Pedestrian inertial navigation based on CNN-SVM gait recognition algorithm

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Abstract. Pedestrian inertial navigation technology based on inertial measurement unit (IMU) has been widely used in indoor and outdoor applications in recent years. But the IMU has a relatively low measurement accuracy that leads to error accumulation. Zero speed update algorithms (ZUPT) are often used to suppress the accumulation of errors. The key to the zero-speed update algorithm is to accurately find the stance phase in the pedestrian gait cycle. In this paper, an adaptive zero-speed detection algorithm based on CNN-SVM gait recognition is proposed for pedestrian positioning. First, the CNN-SVM algorithm is used to distinguish six gaits and find the optimal detection threshold according to different gaits. At the same time, it is proposed to use the zero-angle velocity update algorithm (ZARU) to correct the angle error, and to improve the accuracy of positioning by combining the information of zero-speed update and zero-angle velocity update through Kalman filter. Finally, the validity of the proposed algorithm is verified by experiments.

1. Introduction

At present, the common method of pedestrian navigation is based on inertial measurement unit (IMU) [1]. But inertia sensors are plagued by severe drift and noise. If noise and drift are not processed, error will accumulate over time, resulting in long-term navigation accuracy cannot be guaranteed.

The most common method of eliminate error is the zero speed update (ZUPT) algorithm [2]. During normal gait cycles, the foot contacts the ground and remains still for a short period periodically, at which time the speed should theoretically be zero, so the speed value measured by the sensor at this time is the speed error. Literature [3] proposed to use the output of accelerometer or gyroscope to construct the zero velocity detector. In the literature [4], the zero velocity detection was formalized as a binary hypothesis testing problem and generalized likelihood ratio test (GLRT) detectors were proposed. The literature [5-6] uses the value of acceleration and gyroscope and the variance between acceleration and gyroscope to construct a zero speed detector with multiple conditions. In the existing ZUPT methods, the detection of stance phase adopts a fixed threshold, which leads to limited precision as the threshold may vary for different gait. Therefore, this paper proposes an adaptive zero-speed detection algorithm, which improves the accuracy of stance phase detection.

ZUPT-based Kalman filter method cannot estimate heading error due to poor observability [7]. In order to eliminate the accumulation of heading error, a new gyro drift reduction method is proposed [8], which combines heuristic drift reduction method with supplementary filter. The literature [9] is proposed to estimate the direction with two stages of Kalman filtering, the accuracy of the roll angle
and the pitch angle reaches 1 degree, and the accuracy of the yaw angle reaches 0.6 degrees. In the literature [10], the measurement variance of the sensor can be adjusted according to the gait type by using the EFK-HDR-CHAIN-FGH directional estimation algorithm. The literature [11] reduces adversity drift by means of multi sensors fusion and dual gait analysis. A method for estimating magnetic disturbances in real time during walking is proposed in the literature [12] to correct the drift error of gyroscopes. In this paper, heading error is corrected by the zero-angle rate update method (ZARU), which mainly uses the angular velocity difference in the stance phase as observations of the Kalman filter to correct the heading error.

Gait classification is the basis for adaptive threshold selection, and the commonly used gait classification methods include hidden Markov model (HMM), support vector machine (SVM), probability neural network (PNN). In the literature [13], we propose a new gait recognition method (LCWSnet algorithm) based on long-term memory network (LSTM) and reel neural network (CNN). In the literature [14], a bidirectional short-term memory recursive neural network (BLSTM-RNN) is established as gait classification. In this paper, the combined algorithm of reel neural network and support vector machine (CNN-SVM) is used to classify pedestrian gait.

The contents of the following parts of this paper are mainly divided into: The second part mainly introduces the construction process of CNN-SVM and the setting of each parameter. The third part mainly introduces the solution process of inertial navigation. The fourth part introduces the adaptive zero speed detection process, as well as the speed correction and heading correction. The fifth part verifies the proposed algorithm through concrete experiments. The sixth part summarizes this paper and looks forward to the future work.

2. Gait classification
Using softmax function as the classifier of convolutional neural network in CNN model will lead to insufficient generalization ability of the model. In this paper, it is proposed to use a combination of CNN and SVM algorithms [15]. The output of the full connection layer of the CNN model is used as the input of the SVM model. The model can make full use of the advantages of the auto-extraction of the convolution neural network, and the SVM classifier can enhance the robustness and generalization of the model. The framework of CNN-SVM is shown in Figure 1.

![Figure 1. The framework of CNN-SVM.](image)

This paper studies the classification of gait, the input data set is time series composed of the three-axis acceleration value and the three-axis angle velocity value measured by the inertial sensor, so the size of the input data is six dimensions. The size of the output data depends on the division of the motion gait. This paper divides the motion gait into stationary, forward, backward, running, upstairs and downstairs six types of motion. To facilitate the training of the model, the data is standardized by StandardScaler so that the average value of each column of data is zero and the variance is one.

Excitation functions, optimization methods, and some neural network parameters need to be set before training. The excitation function used in this paper is ReLU(The Rectified Linear Unit/Fixed Linear Unit), which is characterized by fast convergence and simple gradient calculation.
When training neural networks, because the data set is large, the amount of computation for gradient and weight updates is large. Therefore, the whole training data is divided into some small batch, according to the batch gradient drop and update parameters. On the other hand, because the number of samples in batches is much smaller than the whole data set, the amount of computation is much smaller. To speed up the convergence of the network, the size of the batch is set to 50. In order to prevent overfitting during CNN's network training, dropout [16] is introduced in the full connection layer as a normalization method, and in each training batch, by ignoring half of the feature detector (let half of the hidden node value is 0), the overfitting phenomenon can be significantly reduced, the model generalization ability is enhanced, and the retention probability in this paper is set to 0.5.

In order to verify the classification accuracy of the established CNN-SVM model, the inertial data is divided into training and test sets. The accuracy of the training set is 97.18% and the accuracy of the test set is 93%.

3. Velocity correction

Pedestrian walking process is cyclical, a gait cycle can be divided into two stages of stance phase and swing phase according to the sensor output inertial data. In the stance phase stage, the foot of the pedestrian is stationary, at this time the speed should theoretically be zero, but because the sensor measurement error causes the output of the accelerator is not zero, then the velocity value is not zero, at this time the difference between the speed and zero speed is the velocity error, can be used as an observation of the Kalman filter to correct the speed.

This article mainly uses the values of generalized likelihood ratio detection, which fusion angle velocity and acceleration. The detector is set to:

\[
T(t) = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{\sigma_a^2} \left\| a(t) - \bar{a}_k \right\|_2^2 + \frac{1}{\sigma_{\omega}^2} \left\| \omega(t) \right\|_2^2 \right)
\]  

The threshold is fixed in the traditional zero-speed detection, but during walking, the amplitude of acceleration and angular rate will be different under different walking conditions, resulting in the value of detector T will not be different in different walking states, if all walking states are detected using fixed thresholds, resulting in incorrect detection results, as shown in Figure 2.

![Figure 2. The stance phase is detected using a fixed threshold in the forward, backward, and running states.](image)

Therefore, this paper proposes to use the zero-speed detection method of adaptive threshold [17], which can select the optimal detection threshold according to the different walking states. The accuracy of zero-speed detection ultimately affects the accuracy of positioning, so the optimal threshold can be selected based on the accuracy of positioning. We require pedestrians to walk on a
fixed path in a fixed walking state, collect data from inertial sensors, and then calculate the positioning error at different thresholds, the threshold corresponding to the optimal threshold when the positioning error is minimal. Then repeat the experiment in an unused walking state to determine the optimal threshold under different walking categories. Table 1 shows the position error corresponding to different detection thresholds in three walking states.

As can be seen from Table 1, for each walking state, the error will vary with the threshold, and the positioning error of different walking states will vary under the same threshold. The optimal threshold for walking forward normally is $1.7 \times 10^6$, the optimal threshold for backward walking is $0.79 \times 10^5$, the optimal threshold for running is $7.1 \times 10^6$.

| Table 1: Positioning errors for different walking states at different thresholds |
|---------------------------------|-----------------|-----------------|
|                                | $0.79 \times 10^5$ | $1.7 \times 10^6$ | $7.1 \times 10^6$ |
| backward                       | 2%               | 7%              | can’t get the trajectory |
| forward                        | 36%              | 1.5%            | 5%               |
| running                        | 36%              | 53%             | 0.006%           |

4. Zero angular velocity heading correction

On the basis of not adding other sensors, this paper uses the zero angular rate update algorithm (ZARU) [18] to correct the heading error. The principle of ZARU is mainly to use the angular velocity output value in the zero-speed interval as an angular velocity error. The angular velocity error is used as the observation value of Kalman filter, which inhibits the drift of angular velocity, corrects the navigation error and improves the accuracy of pedestrian navigation system.

The state transfer equation in the inertial navigation system is:

$$x_k = F_{k,k-1}x_{k-1} + G_{k-1}w_{k-1}$$

(2)

The observation equation is:

$$z_k = H_k x_k + v_k$$

(3)

The observation matrix $H_k$ has the following form:

$$H_k = \begin{bmatrix}
0_{3x3} & I_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x3} \\
0_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x3} & I_{3x3}
\end{bmatrix}$$

(4)

5. Experiment

To verify the validity of the method proposed in this paper, we conducted a series of experiments using MTI-G-710 from XSENS of the Netherlands. In the experiment, the inertial sensor module is mounted on the back of the foot as shown in Figure 3, connecting the computer with a USB cable, and the inertial data of the computer when the mobile phone is placed in the hands of pedestrians.
5.1. Gait classification result

In order to verify the accuracy of the gait classification method based on CNN-SVM proposed in this paper, we set the number of iterations of the neural network to be 100, and the 100 iterations as shown in Figure 4. It can be seen that the accuracy of the training set and the accuracy of the test set finally tend to be consistent, the accuracy of the test set is stable at about 93%, and the accuracy of the training set is stable at about 97%. It is explained that the established neural network has achieved good classification performance.

In order to further verify the advantages of CNN-SVM, the classification results of CNN-SVM were compared with those of CNN and SVM alone, the classification results of several algorithms are shown in Table 2. It can be seen from the table 2 that CNN's classification accuracy is 94.01%, SVM's classification accuracy is 76.64%, and CNN-SVM algorithm's classification accuracy is 97.18%. The CNN-SVM algorithm’s classification accuracy compared with CNN's accuracy is improved by 3.17%, compared with SVM's accuracy is improved by 20.54%, so the CNN-SVM classification algorithm proposed in this paper is obviously better than using CNN and SVM algorithm alone.

From the Table 3 can be seen in the backward, stationary, forward walking and running classification accuracy is relatively high, and the classification accuracy of the upstairs and downstairs is relatively low, because upstairs and downstairs only gravity center has obvious changes, other characteristics and normal walking similar. So the error rate between the stairs is relatively high. When pedestrians stand still, the values of acceleration and angular rate tend to be fixed, so the classification accuracy of stationary is highest.
Table 2: Classification accuracy under different methods

| Classification method | Classification accuracy |
|-----------------------|-------------------------|
| CNN                   | 94.01%                  |
| SVM                   | 76.64%                  |
| CNN-SVM               | 97.18%                  |

Table 3: CNN-SVM’s confusion matrix.

|                  | backward | stationary | forward | running | upstairs | downstairs |
|------------------|----------|------------|---------|---------|----------|------------|
| backward         | 97.32%   | 0%         | 0.24%   | 1.22%   | 0.43%    | 0.79%      |
| stationary       | 0%       | 100%       | 0%      | 0%      | 0%       | 0%         |
| forward          | 2.95%    | 0%         | 93.73%  | 1.84%   | 1.23%    | 0.61%      |
| running          | 3.62%    | 0%         | 0.94%   | 93.27%  | 0.94%    | 1.23%      |
| upstairs         | 1.47%    | 0.18%      | 0.88%   | 1.36%   | 88.16%   | 7.95%      |
| downstairs       | 4.61%    | 0.26%      | 0.32%   | 1.95%   | 8.51%    | 84.35%     |

5.2. Heading correction experiment
In order to verify the effectiveness of the heading correction method proposed in this paper, pedestrians follow the path of straight lines, straight lines are shown in Figure 7 corridors, a total of 31 meters. It can be seen from the figure 8 that the pedestrian trajectory with ZUPT will gradually deviate from the real trajectory over time. The trajectory after correct of the heading using the ZARU algorithm is obviously closer to the true trajectory than the trajectory without the heading correction. Only the track end point of ZUPT is 1.2 meters from the end of the real track, which is 3.8% of the total walking distance, while the track end point of ZUPT and ZARU is 0.6 meters from the end point of the real track, which is 1.9% of the total walking distance. Figure 8 proves the effectiveness of the route correction method proposed in this paper.

Figure 5. A corridor that walks in a straight line.
6. Conclusion
This paper sets the zero-speed correction of dynamic threshold according to CNN-SVM's gait classification method to pedestrian position. According to the results of gait classification, adaptive selection of the gait makes the optimal threshold with the smallest positioning error to carry out the detection of the stance phase. In addition to velocity, heading drift is another major cause of positioning error, and the direction is corrected by using the zero-angle rate correction method. The experimental result classification accuracy of CNN-SVM in gait is 97%, which shows that the classification accuracy of CNN-SVM is better than that of CNN alone or SVM alone. The experimental result of heading correction is closer to the actual walking path than the trajectory without the correction, which shows that the heading correction proposed in this paper can reduce the positioning error of pedestrians.

Because the state of pedestrian walking is complex and random, it is necessary to design more adaptable gait detection algorithm, which can detect more gait. The inertial sensor of this paper is mounted on one foot, which can be installed on both feet, and the data of both feet can be analyzed to further improve the stability and accuracy of pedestrian positioning system.

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