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Step length estimation algorithm based on different walking states

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Abstract

Aiming at the problem of accuracy divergence when commonly used nonlinear empirical step-length estimation models are applied to scenes of multi-motion behavior, a step-length estimation algorithm based on different walking states is proposed. Fitting K value calculation curves for different motion states under different walking states, including forward, backward, left shift, and right shift, so as to improve the accuracy of step length estimation.

Keywords

Step size estimation; adaptive algorithm; least squares method.

1. Introduction

In the PDR system, the error of step size estimation directly determines the accuracy of positioning. The step size error continues to accumulate over time, which is an important cause of positioning error. The step size models commonly used at home and abroad are: constant model[1-3], linear model[4-5], nonlinear model[6-9], and some other models [10]. These models cannot be used to estimate the step length of all motion behaviors. In order to adapt to the step size estimation in a variety of sports behaviors, this paper proposes an adaptive step size estimation algorithm based on the existing nonlinear empirical step size estimation model.

2. Adaptive step size estimation algorithm

2.1. Nonlinear empirical step size estimation model

Among the many empirical model step length estimation algorithms suitable for waist PDR systems, the difference between the maximum and minimum acceleration within one step is the most commonly used feature in the empirical model. At present, the nonlinear step size model that is often used by researchers and has high accuracy is shown in formula (1):

$$step\_length = K * \sqrt[4]{A_{\max} - A_{\min}} \tag{1}$$

In the formula, $step\_length$ is the estimated step length for each step; $A_{\max}$ and $A_{\min}$ are the maximum and minimum values of the three-axis acceleration modulus of the person at each step, which can be obtained in conjunction with gait detection; K is the calibration coefficient of the model, usually a fixed value. The model algorithm contains only one parameter to be sought, and the required features are easy to obtain, the algorithm calculation is simple and easy to implement, and can basically meet the real-time nature of step estimation.

This algorithm has good applicability to normal forward walking motion behavior, but its step size estimation accuracy will quickly diverge when there are motion behaviors such as back, left, and right. Therefore, this paper improves the empirical model and proposes an adaptive step size estimation algorithm that can be applied to more walking states.

From the analysis of the walking characteristics of the personnel, it can be seen that the step length changes in real time while walking, and the step length changes in different walking states. Therefore, when designing the step-length estimation algorithm, the applicability of the algorithm in different walking states must be considered.

From the above step length estimation empirical model formula (1), it can be seen that the accurate acquisition of the step length coefficient K directly affects the estimation accuracy of the step length. Although the above-mentioned empirical model step-length estimation algorithm can be used for step-length estimation in a variety of walking states, most research documents do not specifically introduce the value conditions and calculation methods of the coefficient K when using the above-mentioned step-length estimation model. There is no proper K value for different walking states. Therefore, under complex human movement behavior, the accuracy of the aforementioned step-length estimation algorithm cannot meet the high-precision positioning requirements.

2.2. Adaptive step size estimation algorithm

In the two-dimensional plane motion behavior, the difference in the change of the person's step length under different walking modes is mainly reflected in the different changes in the acceleration and cadence. If the gait characteristics and acceleration of the person can be combined on the basis of the above experience model The domain feature sets the constraint conditions and obtains the appropriate step size coefficient K, which can effectively improve the accuracy of the step size estimation. Therefore, in the reference [1] of this article, the relationship between the step length coefficient K and the acceleration of the personnel is established, and the relationship is established as shown in (2), and an algorithm that can update the K value in real time according to the change of the acceleration of the personnel is proposed.

$$K = a * A_{\max}^2 + b * A_{\max} + c \tag{2}$$

K is the coefficient of the step size model and m is the acceleration modulus value and a, b, c are constant coefficients in the formula.

The main idea of the above-mentioned step-length coefficient K value update algorithm: first collect the constant walking data of people under different motion behaviors, and calculate multiple sets of $\overline{K}$ and $\overline{A_{\max}}$ values.

Then use the least square method for curve fitting to solve the constant coefficients a, b, and c in formula (2); finally, bring the calculated constant coefficients back into formula (2) to update the step coefficient K in real time. The algorithm is shown in formula (3):

$$\begin{cases} \overline{K} = a * \overline{A_{\max}^2} + b * \overline{A_{\max}} + c \\ \overline{K} = L_{real} / L_{estimated} \end{cases} \tag{3}$$

In the formula, $\overline{K}$ represents the mean value of the step length coefficient in a set of experimental data, which can be obtained by the ratio of the actual distance L_{real} of the walking trajectory to the estimated distance $L_{estimated}$ of the walking trajectory. $\overline{A_{\max}}$ represents the average value of the maximum set of three-axis acceleration modulus values of a group of experimental data personnel at each step. In summary, when estimating the step length of the two-dimensional plane motion behavior, first fit the K value calculation curve of different walking states, including forward, backward, left shift, and right shift 4 motion behaviors.

Then the result provided by the behavior recognition system is used as a constraint condition, and the most suitable step size estimation formula is selected to improve the step size

estimation and the positioning accuracy of the PDR system. The two-dimensional plane motion step length estimation algorithm model is:

$$\begin{cases} step\_length_{2D} = K_i \sqrt[4]{A_{\max} - A_{\min}} \\ K_i = a_i * A_{\max}^2 + b_i * A_{\max} + c_i \end{cases} \tag{4}$$

In the formula, $step\_length_{2D}$ is the estimated step length of the personnel at each step; $A_{\max}$ and $A_{\min}$ are the maximum and minimum values of the three-axis acceleration modulus of the personnel at each step; $K_i (i = 1, 2, 3, 4)$ represents the four movement modes of forward, backward, leftward and rightward respectively The curve fitting formula calculation result of the step coefficient K; a_i、b_i、c_i are the k fitting coefficients under different motion behaviors.

3. Experiment

In order to obtain the value of the step length coefficient K under different exercises, first collect 100 sets of data of 10 experimenters under different exercise states. The experimenters are required to walk 50 meters at a constant speed in each exercise, and extract 100 sets of step lengths. Coefficient mean value $\overline{K}$ and corresponding acceleration $\overline{A_{\max}}$ value. Then use formula (3) to perform least-squares fitting to obtain the corresponding coefficient values under different sports. Figure 1 shows the K value fitting curve under different walking states.

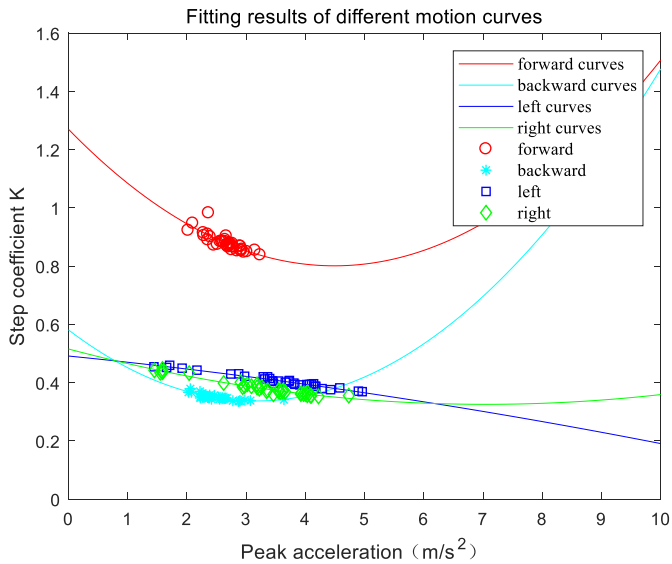

Fig. 1 Step coefficient fitting

After obtaining the K-value fitting curves in different motion states, this paper selects the empirical model step-length estimation algorithm with fixed K value and the adaptive behavior step-length estimation algorithm for experimental verification. The two algorithms are compared in terms of universality and superiority. Among them, the empirical model step length coefficient K takes a common value of 0.5. In this paper, IMU positioning terminal is used to collect raw acceleration data for experimental simulation, and the above two algorithms are written in the underlying program for experimental verification.

In order to obtain more objective experimental results, a total of 10 people were selected to participate in the experimental test, including 5 men and 5 women. Each tester repeated the experiment 5 times, and a total of 50 sets of experimental result data were selected. For each test, each experimenter designs 5 sets of experiments, including forward, backward, leftward, rightward, and running, and the experimenter is required to complete the test on the specified straight-line distance. Among them, walking forward 50 meters, considering that backward, left

and right shifts are unconventional motion behaviors, the test distance is specified as 25 meters, and the tester is required to have basically the same pace under the same motion behavior.

Table 1 Mean step error when forward

Test Numble	Testers	Empirical model(%)	Adaptive step size(%)
1	A	3.21	1.51
2	B	4.69	2.33
3	C	3.53	1.65
4	D	3.41	1.98
5	E	5.76	1.78
6	F	4.65	2.01
7	G	5.32	2.57
8	H	3.02	1.86
9	I	4.01	1.72
10	J	4.79	2.54

Table 2 Mean step error when backward

Test Numble	Testers	Empirical model(%)	Adaptive step size(%)
1	A	40.35	1.02
2	B	36.45	0.82
3	C	42.56	1.56
4	D	46.67	1.38
5	E	34.31	1.58
6	F	37.89	1.87
7	G	31.78	0.98
8	H	39.25	2.09
9	I	45.23	2.14
10	J	38.25	1.78

Table 3 Mean step error when left shift

Test Numble	Testers	Empirical model(%)	Adaptive step size(%)
1	A	16.69	2.31
2	B	15.35	1.65
3	C	17.26	3.24
4	D	16.45	2.56
5	E	14.24	1.35
6	F	17.47	2.73
7	G	15.67	1.26
8	H	16.53	1.87
9	I	13.34	3.09
10	J	15.38	3.52

Table 4 Mean step error when right shift

Test Numble	Testers	Empirical model(%)	Adaptive step size(%)
1	A	10.24	1.65
2	B	9.56	2.29
3	C	9.75	1.95
4	D	8.36	1.32
5	E	10.35	2.76
6	F	9.24	3.54
7	G	7.39	2.43
8	H	8.29	1.87
9	I	9.27	1.62
10	J	9.18	2.03

4. Summary

As shown in above Tables, there is a comparison effect diagram of the step length estimation of the two algorithms under different motion behaviors of a randomly selected tester. It can be seen that the adaptive behavior step size estimation algorithm is obviously better than the empirical model step size estimation algorithm with a fixed K value, and is closer to the actual step size.

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