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Optimizing Pedestrian Dead Reckoning (PDR) Accuracy through Motion Behavior Recognition and Dynamic Step Length Adjustment

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Abstract:

The Pedestrian Dead Reckoning (PDR) algorithm is a method for determining pedestrian position by integrating inertial data from an inertial measurement unit (IMU), the subject's movement behavior, and environmental information. The accuracy of the PDR algorithm relies on key system parameters, such as step count, step length, and the subject's movement behavior. This study employs combined acceleration data to count pedestrian steps, utilizes the K-nearest neighbor (KNN) method to estimate the subject's movement behavior, and dynamically adjusts the step length estimation model based on the recognized behavior patterns. Consequently, this approach achieves high-precision pedestrian position estimation, maintaining an average error within 3% of the total distance traveled.

Keywords:

Behavior recognition; Step length.

1. Introduction

People's activities are more and more concentrated indoors today, and the demand for location has gradually increased. However, satellite positioning systems such as GPS will lose their function due to the signal being blocked. The inertial positioning technology has received extensive attention due to its strong autonomy, high reliability, and the absence of external nodes. The PDR algorithm is the most common type of inertial positioning algorithm. The number of steps and the step length are the main reasons that limit the positioning accuracy of the PDR algorithm [1]. This paper uses the combined acceleration to count the number of pedestrian steps, uses the K nearest neighbor method to identify the pedestrian's movement behavior, and adjusts the parameters of the step size estimation model according to the behavior recognition results, ultimately improving the positioning accuracy of the PDR algorithm.

2. Behavior recognition and step size estimation

2.1 Step Count

In the process of movement, the combined acceleration of pedestrians presents a periodic change. In each step, there will be a wave crest and a trough in the combined acceleration. By counting the number of crests and troughs, the number of pedestrian steps during the movement can be counted.

2.2 Behavior Recognition

2.2.1 KNN algorithm

K nearest neighbor (KNN) is a common machine learning algorithm. The basic idea of the algorithm is: if the current sample has K nearest neighbors in the feature space, and most of these samples belong to a certain category, the sample is also classified into this category. Among them, K is an arbitrary positive integer, which represents the selection of several nearest samples. The accuracy of the KNN classification algorithm can be changed by adjusting the value of K. For example, the feature space shown in Figure 1 contains two types of data: one is a red triangle, and the other is a blue square. The green samples need to be correctly classified. When the value of K is 3, the algorithm classifies the samples as category one. When the value of K is 5, the algorithm classifies the samples as category

3. Therefore, we need to choose the appropriate K value according to the actual situation.

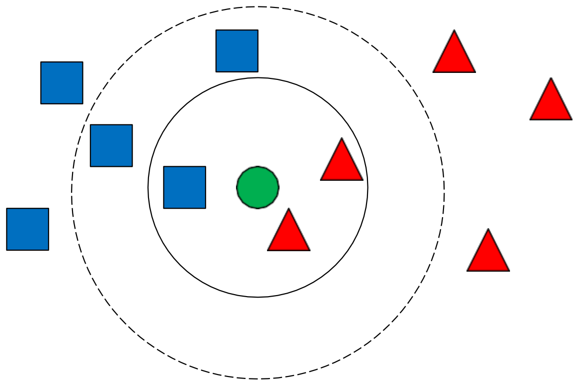

Fig. 1 KNN classification algorithm diagram

The key steps of the KNN algorithm are as follows:

(1) Calculate the distance information between the current sample and each sample in the feature space. Euclidean distance is usually chosen as a measure of distance.

(2) The distance information obtained in the previous step is arranged in ascending order.

(3) Select the K samples closest to the current sample.

(4) Count the categories to which the K samples belong.

(5) Use the category with the highest frequency among the K samples as the predicted classification of the current sample.

3.1.1 Data set construction and feature selection

In this article, we collected motion data of 10 testers on daily behaviors such as walking, running, standing still, going upstairs, going downstairs. The acceleration and resultant acceleration in the three axes output by the inertial positioning terminal are selected as feature vectors, and mean, variance, peak, frequency, and average crossover values are selected as vector feature information to estimate the tester's motion behavior.

3.1.2 Training and classification

The samples in the data set are normalized and divided according to a ratio of 8: 2, 80% of the data is used as the training subset, and 20% of the data is used as the test set. Figure 2 is the accuracy of the recognition of behavior under different K values. It can be seen that when K = 3, the accuracy of the classification algorithm is the highest.

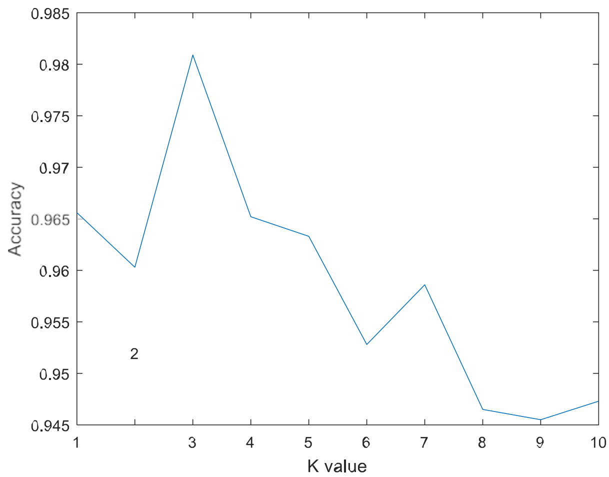

Fig. 2 The accuracy of KNN classification algorithm

4. Experiment

4.1 Behavior Recognition Algorithm Verification

This article selected 5 volunteers to participate in the experiment, including 3 men and 2 women. Each volunteer completed the movements of going upstairs, going downstairs, walking, running, and standing, and each movement was repeated 100 times. The final experimental results are shown in Table 1.

Table 1 Behavior Recognition Results

Testers	Upstairs	Downstairs	Walking	Running	Quiescent	Recognition Accuracy
1	100	92	96	100	100	97.6%
2	96	87	93	95	100	94.2%
3	96	93	92	100	100	96.2%
4	93	95	89	100	100	95.4%
5	89	91	95	92	100	93.4%
Accuracy	94.8%	91.6%	93%	97.4%	100%	

4.2 Verification of Positioning Algorithm

This paper verifies the effectiveness of the algorithm by compared with the traditional PDR algorithm. The tester conducted a walking experiment in which multiple sports modes were mixed in the parking lot, and the total walking distance was 500m. The results of the two positioning algorithms are shown in Table 2.

Table 2 Positioning Result

Testers	Starting point (m)	PDR algorithm positioning (m)	Behavioral-constraint PDR algorithm (m)
1	(0,0,0)	(21.5,15.1,0.2)	(12.3,11.5,0.2)
2	(0,0,0)	(17.2,18.5,0.3)	(15.5,10.2,0.5)
3	(0,0,0)	(15.2,16.8,0.1)	(9.5,12.3,0.2)
4	(0,0,0)	(12.5,9.5,0.2)	(10.5,6.8,0.3)
5	(0,0,0)	(12.5,9.5,0.2)	(10.5,6.8,0.3)
Average error	-	23.47	14.53

5. Summary

In this paper, we employ the K-Nearest Neighbors (KNN) algorithm to effectively identify the movement behaviors of pedestrians. By leveraging this behavior recognition, we are able to adjust the correction coefficient within the step size estimation model. This adjustment is crucial as it significantly enhances the positioning accuracy of the Pedestrian Dead Reckoning (PDR) algorithm. To validate the efficacy of our approach, we conducted extensive experimental evaluations. The results are compelling, with the behavior recognition algorithm achieving an impressive accuracy rate of 95.3%. Furthermore, the positioning error was consistently maintained below 3% of the total distance traveled, showcasing the precision and reliability of our method. These findings underscore the high practical value of our overall algorithm, making it a robust solution for applications that require accurate pedestrian tracking and navigation in various environments.

References

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