Accelerometer Based Joint Step Detection and Adaptive Step Length Estimation Algorithm Using Handheld Devices

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Abstract —The pedestrian inertial navigation systems are generally based on Pedestrian Dead Reckoning (PDR) algorithm. Considering the physiological characteristics of pedestrian movement, we use the cyclical characteristics and statistics of acceleration waveform and features which are associated with the walking speed to estimate the stride length. Due to the randomness of the pedestrian hand-held habit, the step events cannot always be detected by using the periods of zero velocity updates (ZUPTs). Furthermore, the signal patterns of the sensor could differ significantly depending on the carrying modes and the user's hand motion. Hence, the step detection and the associated adaptive step length model using a handheld device equipped with accelerometer is required to obtain high-accurate measurements. To achieve this goal, a compositional algorithm of empirical formula and Back-propagation neural network by using handheld devices is proposed to estimate the step length, as well as achieve the accuracy of step detection higher than 98%. Furthermore, the proposed joint step detection and adaptive step length estimation algorithm can help much in the development of Pedestrian Navigation Devices (PNDs) based on the handheld inertial sensors.

Index Terms—Pedestrian inertial navigation; handheld devices; step detection; step length estimation; accelerometer

I. INTRODUCTION

Nowadays, the most of the handheld devices have been integrated with the gyroscope, accelerometer, magnetometer, and barometer to provide the data needed for pedestrian navigation sensors. With the development of Micro Electro Mechanical Systems (MEMS) technique and its wide applications in smart phones and many other handheld devices, the demand for navigating the pedestrian by using a hand-held mobile device has remarkably increased over the last few years, especially in GPS denied scenarios [1]. The widespread dissemination of smartphones has prompted a great success of location-based services, like the emergency relief map for indoor intelligent navigation [2]-[4].

Real-time measurement of the process of moving the body motion parameters and then calculate the displacement information is a common approach to realize the indoor positioning, how to obtain human motion parameters of which became the first problem to be solved. To obtain the accurate, as well as real-time human motion parameters, the MEMS sensors are often selected to collect the inertial parameters. The proposed pedestrian navigation algorithm is based on Pedestrian Dead Reckoning (PDR) which consists of step detection, stride length estimation, and heading estimation [5]. The MEMS sensor data which are obtained by using acceleration, angular velocities, and magnetic parameters, are used to reveal the displacement movement of the target.

The step length estimation algorithm by using the MEMS sensors is always recognized as a difficult problem. In step length estimation, a large number of previous literatures indicated that the carrying habit of MEMS sensors is the key to the precision of measurements [6-8]. Although early in 1972 the use of accelerometer was proposed to analyze the process of moving human point of view, the step length estimation algorithm was not until recently that a few years before someone will study the process of moving the body based on accelerometers and gyroscopes equipped on the torso, thighs, legs, feet, and hands. With the help of the parameters of MEMS sensors, we can easily recognize the human actions, calculate the road displacement, and find the travel direction.

When the MEMS sensors are fixed on the body trunk, the accuracy is low and the cost of MEMS sensors is high [9]. When the sensors are fixed on the thigh, since this place does not take advantage of the body's normal moving, MEMS sensors will affect the body's normal travel trajectory, the performance of action recognition is well, whereas the accuracy of step length estimation is low [10]. When the sensors are fixed on the calf, the accuracy of estimating the travel speed and travel displacement is higher than other methods, obtained by the particularity of the trajectory of the calf in the process of moving, whereas this approach requires the strict process of moving approximation inverted pendulum motion [11]. When the MEMS sensors are fixed on the foot, the step length is calculated based on the switch sensor, pressure sensor, ground reaction force, and mobile mode of foot [12]. In this case, although the accuracy of measurements is significantly high, the strict test conditions and high cost of equipment restrict its wide applications.

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Compared to the previously discussed approaches, a novel joint step detection and adaptive step length model using a handheld device only with the accelerometer is required to achieve high accuracy measurements. In this paper, the compositional algorithm of empirical formula and Back-propagation neural network using a smartphone is presented to estimate step length.

The rest of this paper is structured as follows. Section II presents the gait model of pedestrian. Section III shows the steps of the step detection algorithm by using handheld devices in detail. The discussion on the step length estimation method is addressed in Section IV. Extensive experimental results are provided in Section V. Finally, Section VI concludes the paper.

II. Gait Model of Pedestrian

Walking is the most common and frequent movement of the pedestrian. When the pedestrian is walking, the body center of gravity changes constantly in the horizontal direction, as well as in the vertical direction. The development of modern measurement technique helps to conduct the dynamic quantitative analysis with respect to the various parts of the body. The various parts of the body, like the feet, legs, and waist produce a corresponding movement during walking as the acceleration and angular velocity change. Each gait cycle can be divided into two phases [13]: the stance phase and swing phase, as shown in Fig. 1.

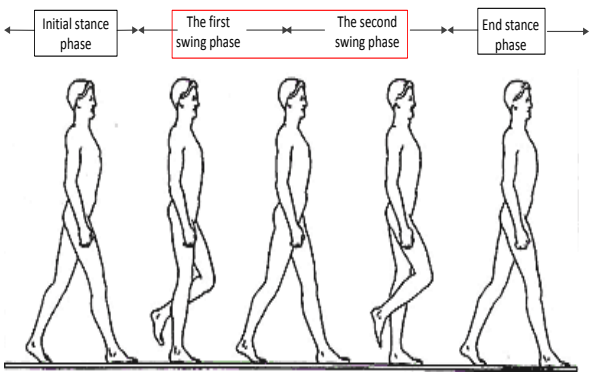

Fig. 1. Physical model of pedestrian movement

The stance phase is the period occupying about 62% of the gait cycle time when the feet touch the ground. Under the normal walking condition, the feet are touching the ground the whole time about 24% of the gait cycle time. The swing phase which consists of the first swing phase and second swing phase is the period occupying about 38% of the gait cycle time when the feet are in the air.

Specifically, the first swing phase begins when the stance phase ends, while the gravity center of the body moves up and is then located at the front foot. The gravity center of the body is located at the back foot in the second swing phase, and moves down at the end of the second swing phase.

III. Step Detection Algorithm

According to the characteristics of pedestrian walking, the output waveform of the tri-axial accelerometer changes periodically while the pedestrian is walking. On this basis, we rely on the cyclicity and eigenvalues of tri-axial acceleration to detect the gait. The output wave form of the tri-axial acceleration is calculated by

$$Acc\_Value = \sqrt{a_x^{\ 2} + a_y^{\ 2} + a_z^{\ 2}} \tag{1}$$

where a_x, a_y, and a_z represent the output wave form in the X, Y, and Z directions of the accelerometer, respectively.

The output wave form of the tri-axial accelerometer always produces multiple peaks, which most probably lead to the mistaken identification of the pedometer. By using the digital low pass filter to modify the output wave form of the tri-axial accelerometer, we can obtain the fine-tuned peak curve and consequently detect the peaks accurately based on the calculation of the number of steps. We adopt the Hamming window function with digital low-pass filter to tri-axial accelerometer. The window length of filter is 10. The filtering results are shown in Fig. 2.

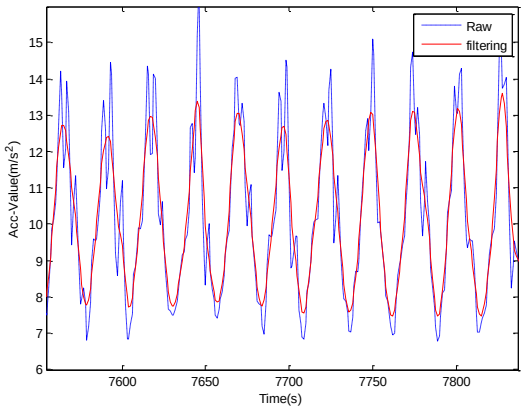

Fig. 2. Comparison between the raw output wave form and the output wave form after filtering

Since the handheld device is held in the swinging hand, the output wave form of the tri-axial accelerometer generates incorrect peaks, as shown in Fig. 3.

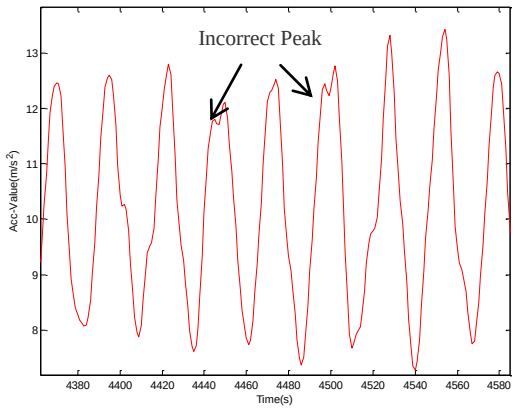

Fig. 3. Output wave form of the tri-axial accelerometer after filtering

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To solve this problem, we set a threshold to eliminate the errors involved in step counting, as shown in (2).

$$\begin{cases} \Delta T > \tau \\ |Acc\_Value - g| > \sigma \end{cases} \tag{2}$$

where ΔT is the time interval between two adjacent peaks, g is the output value of the acceleration. τ and σ are the thresholds for the time and peaks respectively. The values of τ and σ were obtained according to the sample frequency and data analyses and test results.

IV. Step Length Estimation Algorithm

Along with the development of the pedestrian dead reckoning algorithm, the step length estimation algorithm becomes more and more favored. Up to now, the previous studies mainly focused on the situations that the sensors are equipped in the user's phoning or texting hand without considering the handheld sensors. The existed and most representative simple linear model [14], human movement model [15], empirical model and neural network model [16] have paid little attention to the improvement of the accuracy of step length estimation. To fix this gap, a novel step length estimation approach is proposed by using the compositional algorithm of empirical formula and BP neural network.

A. Empirical Formula Based Modeling

Based on the relations between the output wave form of the tri-axial accelerometer and step length [17], we have

$$SL = K\sqrt[4]{Acc_{\max} - Acc_{\min}} \tag{3}$$

where SL is the step length, $Acc_{\max}$ and $Acc_{\min}$ stand for the maximum and minimum output wave form of a tri-axial accelerometer in each step respectively. K is the calibration factor which is obtained by the ratio of the real and estimated reference trajectory distances, as shown in formula (4).

$$K = \frac{d_{real}}{d_{estimated}} \tag{4}$$

Based on formula (4), the step lengths of different pedestrians are estimated by adjusting the values of K.

B. BP Neural Network Based Modeling

BP neural network is known as a multilayer feed forward neural network which is featured with signal prior to transmission and error back propagation [18]. The input signal from the input layer through the hide layer is processed scale by scale until the output layer in the forward pass. Each layer of neurons state affects only the next layer of neurons state.

If the output layer is not expected output, it will be transferred back propagation. According to the forecast error adjustment of network weights and thresholds, BP neural network predicts the output more and more close to the desired output. Fig. 4 shows the structure of a simple BP neural network.

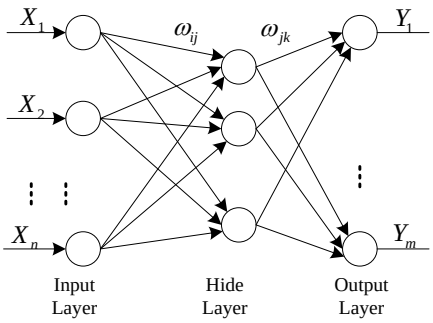

Fig. 4. Structure of BP neural network

In Fig. 4, $X = (X_1, X_2, \cdots, X_n)^T$, $Y = (Y_1, Y_2, \cdots Y_m)^T$ are the input and output vectors. ω_{ij} and ω_{jk} are the weights between the input and hide layers and between the hide and output layers respectively. By setting θ_j and θ_k as the thresholds of the hidden and output layers, we have

$$X_j^{'} = f\left(\sum_{i=1}^{n} \omega_{ij} X_i - \theta_j\right),\ Y_k = f\left(\sum_{i=1}^{n} \omega_{jk} X_j^{'} - \theta_k\right) \tag{5}$$

For simplicity, we set $\theta_j = \omega_{n+1j}$, $X_{n+1} = -1$, $\theta_k = \omega_{jk+1}$, and $X_{k+1}^{'} = -1$. Then, (5) is converted into

$$X_j^{'} = f\left(\sum_{i=1}^{n+1} \omega_{ij} X_i\right),\quad Y_k = f\left(\sum_{i=1}^{n+1} \omega_{jk} X_j^{'}\right) \tag{6}$$

By assuming that the number of training samples is p, and the corresponding expected and actual output are $t^{p_1}(p_1 = 1, 2, \cdots, p)$ and Y^{p_1}, the error is the sum of each output unit error represented by the formula (7).

$$E_{p_1} = \frac{1}{2}\sum_{k=0}^{m}(t_k^{p_1} - Y_k^{p_1})^2 \tag{7}$$

Hence, the training error with respect to the training set equals to

$$E_{all} = \frac{1}{2}\sum_{p_1=1}^{p}\sum_{k=0}^{m}(t_k^{p_1} - Y_k^{p_1})^2 \tag{8}$$

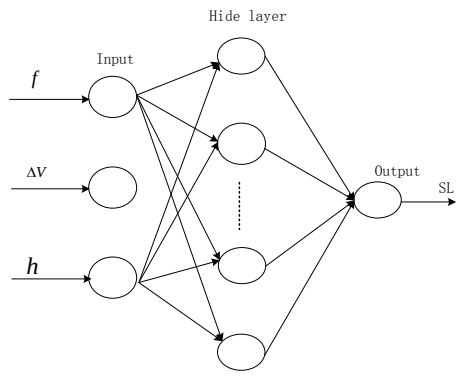

Fig. 5. Structure of BP neural network for step length estimation

We assume that the walking frequency of the pedestrian is f, amount of acceleration change is ΔV, and height of

the pedestrian is h. Then, the non-linear relations from f, ΔV, and h to SL which are characterized by BP neural network (see Fig. 5) is notated as

$$SL=\Phi(f,\Delta V,h) \tag{9}$$

In (9), ΔV is obtained by the variance in the acceleration mode value of a step. The flowchart of BP neural network based modeling for step length estimation consists of the modules of BP neural network construction, training, and prediction, as shown in Fig. 5.

It has associative memory and ability to predict by training the network before BP neural network prediction. Step estimation algorithm based on BP neural network modeling, including BP neural network construction, BP neural network training and BP neural network prediction, the algorithm processes shown in Fig. 6.

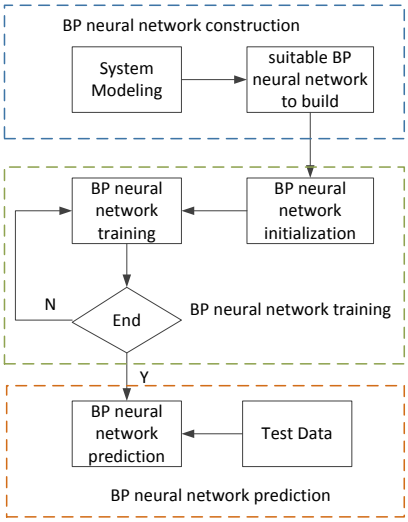

Fig. 6. Flowchart of BP neural network based modeling for step length estimation

C. Composition of Empirical Formula and BP Neural Network

Due to the different height, attitude, and walking frequencies of the pedestrian, the step lengths could vary greatly. Therefore, an efficient calibration factor K in the empirical formula to be used to estimate the step lengths is difficult to be obtained. In BP neural network, the accuracy of estimating the step lengths cannot be guaranteed since the model estimate of the step length is not accurate.

In this paper, the step length is estimated by using the compositional algorithm of empirical formula and BP neural network. As the calibration factor of the experience model does not require statistical user practical step, which can be estimated by BP neural network model and then using the experience formula obtained the step length. By analyzing the obtained, the calibration factor K experiences the greatest impact by height and step frequency of pedestrian, taking into account the non-linear relationship between them, using BP neural network to predict the real-time values for the calibration factor K. Fig. 7 shows the flowchart of the proposed compositional algorithm.

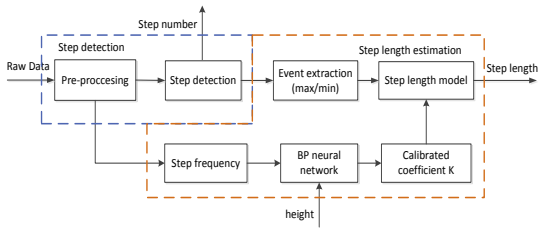

Fig. 7. Flowchart of the proposed compositional algorithm

In the constructed BP neural network, there are 2, l, and 1 nodes in the input, hidden, and output layers respectively, as shown in Fig. 8. The value of l is determined based on the criteria shown below.

$$\begin{aligned} l &< n-1 \\ l &< \sqrt{(m+n)}+a \\ l &= \log_2 n \end{aligned} \tag{10}$$

where n, l, and m are the number of neurons in the input, hidden, and output layers respectively. a is a constant in the range of [0, 10]. Through the actual network training, the system on the number of hidden layer nodes is 5, l=5.

Based on BP neural network, the nonlinear equation modeling of the calibration factor K is established, which impacted by height and step frequency, as shown in Fig. 8.

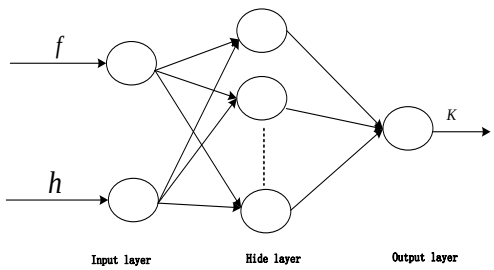

Fig. 8. Structure of BP neural network for step estimation

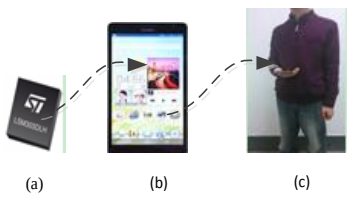

Fig. 9. (a) Photo of the tri-axial accelerometer (b) Photo of a smartphone equipped with the tri-axial accelerometers (c) Photo of a user holding the smartphone

V. Experimental Results

A. Hardware Description

We select the tri-axial accelerometer, LIS303DLHC, equipped in a HUAWEI smartphone for the testing. This tri-axial accelerometer is featured with the measurement range of ±2g, where g is the gravity acceleration. The calibration is conducted to tri-axial accelerometer. The tri-axial accelerometer is the sample rate of 50Hz.

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B. Performance Evaluation

The experimental data are taken by 5 male and 5 female volunteers with the height varying between 158 cm and 186 cm. As shown in Fig. 10, each volunteer holding a smart phone walks along a straight path with the length of 105 m, as well as records the number of steps three times, each time with different constant walking velocities, namely as the fast velocity, slow velocity, and normal velocity.

Fig. 10. A volunteer with a smartphone walking along a straight path

Table I shows the results of step detection. The 5 male and 5 female volunteers are notated as M1, $\cdots$, M5 and F1, $\cdots$, F5 respectively.

TABLE I: STEP DETECTION ALGORITHM PERFORMANCE FOR THE "CONTROLLED" DATA COLLECTION

Volunteers	Height (cm)	Real number of steps	Estimated number of steps
F1	158	164	164
F2	160	160	159
F3	161	167	166
F4	163	165	165
F5	165	159	159
M1	168	148	148
M2	170	151	151
M3	171	154	153
M4	178	148	148
M5	186	137	137
Mean	/	155.3	155

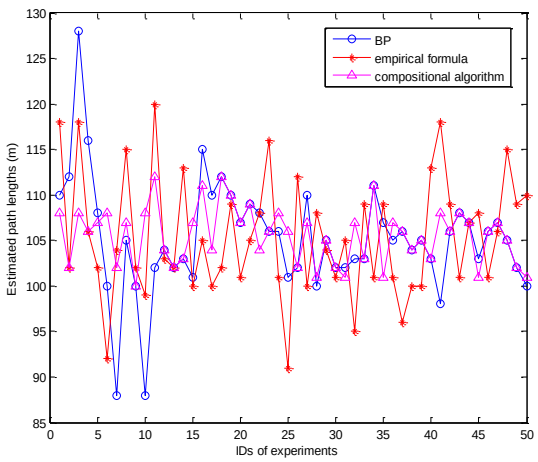

Fig. 11. Results of the estimated path lengths

Fig. 11 shows the estimated path length with respect to each experiment. To illustrate this result clearer, Fig. 12 compares the errors of step length estimation by using the proposed compositional algorithm and the conventional empirical formula based and BP neural network based algorithms. The vertical axis indicates the relative errors between the real and estimated path lengths. The whisker length is limited in the 1.5 interquartile ranges. The + labels outliers in between the 1.5 and 3 interquartile range. Obviously, the relative error of the proposed compositional algorithm is smaller than the ones achieved by the conventional algorithms.

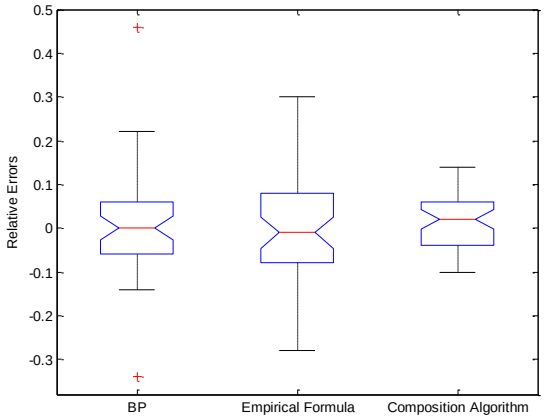

Fig. 12. Comparison of the errors of step length estimation

VI. CONCLUSIONS

In this paper, we have paid significant attention to the accelerometer based joint step detection and step length estimation, as well as gait analysis. The experimental results with respect to 5 male and 5 female volunteers demonstrate that the tri-axial accelerometer based step detection achieves the percentage of correct step detection over 99.4%. Furthermore, the proposed step length estimation algorithm helps much in decreasing the relative errors of the pedestrian navigation. In future, we will continue to discuss the situation that the pedestrian walks with swinging hands. This direction opens many new research options towards the free-inertial tracking of the pedestrian with handheld inertial sensors, which have been widely applied in smart phones nowadays.

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