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Random Forest Algorithm with a Half-Voting and Weighted Decision Trees for Interior Pedestrian Tracking

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Abstract*: The traditional Zero Velocity Updating Algorithm is being used to correct the accumulated errors of the device effectively. However, as the threshold value of the traditional Zero Velocity Updating algorithm is fixed, it is only suitable for a single motion mode. When indoor pedestrian motion includes multiple motion modes, the positioning accuracy will be greatly reduced. In this paper, we propose an adaptive Zero Velocity Updating method for multi-motion mode using half- voting Random Forest. We analysed the selection of Zero Velocity Updating threshold value for stilling, walking, running, going upstairs and downstairs for the interior pedestrian. Then we recognize pedestrian motion by Random Forest with a Half-Voting and Weighted Decision Trees. Finally according to the result of recognition adjust the threshold adaptively to determine the zero velocity intervals accurately. In order to verify the feasibility and effectiveness of the method proposed in this paper, field experiments were carried out with the inertial navigation module developed by our laboratory. The experimental results show that when indoor pedestrians perform multi-mode motion, the positioning error is 0.5m.

Keywords: Zero Velocity Update; Adaptive Threshold; Random Forest; Pedestrian Navigation System

I. INTRODUCTION

Pedestrian navigation is now more and more useful in people's lives. Our daily life is inseparable from navigation. Whether we travel to a strange city or office, we need to navigate. In today's people's lives, the most common method of positioning navigation is GPS navigation, because it can work around the clock, accurate positioning, and weather proof. However, its shortcomings cannot be ignored: when obstacles are blocked, satellite navigation is prone to signal loss and inaccurate positioning, so GPS navigation is often used in Buildings, Forest, Valleys and other Environments. The use of MEMS IMU for pedestrian navigation positioning can be used to navigate indoors, solving the problem that GPS cannot be accurately located when satellite signals are blocked. MEMS IMU is easy to use and unconstrained by the environment. It has great value in hospitals such as patient positioning, shopping mall navigation and other daily navigation and military operations [1].

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The advantages of MEMS IMU are small size and light weight, so pedestrians can wear on the upper and other components.

However, due to the long-time of use, the systematic error of MEMS inertial devices has become larger and larger. Large positioning deviations cannot satisfy people's need for positioning accuracy. For this problem, a ZUPT algorithm is often used to suppress navigation errors. Zero Velocity Detection is the detection of "Zero Transients" in pedestrian motion and triggers ZUPT. The accuracy of the ZUPT algorithm depends to a large extent on the accuracy of the zero velocity interval selection [3]. Many scholars have explored detectors that use accelerometers and gyroscope outputs to determine the zero velocity range: for example, Zhang R et al. [4] designed an adaptive attitude phase detection method. In this method, an additional accelerometer is attached to the chest and the corresponding Zero Velocity Detection Threshold is updated with the difference in maximum acceleration changes extracted from the chest acceleration. Park S.K et al. [5] A zero-velocity interval detection method based on Markov model is designed, which needs to be judged by the output of the y- axis gyroscope. Ma M et al. [6], the threshold is updated using the amplitude peak of the y-axis gyroscope. The above three methods have achieved good results in walking and running. However, pedestrian accuracy is poor when walking up and down the building. Ren M et al. [7] proposed a method for constructing detection using gait periodic velocity changes. This method works well when pedestrians go up and down the stairs. The disadvantage is that the zero velocity detection of the previous step will affect the detection of the current step. There is also some non-inertial navigation information combined navigation to improve positioning accuracy: Raul Mur-Artal et al [8] proposed the ORB-SLAM2 algorithm based on visual positioning. It uses relocation and loopback detection to locate large scene environments. The navigation and positioning system of the Finnish Geospatial Institute [9] proposed a positioning method based on inertial device and visual fusion. The visual navigation results correct the inertial navigation results. Wuhan University has proposed a method based on camera, inertial device and Wi-Fi positioning. The results of the Wi-Fi and camera are used to correct the positioning results during inertia.

Although the use of additional sensors can improve detection accuracy, these methods require prior information to obtain support and the equipment is expensive. Considering the cost and accuracy requirements, we propose a Half-Voting Random Forest to process the inertial device output information to determine the pedestrian motion pattern. Then, the threshold is adaptively adjusted according to the pedestrian motion mode to determine an accurate Zero-Velocity interval, thereby improving the positioning accuracy.

II. ZERO VELOCITY DETECTION

A. Zero velocity state determination

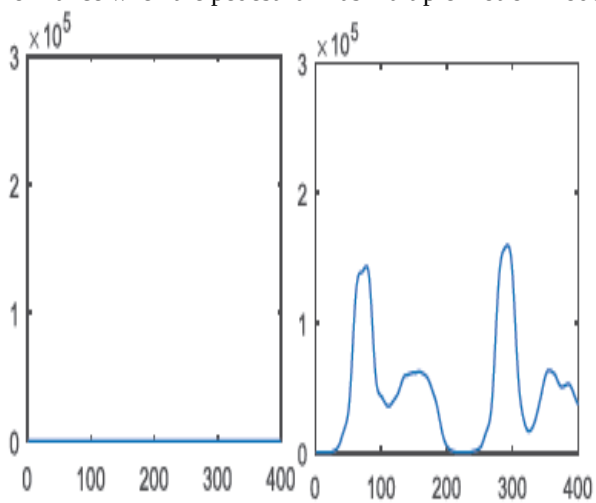
Since the inertial conduction device generates cumulative errors during operation, long-term operation causes the positioning result to diverge. Therefore, Zero Velocity Update (ZUPT) is introduced in the positioning process to correct the cumulative error. When the foot is detected to be completely stationary on the ground or in the supporting phase of walking, the stationary gait is used to trigger ZUPT. We use the method of joint judgment based on acceleration information and angular velocity information to determine the Zero-Velocity state time. The zero velocity determination formula [10] at time K is:

$$T(k)=\frac{1}{w}\sum_{i=k}^{k+W-1}\left(\frac{1}{\sigma_{\omega}^{2}}\|\omega(l)\|^{2}+\frac{1}{\sigma_{a}^{2}}\left\|a(l)-g\frac{m_{a}}{\|m_{a}\|}\right\|^{2}\right)<\gamma \qquad (1)$$

In the formula, ***T(k)*** is a function of acceleration and angular velocity at time ***k***; ***γ*** is zero velocity decision threshold; ***w*** is the width of the time window; σ_{ω} angular error of the angular velocity measurement; σ_{ω} is the standard deviation of the acceleration measurement error; ***g*** is the acceleration of gravity; ***ω(l)*** and ***a(l)*** are the angular velocity and acceleration values at time l in the time window, $\|.\|$ is 2 norm; m_a is the average of the accelerations of all samples in the time window.

B. ZUPT optimal threshold selection

The ***T(k)*** changes in the five motion modes of standing, walking, running, going upstairs and going downstairs are shown in Fig.1. The figure shows that the ***T(k)*** curve is significantly different under different motion modes. Existing Zero Velocity Detection methods cannot provide good performance when the pedestrian has multiple motion modes.



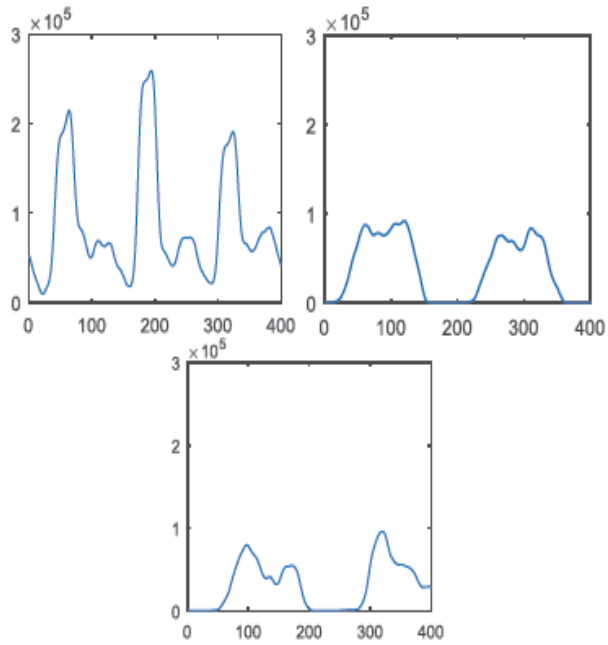


Figure 1: T(k) in different motion modes (The X axis represents time k and the Y axis represents T(x))

In existing zero velocity detection methods, zero velocity detection threshold is the optimal threshold when walking. When the pedestrian walks and then runs alternately, the zero velocity interval detection result is shown in Fig.2

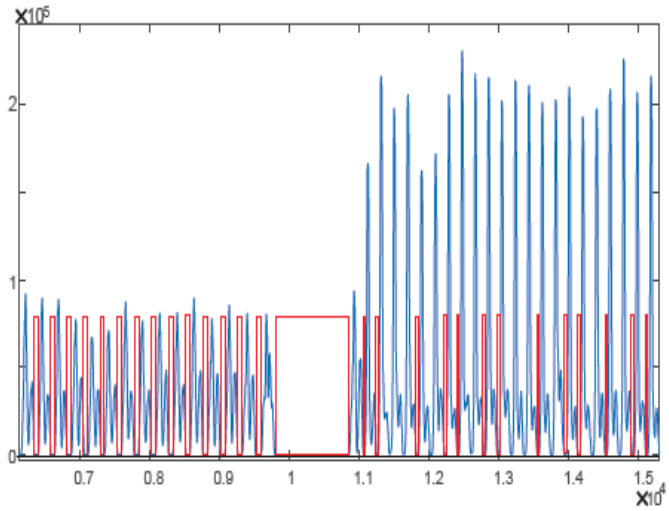


Figure 2: Detection result in existing zero velocity detection methods (The X axis represents time k and the Y axis represents T(x))

From the above figure, the fixed threshold results in inaccurate zero velocity interval detection. In order to avoid the problems caused by the above fixed threshold, we use the traversal method [11] to select the optimal threshold: First, we determine the lowest point and the second lowest point according to ***T(k)*** as the ordinate values ***y1*** and ***y2***; Then, the zero velocity threshold ***γ*** is sequentially traversed from ***y1*** to ***y2*** at intervals of Δy, and the corresponding positioning results are sequentially input; Finally, the threshold corresponding to the optimal positioning result is selected as the optimal threshold for the zero velocity detection of this motion.

III. HALF-VOTING RANDOM FOREST

In this paper, we propose an adaptive ZUPT based on Half-voting Random Forest. First, we use Half-Voting Random Forest to judge the motion modes of pedestrians. Then, according to the motion mode of pedestrians, the zero velocity threshold is assigned correspondingly. Finally, we have ZUPT.

A. Random Forest

Random Forest is a combined classifier algorithm. The model contains many decision trees. Each decision tree is constructed by two stochastic processes, that is, the training samples are randomly extracted from the training sample dataset according to the Bagging algorithm, and the feature set is obtained by random sampling from the feature set. The decision tree model is then constructed using these training sample sets and feature sets. These decision trees form the entire Random Forest model. When making data predictions, the Random Forest model uses all decision tree predictions and then votes to determine the final predictions of the model. Its construction flow chart is shown in Fig. 3

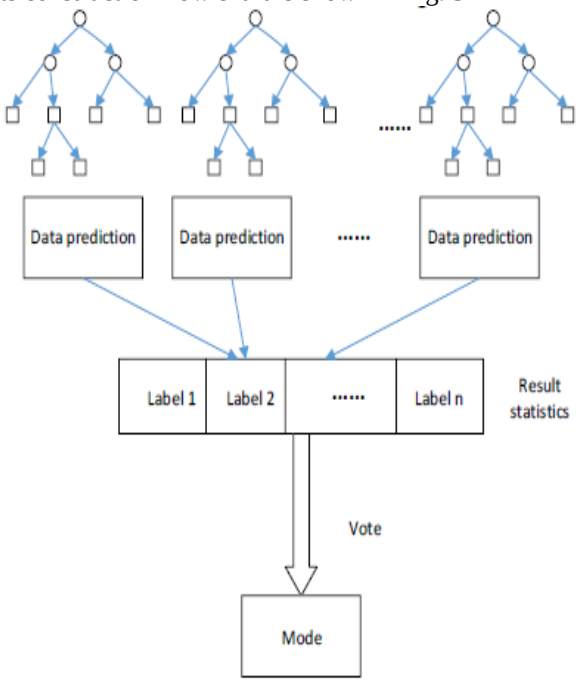


Figure 3: Random Forest flow chart

B. Half-voting Random Forest

(1) Weighted decision tree

First, the improvement of Random Forest is to weight the decision tree. Because the prediction ability of each decision tree is different, we determine the voting weight of the decision tree by its classification performance and the sample's statistical feature. The weighted decision tree voting method can improve the accuracy of the Random Forest model. Usually, approximately 67% of the total training sample set is extracted for decision tree construction. The data that are extracted are called the data in the bag; otherwise, the data are called the out-of-bag data (Out-of-Bag, OOB). The assessment of the predictive power of the decision tree using out-of-bag data is an OOB estimate.

At the same time that the Random Forest model is constructed, each decision tree obtains a corresponding OOB evaluation value to assign its weight. Define the voting weight of the decision tree as P_{OOB} expressed as, $P_{OOB} = a \times \frac{S+}{S}$, S+ is the correct sample number for OOB prediction, S is the total sample number for OOB assessment and α is the adjustment factor. The experiment flow chart is shown in Fig. 4:

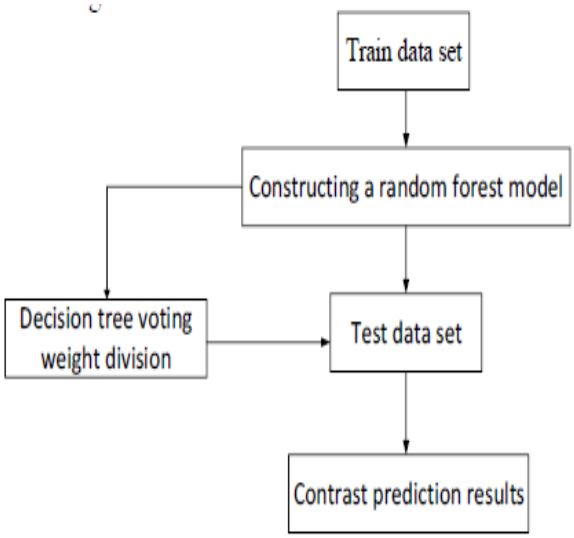


Figure 4: Voting weighted algorithm flow

2) Half vote mode

Second, the improvement of the Random Forest is to use the half-voting mode when voting to determine the model. That is, if the number of votes for a certain classification label has reached half of the total voting volume. This classification label is output as the final prediction result of the model. It can improve the efficiency of the Random Forest. The experiment process is shown in Fig. 5:

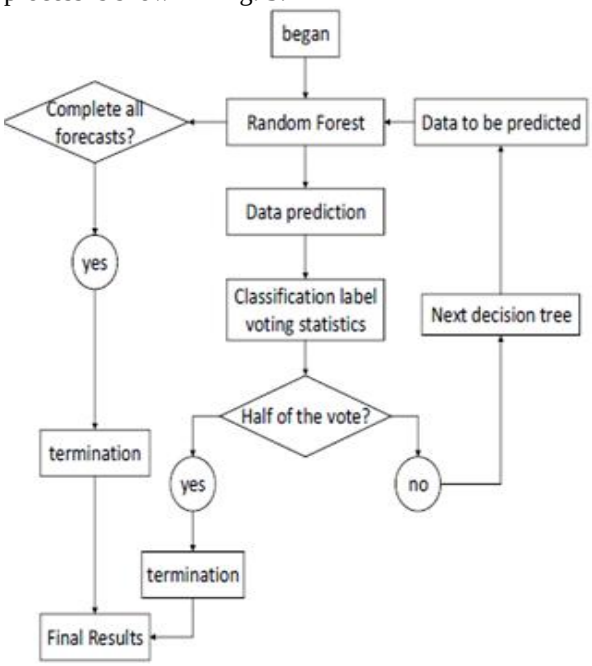


Figure 5: Half vote mode work flow chart

C. Algorithm Steps of Half-voting Random Forest

Step 1: We randomly extract a certain number of training samples from the total training samples by the Bagging algorithm. These samples are a collection of training samples for the construction of a decision tree model.
Step 2: When a Random Forest constructs a single decision tree, it is randomly sampled in the total feature set. Then a sub-feature set is obtained as a set of attribute selections for the meta-classifier
Step 3: After the above two random sampling processes, we obtain a training sample set and feature set for decision tree construction. Then let the decision tree grow freely without pruning. The OOB estimation is performed according to the out-of-bag data in the Bagging algorithm in step one, and then the decision tree is weighted.
Step 4: Count the number of votes in the decision tree vote received by each classification label. If the number of votes for a certain classification label has reached half of the total number of votes, this classification label is output as the final prediction result of the model.

IV. ADAPTIVE THREHOLD

A. Data pre-processing and feature extraction

The MEMS-IMU integrated three-axis accelerometer and gyroscope are fixed on the pedestrian's foot to record pedestrian motion data information. After obtaining the angular velocity and acceleration information for the pedestrian's foot, we use the Butterworth Low-Pass Filter [12] to filter the acquired original signal to obtain a smooth signal. Then according to the movement of the foot: from the heel off the ground, the toes of the ground, the heel to the ground, the foot surface is flat to the ground, to the heel is again off the ground, the movement of the pedestrian is divided by period.

After periodically dividing the pedestrian's foot motion, we extract the corresponding feature vector from the processed data to identify the pedestrian's motion mode. We mainly use the following as the data feature values: Mean, Standard Deviation, Maximum Value, Pearson Correlation Coefficient, Absolute Median Difference, Skewness, and Interquartile Range.

$$\textbf{Mean} = \frac{1}{2}\sum_{i=1}^{n} a_i \tag{2}$$

Where mean denotes the acceleration mean, $\boldsymbol{a_i}$ denotes the acceleration value of the *i-th* sample point; $\boldsymbol{n}$ denotes the number of periodic data.

Standard deviation:

$$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - mean)^2} \tag{3}$$

Maximum value:

$$\textbf{Max} = \textbf{Max}\ (\mathbf{a_i}) \tag{4}$$

Pearson correlation coefficient:

$$\rho_{x,y} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})}} \tag{5}$$

$\rho_{x,y}$ is the correlation coefficient between the x-axis and y-axis data.

$$\rho_{y,z} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Z_i - \overline{Z})}{\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}\sqrt{\sum_{i=1}^{n}(Z_i - \overline{Z})^2}} \tag{6}$$

$\rho_{y,z}$ is the correlation coefficient between the y-axis and z-axis data.

$$\rho_{x,z} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Z_i - \overline{Z})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Z_i - \overline{Z})^2}} \tag{7}$$

$\rho_{x,z}$ is the correlation coefficient between the y-axis and z-axis data.

Absolute median difference: Data estimation is robust. Compared with the standard deviation, it has a better estimation effect on data with many "wild points" and is less affected by "wild points". The formula is as follows

$$\textbf{MAD} = \textbf{Median}\ (\mathbf{X_i} - \textbf{Median}(\mathbf{X})) \tag{8}$$

Interquartile range (IQR): All values are arranged from small to large and divided into four equal parts. The value at the three dividing points is the four points. The difference between the third quartile and the first quartile is the interquartile range, indicating the dispersion of the variables in the statistics. It combines with the Pearson correlation coefficient to improve recognition of the run.

Acceleration $\boldsymbol{a_i}$ is sorted from small to large as $\boldsymbol{b_i}$ i=1,2,… , N. The position of the quartile is P_j=1 + (N-1) / 4, . j=1,2,3 is the number of divisions. $K_j$is the integer part of P_j , r_j is the fractional part. Q_j and IQR are as follows:

$$Q_j = b_{k_j} + (b_{k_j} - 1)r_j \tag{9}$$

$$\textbf{IQR} = \mathbf{Q_3} - \mathbf{Q_1} \tag{10}$$

B. Adaptive ZUPT in multi-motion mode

The Half-Voting Random Forest model is trained according to the feature and the corresponding motion modes. Because the pedestrian motion pattern is variable and the threshold is fixed in the existing method, the positioning accuracy is poor. We use the Half-Voting Random Forest to process the data of the foot inertial device and identify the pedestrian motion modes. The threshold is adaptively changed according to the corresponding mode. The steps are as follows:

1)Half-voting Random Forest model offline training

Phase:

The number of decision trees is $\boldsymbol{n}$ = 100 and we collected the data feature vector of the pedestrian's foot inertial device. After data pre-processing and feature vector extraction, we obtain the feature vectors under five motion modes. The total sample size is 1500, where 300 are standing still, 300 are walking, 300 are running, 300 are upstairs, and 300 are downstairs.

The output corresponding vectors are [0 0 0], [0 0 1], [0 1 0], [1 0 0], [0 1 1], [1 1 0], respectively. We use input and output to train the Half-voting Random Forest model. After getting the trained model, we use 500 test samples to test the correct rate of the model. The test results are shown in Table I. Use the traversed algorithm in the previous section to get the optimal threshold, as shown in Table II.

Table I. Half-Voting Random Forest Model Test Table

Motion Mode	Test Sample	Correct Sample	Correct Rate
Stand Still	100	100	100%
Walk	100	100	100%
Run	100	98	98%
Walk Upstairs	100	100	100%
Walk Downstairs	100	99	99%

Table II. The optimal Threshold for Motion Modes

Motion Mode	Test Sample
Stand Still	500
Walk	30000
Run	40000
Walk Upstairs	4000
Walk Downstairs	3000

2) Half-voting Random Forest adaptive threshold adjustment phase:

With the trained model, we recognize the pedestrian's motion and then assign the threshold for the ZUPT. The steps are as follows:

Step 1: Collect the raw data from the inertial device and smooth the original data.

Step 2: Group the data information, and each step is a set. Pedestrians take ***n*** steps and the data are divided into ***n*** sets.

Step 3: Extract the feature of pedestrian from each set of data, and input the feature into the trained Half-voting Random Forest model, and vote for the pedestrian motion mode.

Step 4: Select the optimal Zero Velocity Threshold for the motion mode. Determine the Zero Velocity Interval of the gait and then trigger ZUPT. The error is corrected by EKF (Extended Kalman Filter).

Step 5: Output the motion track of the pedestrian.

V. RESULT AND DISCUSSION

1) Overall technical process

The technical implementation steps are as follows: (1) First, the data of the inertial device are processed and the gait features are extracted, and judge the pedestrian motion mode by Half-voting Random Forest. (2) The threshold of ZUPT is adaptively adjusted according to different motion modes. (3) Zero velocity triggers EKF for ZUPT.

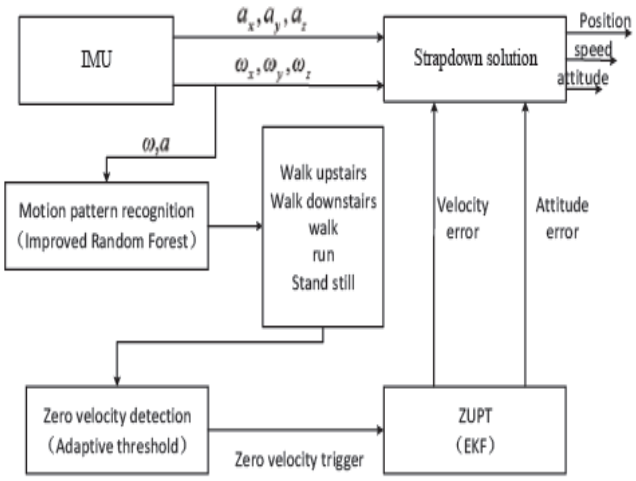


Figure 6: The proposed method flow chart

2) Threshold adaptive adjustment verification and positioning result analysis

In order to verify the effectiveness of the proposed method, we conducted a site experiment using the MIMU pedestrian navigation module developed by our laboratory. We tied the navigation module above the pedestrian's upper and the pedestrian walked indoors.

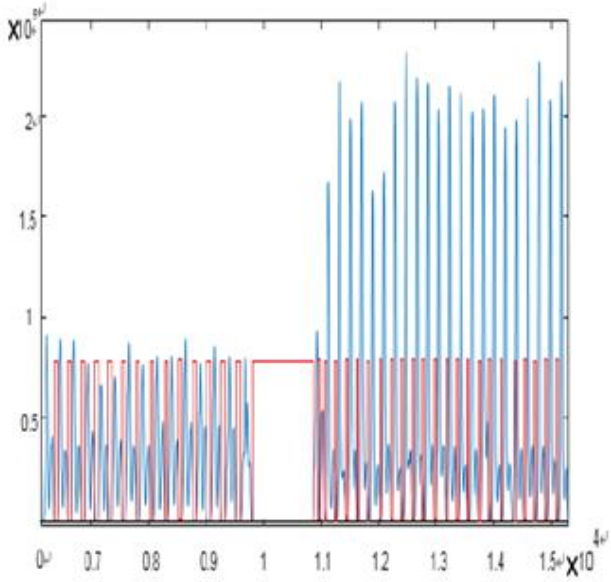


Figure 7: Detection Result in adaptive zero velocity detection methods (The x axis represents time k and the y axis represents T(x))

The experiment site was selected on the sixth floor of the teaching building of Beijing Information Science and Technology University. The starting point for walking is near the 6th floor stairway. Pedestrian walked and ran on the 6th floor corridor. Then he descended from the stairs and walked to the 5th floor. He walked and ran on the 5th floor corridor, then go up the stairs to the 6th floor and return to the starting point. The zero velocity detection results of the proposed method are shown in the Fig.5. The trajectory obtained by the proposed method is compared with the existing method as Fig.6, where the red circle denotes the starting point and the black circle denotes the end point.

According to the zero velocity detection result in the above figure (high state represents zero velocity moment, low state represents non-zero velocity moment). Compared with the adaptive zero velocity detection method (Fig.2), the existing method has missed a large number of zero velocity intervals, and almost no effective detection can be achieved during the whole running period. However, the method proposed in this work can detect the Zero Velocity Interval with high precision, and has no false detection problem during the swing period of the foot.

The experiment results show that when the pedestrians perform multiple motion modes, the positioning result of the adaptive ZUPT proposed in this paper is 0.5 m, 0.5% in the horizontal two-dimensional space, and 0 m in the vertical direction.

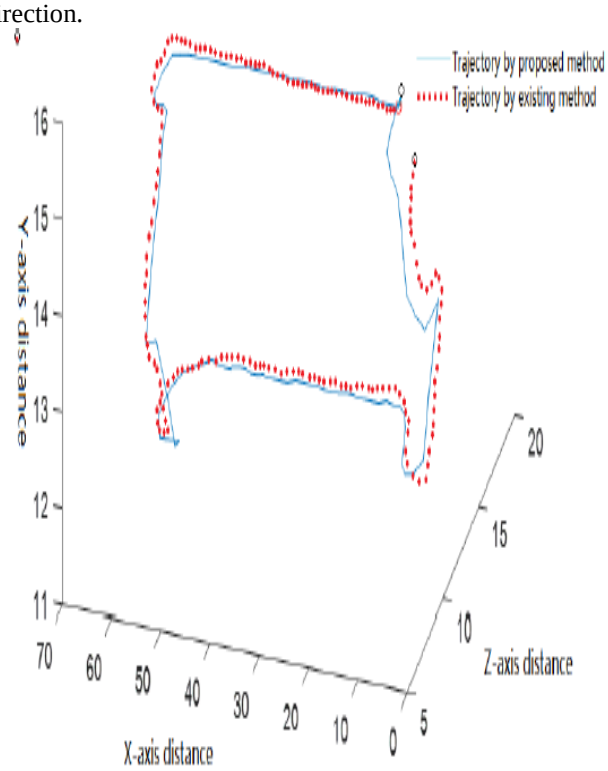


Figure 8: Motion trajectories by two methods

The positioning accuracy is much higher than that of the existing ZUPT. In the figure, since the default threshold of the existing ZUPT is the threshold of human walking, the positioning results of the two algorithms are the same at the beginning. When the pedestrians started running and going up and down the stairs, the positioning accuracy of the existing ZUPT began to decline. However, the adaptive ZUPT detects the pedestrian's motion modes and assigns a corresponding threshold, accurately detecting the zero velocity interval, and reduces the positioning error

VI. CONCLUSION

In this paper, a pedestrian adaptive ZUPT method based on Half-voting Random Forest is proposed. The Half-voting Random Forest is used to analyze the data feature of the pedestrian foot inertial sensor to recognize the pedestrian motion modes. The optimal threshold is set according to the motion mode. Detect the zero velocity and trigger ZUPT, and finally output the final positioning result. Experimental verification shows that: we can recognize the five motion modes accurately: stationary, walking, running, going upstairs or going downstairs. And the recognition rate is almost 100%; The two-dimensional spatial positioning accuracy reaches 0.5 meters, and the vertical direction reaches 0 meters under the pedestrian multi-motion mode

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