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An Improved Three-dimensional Indoor Positioning Algorithm Based on Pedestrian Dead Reckoning

Xuezhi Dong
School of Physics and Electronics
Central South University
Changsha, China
202212078@csu.edu.cn

Jiaxun Xiao*
School of Physics and Electronics
Central South University
Changsha, China
* Corresponding author: xiaojiaxun@csu.edu.com

***Abstract*—Due to the complex indoor environment of the buildings, Two-dimensional (2D) indoor positioning is difficult to meet the needs of people. Therefore, it is necessary to make some improvements in three-dimensional (3D) indoor positioning. In this paper, a 3D indoor positioning algorithm based on improved pedestrian dead-reckoning (PDR) is proposed. The PDR was improved in motion pattern recognition and step detection. For motion pattern recognition, an improved support vector machine (SVM) method is proposed, which use the confidence threshold to improve the recognition accuracy of the SVM in continuous motion state. For step detection, an improved step detection method is proposed, which sets the peak threshold and valley threshold for acceleration, and the idea of zero-crossing detection method is also used to improve the accuracy of peak detection method. The experimental result of 3D environment shows that the accuracy of motion pattern recognition and step detection is 96.43% and 99.87% respectively and the mean error of the positioning result is 0.63m, which has a reduction of 75.8% compared to the traditional PDR algorithm.**

Keywords-indoor three-dimensional positioning, pedestrian dead reckoning, motion pattern recognition, step detection

I. INTRODUCTION

With the rapid development of mobile devices and communication technology, Location Based Service (LBS) [1,2] has been an indispensable part of the people's daily life. Global Navigation Satellite System (GNSS) has been widely used in outdoor environment, however, GNSS show poor performance in indoor environment because of the obstruction of metal and concrete [3]. Thus, there are many researches on various indoor positioning techniques [4,5].

With the development of the micro-electro-mechanical systems (MEMS) technology, smartphones are equipped with inertial sensors such as accelerometer and gyroscope, and magnetometer, barometer etc. Inertial sensors can measure pedestrian's acceleration and angular velocity to obtain the motion distance and direction. Pedestrian dead-reckoning (PDR) is the algorithm that calculates pedestrian's position by using inertial sensors, which does not require more external facilities to achieve localization and gets less affect from the environment [6]. PDR algorithm includes three parts: step detection, step length estimation and heading estimation.

At present, researches [7,8] on indoor positioning mainly focus on planes, but less on 3D environment. In addition, most researches on 3D positioning only focus on the floor discrimination, but less on the information of the stairwells. Geng et al. [9] used the barometer to obtain the height information of pedestrian in the stairwell when positioning, but the barometer can be disturbed easily by the environment. In order to minimize the environmental disturbance, different motion patterns can be analyzed to suit the localization of stairwell. Motion pattern recognition consists of four parts: data pre-processing, feature extraction and selection, classification and post-classification refining [10]. Most researchers [11,12] mainly focused on the improvement of motion pattern recognition algorithms in data pre-processing or feature extraction and selection, but less in post-classification refining. Support vector machine (SVM) has been proofed by researchers [13,14] that it performs well in motion pattern recognition. Therefore, in this work, motion pattern recognition algorithm is improved in post-classification refining part, and SVM is used for classification. The main idea of SVM is to find a hyperplane that separate two types of data points as far as possible from the classification plane [15]. In order to improve the accuracy of motion pattern recognition, the effect of confidence score of recognition results is considered. Confidence score of the SVM classifier is the distance from the input features to the hyperplane [16], and a threshold of confidence score was set to discard the unexpected output in this paper.

When a pedestrian walks, there are cyclical changes in vertical acceleration. Peak Detection (PD) and Zero-Crossing Detection (ZCD) are two mainstream step detection methods, which measure the steps by detecting the peaks or zero-crossing points of vertical acceleration [17]. Researchers in [18] and [19] try to combine the PD and the ZCD, but didn't take the different motion pattern of the pedestrian into consideration. The method proposed in this paper improved PD using the idea of ZCD, which improved the accuracy of step detection in different motion pattern by setting different acceleration peak threshold and valley threshold.

In this work, the algorithm aims to improve the accuracy of PDR algorithm and the main contributions are summarized as follows.

- For the motion pattern recognition, the confidence score is used to judge the reliability of the recognition results, an improved SVM method is proposed to improve the accuracy of pattern recognition based on the confidence threshold.
- The peak detection method is improved with the inspiration of the zero-crossing detection, the different

acceleration peak threshold and the valley threshold are set to improve the accuracy of step detection in different motion pattern.

The rest of this paper is organized as follows. In Section II, the improved methods are introduced. Section III shows the experiments and the discussion of results. Section IV draws the conclusions.

II. MATERIALS AND METHODS

A. PDR Positioning

PDR algorithm calculates the current position by estimating or known velocity and time under the condition that the previous position is known. Assuming that the coordinates of the starting point are known as (x_0,y_0) , then the position coordinates of the k-th step as (x_k,y_k) are calculated as follow:

$$\begin{cases} x_k=x_{k-1}+S_k\cos\theta_k \\ y_k=y_{k-1}+S_k\sin\theta_k \end{cases} \tag{1}$$

where x_{k-1} and y_{k-1} represent the horizontal and vertical coordinates of the pedestrian at the (k-1)-th step respectively. S_k and θ_k represent the step length and heading angle of the k-th step respectively.

In 3D environment, the amount of height change of the pedestrian needs to be calculated. In this work, the 3D position coordinates of the k-th step as (x_k,y_k,z_k) are calculated as follow:

$$\begin{cases} x_k=x_{k-1}+mW\cos\theta_k+(1-m)S_k\cos\theta_k \\ y_k=y_{k-1}+mW\sin\theta_k+(1-m)S_k\sin\theta_k \\ z_k=z_{k-1}+mnH \end{cases} \tag{2}$$

where $(x_{k-1},y_{k-1},z_{k-1})$ and (x_k,y_k,z_k) are the position coordinates after the (k-1)-st step and k-th step respectively; W and H are the width and height of the stair step; m and n are related to the motion pattern, in this paper, four motion patterns were discussed about: standing, walking, going upstairs and going downstairs. When walking, m=0; when going upstairs, m=1 and n=1; when going downstairs, m=1 and n=-1; the meaning of other parameters are the same as in (1).

B. Improved-SVM-Based Motion Pattern Recognition

For the four motion patterns, in this work, four binary SVM classifiers were set for classification, each classifier is used to classify one motion pattern. The acceleration data were divided by sliding window, and features for classification were extracted from the data in each window.

Suppose there is a data set $\{(X_1,y_1),(X_2,y_2)\cdots,(X_n,y_n)\}$ that need to be separated into two classes, where $X_i\in R^n$ is a feature vector and $y_i\in\{-1,+1\}$ is the corresponding class label. After training, there are p binary classifiers in the testing phase and the confidence score CS_j of input vector X in the j-th binary classifier is

$$CS_j=\sum_{i\in SV}\alpha_i y_i K(X_i,X)+b_j \tag{3}$$

Where j=1,2…p, α_i is the Lagrange multiplier, SV is the set of support vectors, $K(X_i,X)$ is kernel function, b is the bias term. The maximum confidence score CS is

$$CS=\max\{CS_1,CS_2...CS_P\} \tag{4}$$

The motion pattern recognition result is the class corresponding to the maximum confidence score CS.

However, the confidence scores of the four motion patterns may all be negative sometimes, and if the motion pattern recognition only based on the maximum confidence score, then the recognition result is unreliable in this case. It may be caused by the following two reasons: (1) The training set only contained the data of single motion pattern. When testing, the data from the motion transformation may cause the misclassification. (2) When the motion changed, the multiple motion patterns may appear in one sliding window, so it is difficult to recognize it to a certain pattern.

In order to solve these problems, this paper proposed the confidence threshold μ. When the maximum confidence score is higher than or equal to the threshold, corresponding motion pattern is identified; when the maximum confidence score is lower than the threshold, then the previous pattern will be recognized as the current pattern. The confidence threshold is given according to experiment. The flow chat of motion pattern recognition is show in Figure 1.

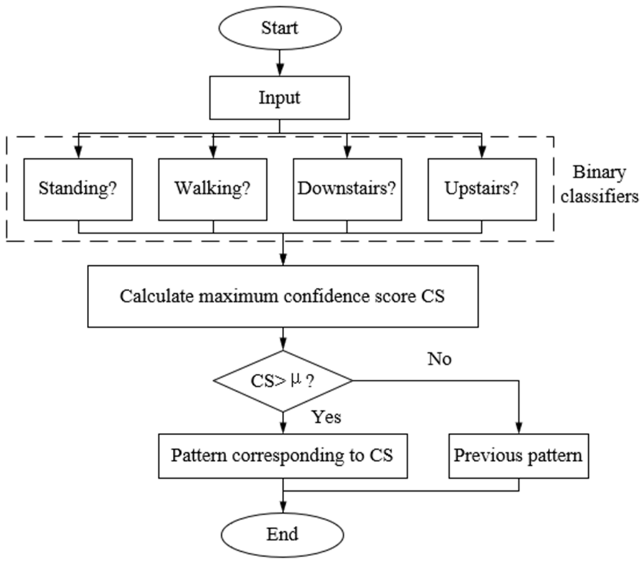

Figure 1. The flow chart of motion pattern recognition

C. Improved Step Detection

In order to combine PD and ZCD, the gravitational acceleration is filtered out at the beginning.

$$a=a_z-g \tag{5}$$

where a is the vertical acceleration, a_z is the raw z-axis acceleration, and g is the gravitational acceleration.

Due to the noise of the sensors, multiple zero points and pseudo peaks may appear in one step, which cause the error of step detection. In order to solve this problem, the valley threshold was set, and a Zero Crossing-Peak-Variable Double Threshold (ZC-P-VDT) method was proposed. The threshold is given according to experiment.

The main process of the ZC-P-VDT method is as follows:

First detect the zero-crossing point, if two adjacent data points, the former is positive and the latter is negative, then the zero-crossing point is a falling zero-crossing point, and conversely is a rising zero-crossing point. Next, find the maximum value Max_cross between the rising zero-crossing point and the falling zero-crossing point.

Next, the motion pattern of the window where Max_cross located is determined, and peak threshold Thre_p and valley threshold Thre_v are set. Compare the maximum value with the peak threshold, if Max_cross > Thre_P, it will be recorded as the peak; otherwise find the next maximum value. The peak threshold and valley threshold are based on a large number of experiments and different motion modes with different thresholds.

Next calculate the time interval Δt between the current peak and the previous peak, compare Δt with the time threshold Thre_T; if Δt < Thre_T, the larger of the two is the new peak, otherwise the current peak is recorded as the new peak. The time threshold is based on walking frequency.

After that, the two minimum values Min_cross were found between the falling and rising zero-crossing point in each of the two windows before and after this new peak. Only when the two Min_cross are lower than the valley threshold, the new peak can be considered as a step.

III. Experiment, Results and Discussion

A. Experiment Area, Platforms and Setup

The experiments were conducted at the 4th, 5th, 6th floors in School of Physics and Electronics, Central South University. The size of each floor is around 50×16 m^2 and the height between floors is 3.6 m. The width of one stair step is 30 cm and the height is 15 cm. For each floor, there are a main corridor which is 40 m long and a lobby whose size is 8×9 m^2. The area of experiment is the lobby and the stairwell.

B. Data Collection and pre-processing

Two android phones which have inertial sensors such as accelerometer and gyroscope were used to collect data. All sensor data were output by an APP which developed by Android Studio. Low-cost MEMS inertial sensors may suffer from severe operational bias and thermal drift, so simple manual correction was made to the two phones [20].

When collecting, the experimenter should keep the phone screen faced up and parallel to the ground. The phone was lifted to the height of 1.4 m from the ground. The three-axis acceleration and angular velocity were collected. The z-axis positive direction vertically upward, and the experimenter faced to the positive direction of the y-axis. The sampling frequency is 25Hz, which was based on Ref [21] and many experiments.

After collecting, the data needs to be smoothed and segmented. In this work, Kalman filter was used to smooth the data. The motion frequency is 0.5~3 Hz. According to this, the size of sliding window is 64 samples to ensure that each sliding window contains at least one complete step.

C. Feature Extraction and Selection

23 features were extracted in this work, including 16 time-domain features and 7 frequency-domain features. The principle of feature selection in this work is that at least one motion pattern can be recognized by one feature. After feature selection, 8 features were finally selected for classification, including combined acceleration variance, combined acceleration standard deviation, combined acceleration over-mean times, maximum z-axis acceleration, y-axis acceleration quadrature spacing, yz-axis acceleration correlation coefficient, combined acceleration skewness and maximum amplitude.

D. Motion Pattern Recognition

The training set consists of 960 samples, of which 240 samples for each motion pattern. Multiple continuous motion experiments were conducted in testing phase, and compared with traditional SVM methods. The experimenter changed the motion pattern randomly. According to experiments, the confidence threshold is 0.2. Table 1 shows the comparison of recognition accuracy in continuous motion experiments.

TABLE 1. Comparison of Recognition Accuracy in Continuous Motion Experiments

Method	Standing	Walking	Upstairs	Downstairs	Total
SVM	65.43%	92.14%	95.65%	94.24%	87.09%
Improved SVM	98.77%	94.29%	97.10%	97.30%	96.43%

According to Table 1, the improved SVM method showed better performance than the traditional SVM method in continuous motion. It is substantial in improving the recognition accuracy when using the improved SVM in standing case. When pedestrian is standing, the acceleration will not change theoretically, but the error of sensors will have tiny fluctuations in acceleration data which is unavoidable. At this time, even if the confidence scores corresponding to four motion patterns are all low, the traditional SVM classifier will still recognize the motion pattern with the maximum confidence score as the result, which wiil lead to the result that not match the real situation. When using the improved SVM, this problem will be solved by the existence of the confidence threshold. Thus, the proposed method is practicable.

E. ZC-P-VDT

The ZC-P-VDT method is used for step detection. 60 experiments were conducted in walking, upstairs and downstairs three motion patterns, which consist of 10 steps of horizontal straight walking for 40 times, 20 steps and 30 steps of horizontal straight walking each for 10 times, 12 steps each of going upstairs and downstairs for 12 times, there were 1440 steps in total. According to experiment, the peak thresholds are 0.6 m/s^2 for walking, 0.9 m/s^2 for upstairs and 1.1 m/s^2 for downstairs. The valley thresholds are -0.3 m/s^2 for walking, -0.6 m/s^2 for upstairs and downstairs. The time thresholds are

0.3 s for all. Table 2 shows the comparison of PD and ZC-P-VDT.

TABLE 2. COMPARISON OF THE ACCURACY OF PD AND ZC-P-VDT

Method	Walking	Upstairs	Downstairs	Total
PD	98.67%	99.72%	99.72%	99.32%
ZC-P-VDT	99.89%	100%	99.72%	99.87%

According to motion data, when the pedestrian walking, the peak of z-axis acceleration is lower than going upstairs or downstairs. The pseudo-peak is closer to acceleration peak in walking pattern, which cause the error of step detection. The ZC-P-VDT method sets the peak threshold, valley threshold and time threshold for different motion patterns, which avoid the influence of pseudo-peak as much as possible and improve the accuracy of step detection.

F. Improved PDR 3D Indoor Positioning

The experimenter started at the lobby of the 6th floor, went down to the 4th floor and returned to 6th floor. The complete process can be divided into four phases: standing (on the 6th floor), walking (on the 6th floor), going downstairs (from the 6th floor to the 4th floor) and going upstairs (from the 4th floor to the 6th floor). The whole process has 173 steps, including 77 steps of walking, 48 steps of going upstairs and 48 steps of going downstairs.

The improved PDR was used for indoor positioning, which combined with improved-SVM-based motion pattern recognition and ZC-P-VDT. As for step length estimation, Nonlinear Step Length (NSL) model that proposed in Ref.[22] was used in this paper, and for heading estimation, the quaternion method [23] was used in this work.

Figure 2 and Figure 3 show the positioning trajectory by using the improved PDR method. Figure 4 shows the error of each step by using the improved PDR method.

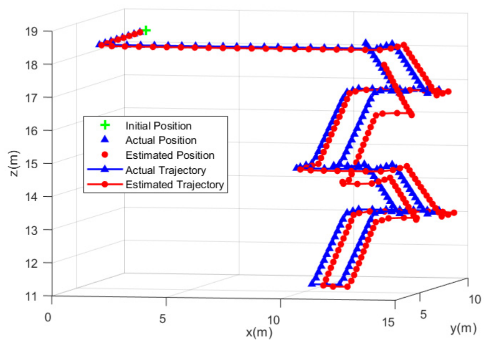

Figure 2. Positioning trajectory by using improved PDR method.

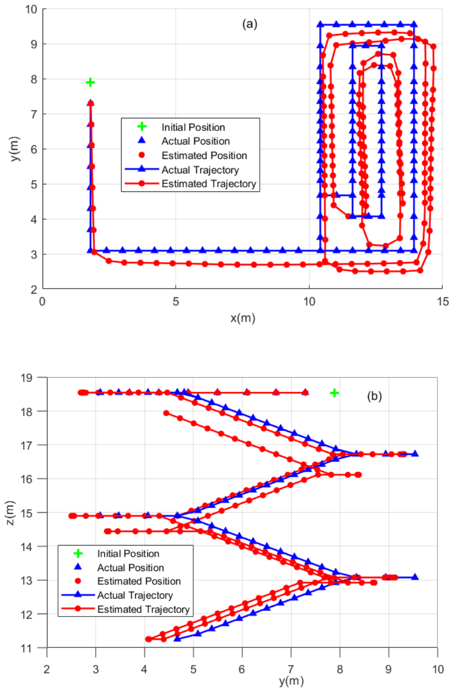

Figure 3. Positioning trajectory by using improved PDR: (a) side view; (b) top view

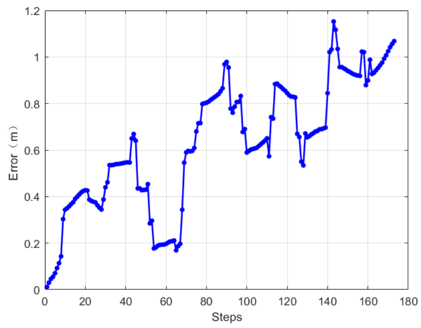

Figure 4. Positioning results by using improved PDR method.

As can be seen from Figure 2 and Figure 3, the positioning trajectory is similar with the actual trajectory when using the improved PDR algorithm. Figure 4 shows the positioning error of each step. As can be seen that the position error of first 140 steps which are less than 1 m and most are less than 0.8 m, but the error began to be more than 1 m since the 141th step. This was because the actual motion mode of step 141 is "upstairs" while the results of recognition was "walking", which means the estimation of position is not accurate, and the next position is estimated based on current position, so the error will increase gradually.

Table 3 shows the comparison of the mean error and root mean square error (RMSE) of some positioning methods.

TABLE 3. POSITIONING RESULTS OF DIFFERENT METHODS

Method	Mean Error	RMSE
Method in this work	0.63 m	0.69 m
Method in [9]	1.04 m	1.08 m
Traditional PDR	2.60 m	2.68 m

According to Table 3, the positioning mean error of traditional PDR is 2.60 m, and the mean error of the improved PDR algorithm is 0.63 m, there is a reduction of 75.8%. The method in [9] used the barometer, which can be disturbed easily by the environment. The mean error of method in [9] is 1.04 m, and the RMSE is 1.08 m, which are higher than the method in this work. The positioning results show that the proposed method has better performance in positioning than other two methods due to the little influence from the environment.

IV. CONCLUSIONS

In this paper, a PDR method for 3D indoor positioning scheme under motion conditions was proposed. In order to solve the problem that the SVM may recognize the motion pattern mistakenly when pedestrian is in a continuous motion, a confidence threshold was set to judge the credibility of recognition results, and an improved method based on confidence threshold is proposed, which achieved the recognition accuracy of 96.43%. In order to avoid the influence caused by pseudo-peak in step detection, the PD algorithm is improved with the idea of zero-crossing detection method. Using the peak threshold and valley threshold of acceleration to replace the single peak threshold, which improves the detection accuracy to 99.87%. The results and analysis of the experiments show that the mean error of positioning is 0.63m, which verified the reliability and effectiveness of the positioning algorithm in this paper.

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