a_{pp,t}^{step} \geq a_{\tau}^{step} \end{cases}$
[71]	f_{stride}: the stride frequency $acc_{\max}$: maximum acceleration $acc_{\min}$: minimum acceleration σ_{acc}: acceleration standard deviation h: height of test subjects	Trained a BP-ANN model to stimate the step length. The input vector is $X_k = \{f_{stride}, acc_{\max}, \sigma_{acc}, acc_{\min}, h\}$

not been solved well at present.

b) Heading Estimation

In a foot-mounted SHS system, the headings estimation can be similar to the INSs. However, many SHSs are not based on the foot-mounted methods. In these cases, the ZUPT and ZARU cannot be used to limit the heading drifts due to the loss of zero-rate points, thus the headings can only be corrected by other means.

The simplest way is to estimate the attitude of the measurement units with attitude calculation algorithms, and to derive the headings through the attitudes. Using the map constraints[30, 58, 60, 71] and quasi-static magnetic fields[29, 45, 62–64] summarized above to correct the headings is a method used by many documents.

The heading outputs by the SHS systems are usually two-dimensional, so the general SHS systems will not be able to be used for the estimation of three dimensional trajectories. How to perceive vertical height changes based on inertial sensors is a tricky problem.

3.6 Particle filter

In addition to the previously mentioned ways of using map information for heading constraints, another way to combine maps with INS or SHS systems is through a particle filter. A particle filter is an approximate solution to a Bayesian filter[78]. It approximates an arbitrary probability density function by finding a set of random samples propagating in the state space, and replaces the integral operation with the sample mean to obtain the minimum variance estimation of the system state. A number of particles are randomly generated on the map according to a certain distribution in PDR systems that incorporate particle filtering. Each particle represents a three-dimensional position and has its own weight which is adjusted and updated in real time according to the inputs and status of the system. It is an iterative process that mainly includes the following steps[79]:

Propagation. Each particle updates its own state based on the state of the system at that time. For example, when the SHS system outputs a state {step length, heading}, each particle changes its position and heading according to the state.

Correction. Each updated particle gets its weight according to a system evaluation function or constraint. For example, the weights of the particles that pass through the wall during the update are set to zero.

Re-sample. According to the weight of each particle, a certain number of particles are re-sampled in proportion to form a new set of particles which will enter the next iteration of the update process.

According to [42, 55, 76, 79–81], a general framework for particle filters used in PDR systems is summarized, as shown in Fig. 5.

In the propagation step, the added random noise represents the uncertainty of the estimation results due to IMU measurement noise. The most commonly used random noise is Gaussian noise, of course, but it can also be non-Gaussian noise. The noise variance can be fixed[55, 78] or dynamically changed according to the real-time state measurements[42, 76]. During the determination of the particles' weights, in addition to removing the particles which pass through the wall, other constraints may also be used to determine the weights of the surviving particles. Abdulrahim et al.[54] utilized the cardinal heading aided inertial navigation (CHAIN) method to ensure that the particles whose headings are closer to the main headings are with greater weights. Gu et al.[57] updated the particle weights by considering the prior knowledge of constraints of eight discrete principal directions and human behavior categories. Medina et al.[80] took the location estimated at each step as the center of a circle with a radius of 2 to 3 meters, and calculated the shortest distances from the center of the circle at every 9 degrees to the walls, then endowed the long-distance areas with large weights, and the short-distance areas with small weights. In the resampling process, the number of resampling particles can be fixed[55], or dynamically changed[79]. The number of the particles requires a trade-off between the estimating accuracy and the computational overhead. There are also many resampling methods, such as Kullback-Leibler divergence (KLD) sampling[79], polynomial sampling (straightforward multinomial resampling strategy)[55], etc.

During initializing particles, if there is no prior knowledge, the easiest way is to evenly distribute all particles throughout the map, but this method requires a large number of initial particles in order to cover the entire map space. When the considered map is large, the initial computational costs will be very large, and even the particle update process takes a longer time than motions of one step. In addition, many buildings are symmetrical, and if the initial position is unknown, it is possible that the estimated trajectory is not unique. Therefore, it is necessary to use some auxiliary means to reduce the initialization particles, such as using Wifi to initialize the approximate location, manually setting the initial position, or using magnetometers to estimate the initial heading. When considering the use of particle filter in a PDR system, determining an effective initialization method is an important way of improving the system's efficiency.

4 Technical roadmap of IPDRs

This article uses object-oriented thinking to analyze the various sub-problems involved in the PDR systems, decouples each sub-problem from the specific PDR systems, and analyzes and summarizes each sub-problem separately. Through the analysis and discussion in this paper, we propose a graph structure of IPDR systems, which is composed of nodes and directed edges between

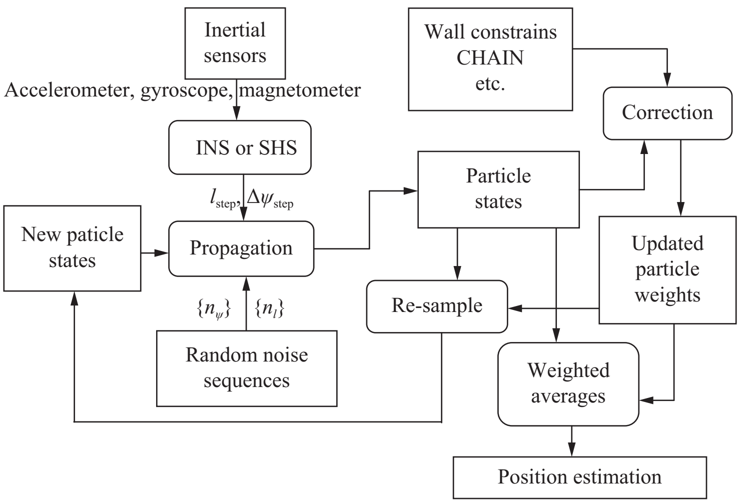


Fig. 5 General framework of PF used in PDR

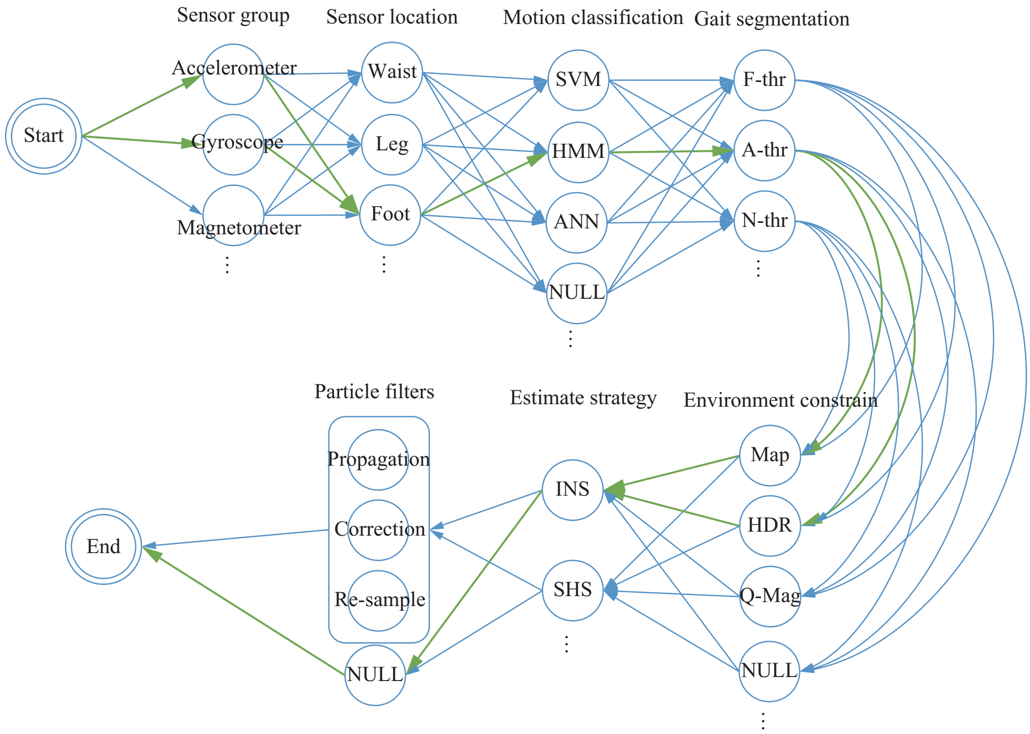


Fig. 6 General technical roadmap of IPDRs

each sub-problem discussed above. A specific set of paths from the beginning node to the end node constitute a subdirected graph, which we call a "technical route" of a specific PDR system. Fig. 6 shows the structure of the IPDR technology roadmap:

The nodes in each stage in Fig. 6 can be combined with each other, i.e., the technical means adopted in each stage are combinations of each individual technology. For example, during the motion classification stage, SVM, HMM, etc. can be used alone or in combination with each other as the motion classification algorithm. A set of paths from the start node to the end node form a technical route. For example, the technical route of a PDR system composed by the bold green lines in Fig. 6 indicates: Using accelerometers and gyroscopes as measurement units, binding them to the feet, classifying motions by using hidden Markov models (HMMs), using adaptive thresholds for gait segmentation, considering maps and heuristic heading constraints, and using INS strategies to estimate the trajectory without using particle filters. The ellipses in Fig. 6 indicate other unlisted technical methods in each section. In this way, we can intuitively choose how to design an inertial sensor-based PDR system. Of course, the diagram depicts only the main frame of the PDR system. It is possible to add more other methods for each section on this basis.

5 Conclusions

This paper does a survey and analysis of pure inertial sensor-based PDR systems (IPDRs) from the macro and micro perspectives. From a macro perspective, this paper proposes a general framework and a generic technology roadmap structure of IPDRs. From the micro perspective, using object-oriented thinking, the IPDR systems are divided into several relatively independent sub-problems to be discussed in detail, and the technical methods applied to these sub-problems in the current literature are summarized. This article provides a clear framework for the follow-up IPDR researchers or designers from these two aspects. IPDR system researchers can conduct in-depth research on each of the sub-issues summarized in this paper, propose new solutions, or improve on existing foundations. It is also possible to combine the existing technical solutions in each sub-problem differently to propose a new technical route.

Many researchers now claim that their proposed IPDR systems have sub-meter accuracies, and the ratio of position error to true trajectory distance is usually less than 3%. More accurately, the state-of-the-art foot-mounted PDR approaches have achieved a error rate less than 0.3%, such as the proposed method by [48], which has achieved a error rate 0.217%, 0.350% and 0.207% respectively in their experiments in which the total length of the route line is about 310 m and the error distance is from 0.160 m to 1.084 m. This has largely reached the expectations of everyday users. With the development of MEMS technology, the characteristics of low cost, small size, low power and high precision will make micro inertial sensors more and more applicable to our daily life. Especially the popularity of handheld devices and the wide application of wearable devices in recent years provide a broad prospect for the development of applications based on microelectromechanical systems (MEMS). Therefore, the IP-

DR systems are expected to be widely used in environments without GNSS signals to provide users with location and navigation services. There is much research on the IPDR systems based on inertial sensors of mobile terminals, but the results are not very significant. To achieve a wide range of applications and popularity, there are still some problems that need to be resolved in the current IPDR systems.

The initialization problem. Since the IPDR systems estimate the relative displacements with respect to the initial position, in the positioning application, without the help of other information, IPDR systems will not be able to obtain the initial position in a map and thus lose the reference point. Even if particle filters are used, the system may not converge to a specific location in a long period of time without initializing an approximate location first, or the position obtained in a symmetrical environment is not unique. Although it is a seemingly feasible method to use Wifi to perform initialization, this involves Wifi positioning, a completely different approach from IPDR, and Wifi signals are not available in many cases. Therefore, how to initialize the position of the IPDR systems is a difficult problem that needs to be solved.

Error accumulation problem. Most of the current standards for measuring the accuracies of the IPDR systems are the percentage of error with respect to the true moving distance. Although numerically, the error percentages of these implementations look very good, under long-distance running conditions, the error distance between the estimated position and the true position will also increase, which means that after a certain period of time, the output errors of the IPDR system may completely exceed the user's acceptable range. Initializing the position intermittently with some known position may be a method of suppressing large absolute errors. However, this in turn depends on the solution of the initialization problem.

Problem of the restriction of activities. So far, almost all proposed IPDR systems are based on trajectory estimations under a limited number of normal motions. In real life, there will be a large number of different types of activities and activity scenes. Under complex motion conditions, it is difficult for existing IPDR systems to achieve the accuracy claimed by the researchers. Although the use of a more powerful classification algorithm for motion classification is a method to improve the performance of IPDR systems in complex motion situations, there are differences in the number of categories and the strategies for motion classification in different literature, and no uniform standards. In addition, there is a lack of authoritative databases for the classification of inertial motion data.

Fixed position problem. The basic premise of the IPDR systems is that the measurement units are fixedly attached to the human body. This is one of the major obstacles for the design of IPDR systems using smart phones. It is difficult for a smartphone to be fixed to a part of a person's body during exercise. Even if it is placed in a trouser pocket, the posture of the smartphone relative to the leg will be constantly changeable. But, considering the wide using of hand-held devices, there is research on hand-held PDR being advanced as well, such as [26, 81]. And the hand-held PDR is also a worthy research area in the future.

Some aids or hybrid navigation systems are currently temporary solutions to the above problems. This article is only for the overview of pure inertial sensor-based PDR systems. Many assisted trajectory estimation methods or integrated navigation systems that use auxiliary sensors other than inertial sensors do have good performance, but they are beyond the scope of this article.

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