# Improvement of Pedestrian Dead Reckoning Algorithm for Indoor Positioning by using Step Length Estimation

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## ABSTRACT

Pedestrian dead reckoning (PDR) can solve the position information by its inertial measurement unit (IMU), which is a method to achieve indoor autonomous positioning without deploying positioning base stations in advance. However, affected by the accumulated error, the positioning accuracy will decrease with the increase of the moving distance. To improve the indoor positioning accuracy, the step length estimation of PDR is improved. A PDR method combining the information on walking frequency, acceleration variance, and fixed step is proposed. Firstly, the pedestrian's walking steps are detected and estimated by the threshold peak method; secondly, the step frequency and acceleration variance are calculated, and the step length estimation model is fitted with the fixed step length of the pedestrian to estimate the step length of each step; then, the fusion algorithm of magnetometer, accelerometer, and gyroscope are used to estimate the heading; finally, combined with the step number, step length, and heading angle, the position information of walking is calculated by dead reckoning. The experimental results show that in the practical distance of 42.6 m, the accuracy of dead reckoning distance based on the combination of step frequency, acceleration variance, and fixed step length can reach 98.47%, which is better than the fixed step length and linear step length version, 5.09% higher than the linear step length and 0.35% higher than the fixed step length version.

## 1. INTRODUCTION

With the continuous development of science and technology, people's demand for accurate location information is increasing. In the outdoor environment, GNSS (Global Navigation Satellite System) such as GPS (Global Positioning System) and BDS (BeiDou navigation satellite system) are widely used in daily life and can meet people's outdoor positioning needs (WU et al., 2014). However, in the indoor environment, the satellite signal is blocked by buildings, which cannot provide accurate location information, while people live indoors mostly. Therefore, the lifestyle inevitably increases the demand for indoor navigation and positioning. At present, most indoor positioning methods use active positioning technologies such as Bluetooth (Bencak et al., 2022), RFID (XIE et al., 2022), WLAN (YAO et al., 2016), UWB (LI et al., 2022), etc (ZHANG et al., 2022). However, in some special environments, relevant signal-transmitting devices may not be installed, and the positioning parameters required for indoor positioning calculation cannot be provided. Therefore, it is very important to develop an independent positioning system that does not rely on GPS and active indoor positioning methods, especially in extreme cases such as no power or high temperature. PDR (pedestrian dead reckoning) is a passive positioning method. This positioning method can autonomously obtain data for analysis without using external equipment such as base stations, calculate the steps, steps length, heading, and other information of travelers, and then fuse these three pieces of information to estimate the movement trajectory of travelers, to achieve positioning.

PDR comes from the traditional INS (inertial navigation systems). INS is a completely autonomous navigation mode, which is widely used in aerospace technology. It only uses its equipment to complete navigation, with little influence from external factors (QIN, 2014). Based on Newton's law of mechanics, INS uses the accelerometer to measure the acceleration relative to the selected coordinate system and then performs double integration to obtain the displacement. The gyroscope is used to measure the angular velocity first, perform one integration operation to obtain the angle, and then integrate again to obtain the radian. Combined with the direction of displacement and angle, the positioning track can be deduced to carry out positioning. However, INS mainly relies on an integral operation to obtain the position information of the carrier, but the sensor itself has uncertainty errors such as zero bias, scale factor, and axial direction, so it requires high accuracy of the inertial unit. In addition, due to the physical shaking of inertial sensors when pedestrians walk, there is a huge accumulation of errors in obtaining pedestrian positioning information directly through integration in inertial navigation. Therefore, some scholars have studied the walking law of pedestrians and proposed the PDR method.

Although the PDR method reduces a part of the cumulative error and improves the positioning accuracy of pedestrians, there are still shortcomings. With the increase in pedestrian walking distance and time, the measurement error of the sensor will continue to accumulate. And with the accumulation of errors, the accuracy of PDR positioning will decrease significantly after some time. Currently, most of the research on PDR focuses on sensor detection and improving the accuracy of step length and heading angle. GUO et al. (2017) combined the quaternion method, HDE algorithm, and iHDE algorithm to solve the course information and revise the course accuracy. BI et al. (2021) realized step number detection and gait cycle estimation through acceleration change trend, reducing the position error of dead reckoning. DENG et al. (2021) put forward a PDR algorithm based on human motion state by detecting step frequency and steps through acceleration data, which improves the positioning accuracy of pedestrians in multiple motion states. BAI et al.

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(2021) used the cuckoo algorithm to dynamically estimate the magnetic error to improve the timeliness of magnetic calibration, thus improving the accuracy of pedestrian heading estimation. These studies have effectively improved the positioning accuracy of the PDR algorithm. However, their research results are mainly focused on the research of heading angle and step number detection. In contrast, the research on improving the step length model to improve the positioning accuracy of the PDR algorithm is relatively small. Based on the above reasons, this paper improves the step length estimation and proposes a PDR location method that combines the step frequency, acceleration variance, and fixed step length of pedestrian walking. This step length estimation model combines the linear step length with the fixed step length. By giving different weights to the linear step length and the fixed step length, and using the fixed step length to constrain the linear step length, the error of step length estimation is reduced. Then, the step length model in this paper is combined with step detection and heading estimation to calculate indoor location information, thus improving the location accuracy of PDR.

## 2. METHODOLOGY

### 2.1 Pedestrian Dead Reckoning Algorithm

As an indoor passive location method, PDR mainly relies on acceleration sensors, gyro sensors, and magnetic field strength sensors to obtain data for analysis, calculate the gait, step length, and heading information of travelers, and then dynamically fuse these three pieces of information to estimate the real-time movement trajectory of pedestrians, to achieve indoor positioning. The principle of PDR positioning is to know the initial position of the pedestrian, use accelerometer, gyroscope, and magnetometer data to calculate the next step length and heading angle, and then calculate the trajectory from the initial position to the current position according to the step length and heading angle (WU et al., 2019). The key information of PDR calculation is displacement calculation and direction estimation. The difficulty is to accurately calculate the displacement and direction of the positioning object from the acceleration, angular velocity, magnetic force, and other data collected by IMU. Its principle is shown in Figure 1:
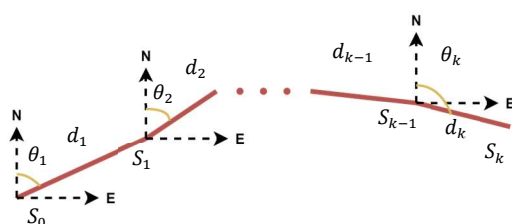


**Figure 1**. Schematic diagram of PDR principle

In Figure 1, $E$ and $N$ respectively represent the due east direction and the due north direction of the pedestrian, $d_n$ represents the step length of the nth step, $\theta_n$ represents the heading angle of the nth step, and $S_n$ represents the position of the pedestrian after the nth step. The general formula is as follows:

$$\begin{cases} E_k = E_0 + \sum_{n=1}^{k} d_n \sin\theta_n \\ N_k = N_0 + \sum_{n=1}^{k} d_n \cos\theta_n \end{cases} \quad (1)$$

The PDR algorithm proposed in this paper mainly includes three main contents: step detection, step length estimation, and heading estimation. The pedestrian indoor positioning structure framework describes the whole process from inertial data

acquisition to position information output in this paper, as shown in Figure 2. In the structure frame, the hardware part integrates inertial sensors such as an accelerometer, magnetometer, and gyroscope. Inertial data such as acceleration, angular velocity, and magnetic field strength are obtained through inertial sensors. Steps are estimated using acceleration information, and step length are estimated using step frequency, acceleration variance, and fixed step length. Combination of accelerometer and magnetometer to calculate heading angle $\varphi_1$. The gyro uses the quaternion method to calculate the heading angle $\varphi_2$. The accelerometer, gyroscope, and magnetometer complement each other, and the EKF (Extended Kalman filter) combination is used to estimate the heading angle (FANG and YI., 2016). According to the information on step length, the number of steps, and heading angle, the pedestrian's position can be calculated by equation (1).
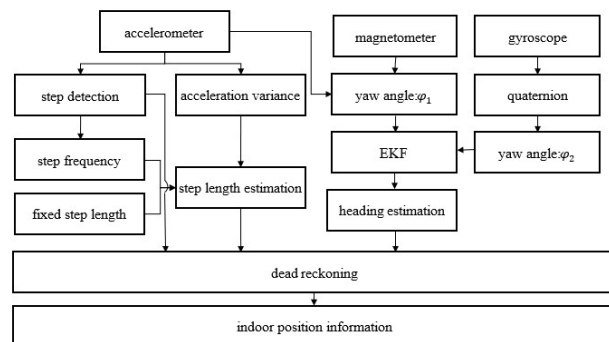


Figure 2. PDR structure frame diagram

### 2.2 Step Detection

The walking process of people has periodicity. The gait cycle of people can be roughly divided into two main stages, one is the stance phase and the other is the swing phase (Robert, 2013). With the help of the gait cycle, we know that when people walk normally, acceleration and deceleration phases alternate in both vertical and horizontal directions. According to the walking characteristics of people at various stages, we can know that the acceleration value changes periodically during pedestrian walking. For example, when the heel lands on the ground, the instantaneous recoil force caused by the impact on the ground will generate a large instantaneous acceleration, so in the vertical direction, the acceleration value will reach a peak. In the stage of standing with one foot, the center of gravity of the human body is relatively stable. When the other foot swings, the corresponding acceleration value will fluctuate in the horizontal direction. Based on the characteristics of human gait in the process of travel, the pedestrian's steps are estimated by the peak threshold detection of acceleration. The step-counting method of peak threshold detection of acceleration can better adapt to the changing relationship between gait cycle and acceleration value at the same time, and achieve high accuracy. The method is as follows:

Firstly, the overall acceleration is calculated, and the three-axis acceleration data is synthesized to better reflect the change in the vertical acceleration of the human body. To highlight the difference, all the calculated combined accelerations must be subtracted from the average value of the combined acceleration over a period, which is conducive to better measure the gait of the human body. The processing of acceleration is as follows:

$$acc_{xyz} = \sqrt{acc_x^2 + acc_y^2 + acc_z^2} \quad (2)$$

$$acc = acc_{xyz} - mean(acc_{xyz}) \qquad (3)$$

where $acc_{xyz}$ is the combined acceleration of the three axes at a certain time; $acc_x$, $acc_y$, and $acc_z$ are the accelerations of the x, y, and z axes at a certain time respectively, $mean(acc_{xyz})$ is the mean value of the combined acceleration over a period of time, and $acc$ is the acceleration of the three axes at a certain time minus the mean value of the combined acceleration. The accuracy of the sensor itself and the way pedestrians hold the sensor will produce different degrees of noise in the data. To eliminate the impact of some noise, the acceleration data calculated by the above formula (3) is preprocessed by a sliding window smoothing filter. Secondly, use the sliding window to traverse the possible peak value of the processed acceleration value. When the acceleration threshold value conforms to $acc > 0.25$ m/s$^2$, it is retained. Finally, considering that there should be a reaction time between the previous step and the next step when walking, to prevent misjudgment of the number of steps, it is necessary to judge the time interval between the previous step and the next step, calculate the time interval between the previous peak and the potential peak, and judge it as an effective step when the time interval is higher than 0.4s. Figure 3 (a) and Figure 3 (b) are acceleration waveforms before and after processing. After processing, it can be seen that the noise of the data is reduced, the data is smoother, and the changing trend of acceleration and the maximum and minimum values of acceleration can be observed more intuitively.
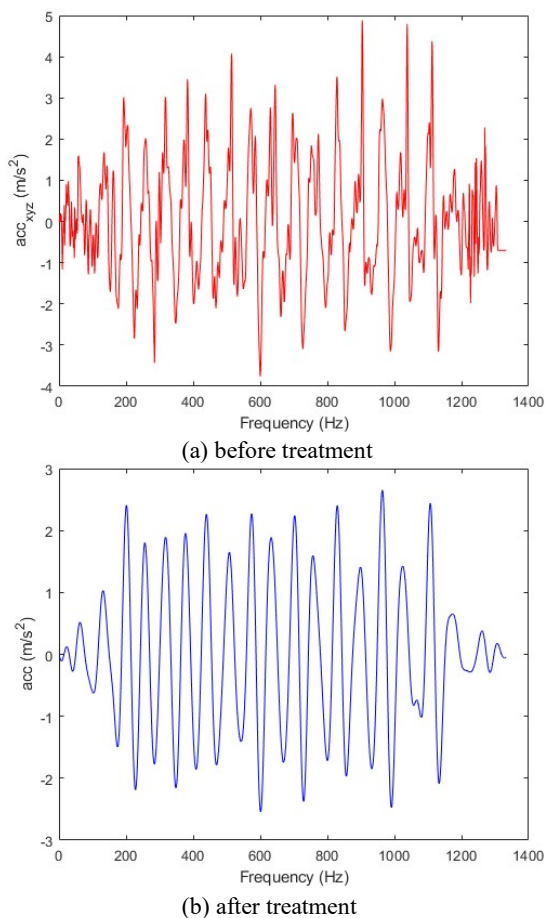


(a) before treatment



(b) after treatment

**Figure 3**. Acceleration waveforms before and after processing

## 2.3 Step Length Estimation

The simplest way to estimate the step length is to directly use a fixed step length, that is, it is assumed that the length of a pedestrian in a single step is fixed. However, the gait of pedestrians may be affected by the environment or behavior, and they do not always walk at a fixed pace (HOU and Jeroen et al., 2021). In addition, if the fixed step length is used as the step length estimation of pedestrian navigation, the error of step length estimation will be superimposed due to the relationship of "walking distance = step length * step number", thus affecting the accuracy of the overall walking distance. The research results of human gait show that the step length is approximately linear with the step frequency (SUN et al., 2008), so another step length estimation method is an adaptive step length estimation model that uses the linear relationship between the step length, the step frequency, and the acceleration when pedestrians walk. (QIAN et al., 2013). However, due to the uncertain error of the sensor in acquiring the acceleration value, such as the sudden occurrence of abnormal values in a short time, there is no scope constraint at this time, and the overall positioning accuracy is easy to be low. Therefore, it is still insufficient to estimate the step length only in the way of fixed step length or in the linear change model of step length with step frequency and acceleration.

Considering that the pedestrian step length is related to the changes in the walking frequency and acceleration, and the step length generally does not have a sudden change, the fixed step length has certain constraints on the step length of each step, based on this, this paper proposes an improved dynamic constraint step length estimation model in combination with the relationships between the pedestrian fixed step length and the pedestrian acceleration and step frequency when walking:

$$SL = K_3 * (K_1 * SF + K_2 * SV + C) + K_4 * FS \qquad (4)$$

where $SL$ represents the estimated pedestrian step length; SF represents the pedestrian's step frequency; SV represents the variance of acceleration; FS represents the fixed step length of the pedestrian, which is calculated by taking one step under normal conditions; $K_3$ and $K_4$ are weighting factors of step frequency and acceleration variance respectively; $K_1$ and $K_2$ are weighting factors of linear step length and fixed step length respectively; Is constant. $K_1$, $K_2$, $K_3$, $K_4$, and C are determined by the walking conditions of different pedestrians and are mainly obtained through walking data training.

## 2.4 Heading Estimation

Heading estimation is very important in dead reckoning because it directly affects the direction of travel. In smartphones, the absolute heading can be calculated by magnetometer and accelerometer, which is also easy to realize. However, the magnetometer will be disturbed by magnetic forces, especially in complex indoor environments (SONG and SHEN., 2013). When the magnetometer is disturbed, the walking direction will be abnormal. The angular velocity integral obtained from the smartphone gyroscope can provide a higher heading angle in a short time, but because it is an integral operation, even small noise will produce large errors over time, which is not suitable for long-term heading estimation. Based on this, this paper uses EKF to fuse the magnetometer, accelerometer, and gyroscope for heading estimation. This method complements the advantages and disadvantages of magnetometer, accelerometer, and gyroscope, and can obtain a relatively stable and high-precision heading angle. The method is as follows:

Firstly, the roll angle and pitch angle are calculated by the accelerometer. Since the gravitational acceleration felt by the z-

axis is constant when the accelerometer is rotating, the heading angle cannot be directly calculated by itself, so the roll angle and pitch angle can be calculated by the accelerometer first. The formula is:

$$\theta = \arctan\left(\frac{a_y}{a_z}\right) \quad (5)$$

$$\gamma = -\arctan\left(\frac{a_x}{\sqrt{a_y^2 + a_z^2}}\right) \quad (6)$$

where: $\theta$ represents roll angle; $\gamma$ represents pitch angle; $a_x$, $a_y$, and $a_z$ respectively represent acceleration components of the three axes.

Secondly, the absolute heading angle is calculated by the accelerometer and magnetometer. Synthesis (5) (6): convert the output value of the three-axis magnetometer from the carrier coordinate system to the navigation coordinate system, and calculate the heading angle:

$$\begin{bmatrix} M_x \\ M_y \\ M_z \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma & \cos\gamma \end{bmatrix} \begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} =$$
$$\begin{bmatrix} \cos\theta & \sin\gamma\sin\theta & \cos\gamma\cos\theta \\ 0 & \cos p & -\sin\gamma \\ -\sin\theta & \sin\gamma\cos\theta & \cos\gamma\cos\theta \end{bmatrix} \begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} \quad (7)$$

$$\varphi_1 = \varphi_0 - arctaan\left(\frac{M_y}{M_x}\right) \quad (8)$$

where: $m_x$, $m_y$, and $m_z$ respectively represent the three-axis components of the three-axis magnetometer; $M_x$, $M_y$, and $M_z$ represent magnetometer components converted into the navigation coordinate system; $\varphi_0$ is the magnetic declination angle, which can be obtained by looking up the table; $\varphi_1$ represents yaw angle calculated by integrating accelerometer and magnetometer.

Then, the quaternion method is used to calculate the heading angle of the three-axis gyroscope. There are three methods to calculate the attitude angle of a gyroscope: direction cosine method, Euler angle method, and quaternion method. Using the quaternion method not only has the advantages of simple calculation and easy operation but also can avoid the "singular point" problem of the Euler angle method. The matrix form of rigid body motion of quaternion can be expressed as:

$$\frac{dQ}{dt} = \frac{1}{2} \begin{bmatrix} 0 & -w_x & -w_y & -w_z \\ w_x & 0 & w_z & -w_y \\ w_y & -w_z & 0 & w_x \\ w_z & -w_y & -w_x & 0 \end{bmatrix} \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \quad (9)$$

where $Q = [q_0 \quad q_1 \quad q_2 \quad q_3]^T$ represents the quaternion vector; $q_0$ is the real part of the quaternion, $q_1$, $q_2$, and $q_3$ are the imaginary parts of the quaternion, where $q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1$; $w = [w_x \quad w_y \quad w_z]^T$ represents the vector of the gyroscope. Use the second-order Runge Kutta method to update the state of quaternions (GUO et al., 2017), and calculate the rotation matrix from quaternions:

$$C_b^n = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_0q_3 - q_1q_2) & 2(q_1q_3 + q_0q_2) \\ 2(q_0q_3 + q_1q_2) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\ 2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_0q_1) & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix} \quad (10)$$

The calculated heading angle $\varphi_2$ is:

$$\varphi_2 = arctan\left(\frac{2(q_0q_3 + q_1q_2)}{q_0^2 + q_1^2 - q_2^2 - q_3^2}\right) \quad (11)$$

Finally, the EKF is used to fuse the magnetometer, accelerometer, and gyroscope for heading estimation, and the final heading angle $\varphi$ is obtained.

## 3. EXPERIMENT AND ANALYSIS

The experimental data in this experiment is collected by an Android mobile phone, which is equipped with a six-axis sensor (lsm6dso) and geomagnetic sensor (ak0991x), and other inertial units. The six-axis sensor (lsm6dso) integrates a three-axis accelerometer and a three-axis gyroscope. The experimental site is selected as a loop passage, and the actual distance is 42.6m. During data acquisition, set the acquisition frequency to 100 Hz. The experimenter walks on the loop passage, holds the smartphone in front of his chest in a horizontal posture, and tries to keep the walking direction straight. In this paper, three methods of step length estimation are selected for experiments. The methods of step length estimation are: (1) directly use the fixed step length of the normal step taken by the experimenter; (2) Linear estimation model based on step frequency and acceleration variance; (3) Based on the combined estimation model of step frequency, acceleration variance, and fixed step length. Figure 4 shows the pedestrian positioning track obtained by the PDR algorithm using different step length estimation models. From the heading, it can be seen that since the three models are the same heading estimation method, the calculated track is circular, which is consistent with the actual walking track. When pedestrians walk in the same direction, the error becomes larger and larger with the increase of time. It is known that the error will have an accumulation effect. It is worth mentioning that three different step length estimation models will have a closed-loop error. That is, the walking path of the laboratory is a closed loop, but the path shown in the experimental results is not closed. It can be seen from the displayed track that the closed-loop error of the linear step is the largest.
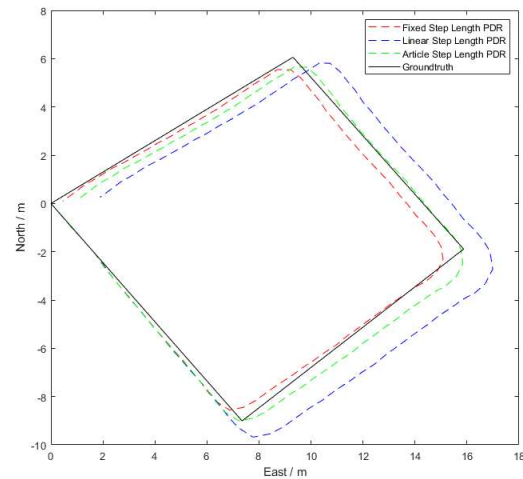


**Figure 4**. Track of PDR

Figure 5 shows the yaw angle estimation result of the PDR algorithm, which walked in four directions during the experiment. It can be seen from the estimation of the heading angle that the estimated value has little change in the heading angle in the same direction. From the point of view of trajectory position, the linear estimation model trajectory based only on the variance of step frequency and acceleration deviates greatly from the actual trajectory and has large errors. The distance results of the fixed-step length estimation model and the estimation model in this paper are highly correlated with the actual trajectory.
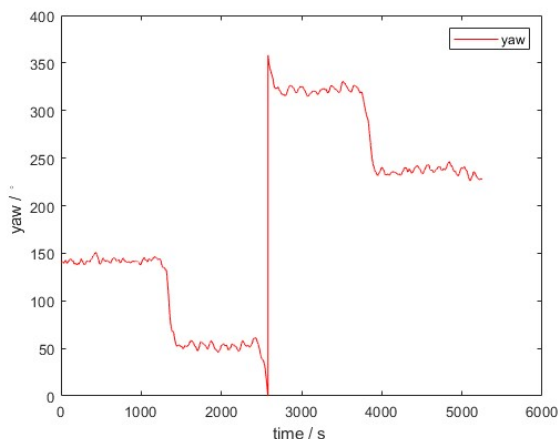
**Figure 5**. Yaw angle estimate

Further, the step length estimation value is analyzed in this paper. Figure 6 shows the step length estimation of each step of the linear step length estimation model and the step length estimation model in this paper. In the experiment, the fixed step length of the experimenter was set to 0.55 m, and the experimenter walked 77 steps in total. By comparing each step length of the three models, it is found that the estimated step length data shows that the single-step length estimation of the linear step length model is between 0.43 m and 0.75 m, and the estimated step length of the model in this paper is between 0.50 m and 0.65 m. Both models conform to the estimation range of the step length, and there are no outliers with large errors. However, the step length estimation in Figure 6 shows that the difference between the maximum and minimum values of the linear step length estimation is 0.32 m, and the difference between the maximum and minimum values of the step length estimation in this model is 0.15 m. By comparison, it is found that the adjacent step length estimates in this model tend to be stable, which is more stable than the linear step length model through this model.
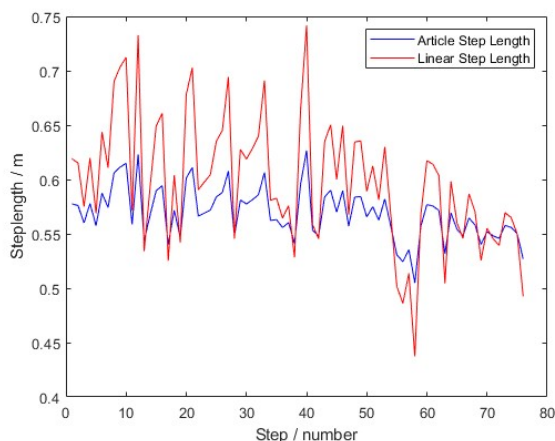


**Figure 6**. Step length estimates

The calculated distance results of different models calculated by experiments are compared with the actual distance respectively (Table 1). The minimum error of the dead reckoning in this paper is only 0.65 m, and the accuracy is 98.47%. The dead reckoning based on the combination of step frequency, acceleration variance, and fixed step length has high step length estimation stability and accuracy. The higher precision range positioning information obtained by this algorithm is better than the fixed step length and/or linear step length version. The range accuracy

is 5.09% higher than that of linear step length dead reckoning and 0.35% higher than that of fixed step length dead reckoning.

Table 1. Dead reckoning distance results

|  | actual distance/m | estimated distance/m | error/m | accuracy |
|---|---|---|---|---|
| fixed step length | 42.60 | 41.80 | 0.80 | 98.12% |
| linear step length | 42.60 | 45.42 | 2.82 | 93.38% |
| this paper proposed | 42.60 | 43.25 | 0.65 | 98.47% |

## 4. CONCLUSION

In this paper, the inertial measurement unit (IMU) built into the smartphone device is used to collect pedestrian walking data, and the pedestrian dead reckoning algorithm is used for indoor positioning. To further improve the positioning accuracy of the PDR algorithm, this paper improves the step length estimation. Based on the shortcomings of fixed step length and linear step length, a step length estimation model combining fixed step length and linear step length is proposed. This model uses the fixed step length of pedestrians, the step frequency, and acceleration variance of pedestrians when walking, and gives different weight factors to adaptively estimate the step length of pedestrians at the time of walking. The steps of this paper mainly include step detection, step length estimation, and heading estimation, and each step is described in detail.

Compared with the fixed step length, the fixed step length is suitable for pedestrians when the step length of each step does not change. In this paper, step length estimation uses attributes such as step frequency and acceleration variance to expand the case of random step length walking, and improve the accuracy of step length estimation under random circumstances. Comparing the step length estimation in this paper with the linear step length, the linear step length only uses the step frequency and acceleration variance to linearly fit the step length, which is vulnerable to the influence of inertial unit measurement error. When the measurement error is large, the accuracy of the entire PDR algorithm will decline. The step length estimation in this paper uses a fixed step length to constrain the situation with large errors. When the measurement error is large, because the step length estimation is combined with fixed step length, this will offset part of the error and improve the estimation accuracy. In conclusion, this paper combines the advantages of the stability of fixed step length and the randomness of linear step length to improve the overall accuracy of step length estimation. In this paper, experiments are carried out in the indoor scene, and the experimental results are compared. the results show that the improved step length estimation method is better than the fixed step length and linear step length versions.

However, some details need to be improved in this paper. In this model, the given parameters need to be fitted with more walking data. To fit a better linear step length formula, more walking data of experimenters are needed. Due to the limited experimental data, the fitting and merging of step length formulas are not perfect. Therefore, a large amount of training data is still needed to obtain a better positioning result. The algorithm in this paper is mainly applicable to the pedestrian indoor location in a two-dimensional plane, but it is not applicable when it comes to height. However, we know that in an indoor environment, there is not only two-dimensional motion but also three-dimensional motion such as going up and down stairs or taking an elevator. Therefore,

the method in this paper still has some limitations. In the near future, we will use the sensor information to identify the pedestrian's motion state in a three-dimensional space environment, combine it with other sensors such as a manometer and altimeter, and then use corresponding positioning methods to achieve a three-dimensional positioning effect for a specific motion state.

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