Sensors & Transducers, Vol. 172, Issue 6, June 2014, pp. 1-6

Sensors & Transducers

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The Improvement of Behavior Recognition Accuracy of Micro Inertial Accelerometer by Secondary Recognition Algorithm

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Received: 2 April 2014 /Accepted: 30 May 2014 /Published: 30 June 2014

Abstract: Behaviors of “still”, “walking”, “running”, “jumping”, “upstairs” and “downstairs” can be recognized by micro inertial accelerometer of low cost. By using the features as inputs to the well-trained BP artificial neural network which is selected as classifier, those behaviors can be recognized. But the experimental results show that the recognition accuracy is not satisfactory. This paper presents secondary recognition algorithm and combine it with BP artificial neural network to improving the recognition accuracy. The Algorithm is verified by the Android mobile platform, and the recognition accuracy can be improved more than 8 %. Through extensive testing statistic analysis, the recognition accuracy can reach 95 % through BP artificial neural network and the secondary recognition, which is a reasonable good result from practical point of view. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Secondary recognition, Micro inertial accelerometer, Behavior recognition, BP artificial neural network.

1. Introduction

Human behaviors recognition technology has been steadily developed in the past 10 years. Recently, researchers began to switch their research interest on PCs to portable devices. However, most of these studies are based on portable devices with integrated optical sensors [1-3]. Considering about the present cost of optical sensors, it will be difficult for those research to find some practical applications. Fortunately, most Android phones can overcome this problem today, because they integrate micro inertial accelerometer, which is cheap, and mobile phones as an essential communication tool also provide a lot of advantage than other portable devices.

In the past few decades, some researchers used wireless data transmission technology to collect data and then input them to PC for post-processing. This approach has high recognition accuracy (99 %) for simple human behavior patterns, but is not practical because it’s not real time processing [4]. Some other researchers also use a single micro inertial accelerometer fixed in a certain place (such as wrists, legs, or sternum) for human behavior pattern recognition and the accuracy of this approach is about 90 % [5-6]. In recent years, some researchers have also used Android phone to study patterns of downstairs and upstairs, but the rate of accuracy is only about 50 % [7].

This paper described a pattern recognition model which carried out the data collection and data processing both on Android phone and the behavior recognition is completed by features, BP artificial neural network and the secondary classification. The experimental results show that the recognition accuracy of this model is over 95 %.

2. Data Collection Device and Features Extraction

The study uses the Mate (Android phone) of Huawei as data collection device for behaviors recognition. The Mate integrates a triaxial micro inertial accelerometer of LIS303DLHC, and the accelerometer is shown in Fig. 1(a). The coordinate axis of accelerometer distributed on Mate is shown in Fig. 1(b).

(a)

(b)

Fig. 1. The map of physical hardware.

The date collection was done by putting Mate into human pants pocket, in which the X-axis, Y-axis, and Z-axis are pointed to the horizontal left, vertical upward and horizontal forward directions respectively. The frequency for data collection is set to 50 Hz, and 150 acceleration data are needed for the recognition of behavior, which means 3 seconds is needed for the recognition of behaviors.

3. Classification and Model Training

The data processing is based on the adaptivity of real-time recognition model, which means the classifier can recognize the real-time behavior through the features which is extracted in the real-time. BP artificial neural network of feed forward is selected as the classifier first. Incremental algorithms are used as the training algorithm of BP artificial neural network. There are 6 neurons for the first hidden layer, 5 neurons for the second hidden layer, 10 neurons for the input layer, and 5 neurons for the output layer.

The study collects the accelerometer data from 17 men and 4 women. Each person is required to collect accelerometer data three times for each behavior, and each time for data collection is regarded as a data sample, which means, each behavior has 63 data samples, thus 5 behaviors ("Still" behavior does not need data sample) have 315 data samples in total. Part of these data samples (training sample) are used as the input of BP artificial neural network to train the BP neural network, the other part of data samples (test samples) are used to test the trained BP neural network. The purpose of the test samples is to test the effect of well-trained BP neural network. After the result of the test meets expectations, the well-trained BP neural network is used to recognize the behaviors.

The variance of micro inertial accelerometer can be calculated by raw acceleration data. According to the variance values, the six behaviors can be divided into two classes. The first class is "walking", "running", "upstairs", "downstairs" and "jumping", and the second class is "still". The first class of pattern is recognized by the BP neural network, and the second class of behavior is recognized by the variance directly. There are five ideal outputs of the BP neural network, for example, (1, 0, 0, 0, 0) as the ideal output of "walking", (0, 1, 0, 0, 0) as the ideal output of "running", (0, 0, 1, 0, 0) as the ideal output of "jumping", (0, 0, 0, 1, 0) as the ideal output of "downstairs", and (0, 0, 0, 0, 1) as the ideal output of "upstairs". The ideal outputs and features of behaviors are selected to train the model.

4. Features Extraction

The Fig. 2 shows the changes of acceleration of Y-axis value of different behaviors.

12 features are calculated for raw acceleration

data, and of which the first 10 features and the ideal output of each behavior in BP neural network is used as the input of BP neural network to train the BP neural network (the last 2 and first 10 features are used for the secondary recognition together). The 12 features are extracted within the time domain which can reduce the burden of the processor effectively.

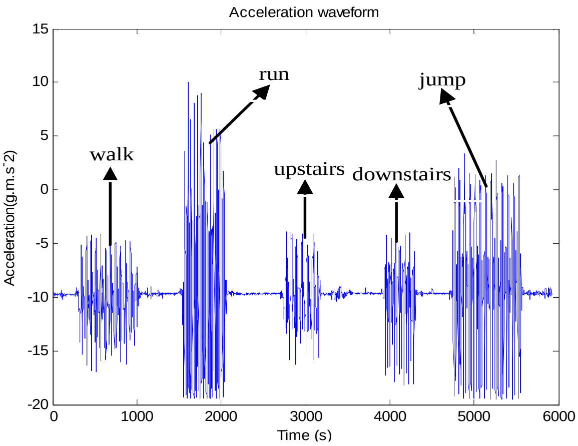

Fig. 2. Triaxial accelerometer data (Y-axis).

The main features are calculated as follows:

$$skewness\_Y(N)=\sum_{i=1}^{N}(((y_i-mean)^3-skewness\_Y(N-1))/(i+1)) \quad (1)$$

Formula (1) indicates the skewness of the accelerometer value of Y-axis within 3 s, where y_i is the accelerometer value of Y-axis, “mean” is the average accelerometer value within 3s;

$$qua_v=\sqrt{x^2{}_v[\frac{3}{4}N]+y^2{}_v[\frac{3}{4}N]+z^2{}_v[\frac{3}{4}N]}-\sqrt{x^2{}_v[\frac{1}{4}N]+y^2{}_v[\frac{1}{4}N]+z^2{}_v[\frac{1}{4}N]} \quad (2)$$

Formula (2) indicates the spacing which is calculated by the 3 s accelerometer values at 3/4 and 1/4 point in the vertical direction, where x_v is the mapping value of X-axis in the vertical direction, y_v is the mapping value of Y-axis in the vertical direction [8-9];

$$qua_v=\sqrt{x^2{}_v[\frac{3}{4}N]+y^2{}_v[\frac{3}{4}N]+z^2{}_v[\frac{3}{4}N]}-\sqrt{x^2{}_v[\frac{1}{4}N]+y^2{}_v[\frac{1}{4}N]+z^2{}_v[\frac{1}{4}N]} \quad (3)$$

Formula (3) indicates the spacing which is calculated by the 3 s accelerometer values at 3/4 and 1/4 point in the horizontal direction, where x_v is the mapping value of X-axis in the horizontal direction, y_v is the mapping value of Y-axis in the horizontal direction [8-9];

$$per\_h3=\sqrt{x^2{}_h[\frac{3}{4}N]+y^2{}_h[\frac{3}{4}N]+z^2{}_h[\frac{3}{4}N]} \quad (4)$$

Formula (4) indicates the value which is the 3/4 point of accelerometer values of 3 axes mapping in horizontal direction within 3 s, where x_h is the mapping value of X-axis in the horizontal direction, y_h is the mapping values of Y-axis in the horizontal direction, z_h is the mapping value of Z-axis in the horizontal direction [10]

$$yz\_correlation=\frac{\sum_{i=1}^{N}((z_i-z_1)(y_i-y_1))}{\sqrt{\sum_{i=1}^{N}(z_i-z_1)^2}\sqrt{\sum_{i=1}^{N}(y_i-y_1)^2}} \quad (5)$$

Formula (5) indicates the cross-correlation coefficient of the Y-axis and Z-axis data within 3 s, where y_i is the value of accelerometer of Y-axis and the z_i is the value of accelerometer of Z-axis [11];

$$a_h m4=\frac{(\sum_{i=1}^{N}(a_h2-a_h1))^2}{N-2} \quad (6)$$

Formula (6) represents the median difference which is calculated by triaxial data mapping in the horizontal direction, where a_h2 and a_h1 are calculated as follows:

$$a_h2=\sqrt{x^2_h[i+2]+y^2_h[i+2]+z^2_h[i+2]}-\sqrt{x^2_h[i+1]+y^2_h[i+1]+z^2_h[i+1]} \quad (7)$$

$$a_h1=\sqrt{x^2{}_h[i+1]+y^2{}_h[i+1]+z^2{}_h[i+1]}-\sqrt{x^2{}_h[i]+y^2{}_h[i]+z^2{}_h[i]} \quad (8)$$

5. The Recognition of BP Artificial Neural Network

Use the well-trained BP artificial neural network for the behavior recognition of real-time. The features are calculated by the algorithm, and the behaviors can be recognized by BP artificial neural network. Fig. 3 shows the distribution of $a_h m4$ of 5 behaviors. “Walking” and “running” can be distinguished from the other three kinds of behaviors according to Fig. 3, which means that $a_h m4$ have high degree of recognition for “walking” and “running”, but low degree of recognition for the other three behaviors. Furthermore, the behaviors will be recognized easily by the BP artificial neural network when all of the features are compared [12-13].

6. Secondary Recognition

For normal behaviors, the recognition of BP artificial neural network could be enough; however, the differential boundary of humans' behaviors is ambiguous. Misrecognition will happen when the behavior of tester is between the two kinds of behaviors. For example, "walking" will be recognized as "upstairs" in the case of "slow walking" or a very light pace of "walking"; and "running" will be recognized as "downstairs" when "jogging". The recognition results of female and male tester are also different. In order to solve those issues, the secondary recognition which is based on the analysis of more features has become necessary.

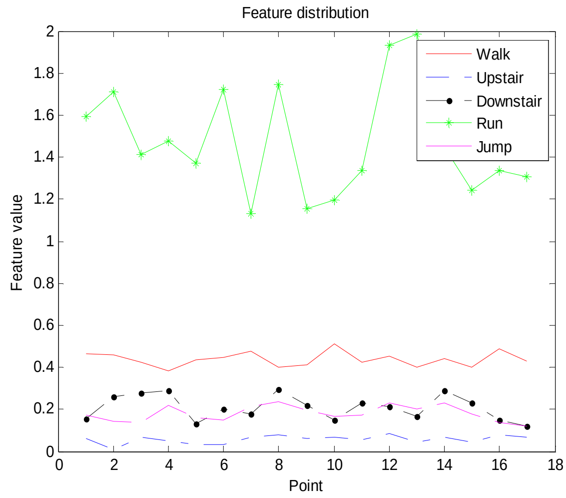

Fig. 3. Distribution of a_hm4 in five different patterns.

In this study, secondary recognition is divided into the following two situations: First, Misrecognition behavior and real behavior after using BP artificial neural network always have one or several features, which will cause big differences within the time domain. Therefore, those features can be used to recognize behavior again (secondary recognition); Second, when there have no features which have high degree of distinction between two kinds of behaviors, we need to redefine the condition of second classification. By analyzing a large quantity of such data, we can find that there always exit several features which have weak distinction in the same direction. Based on the principle of cumulative amplification, the weak distinction of the several features can be added together, so that it will be easier to distinguish the two kinds of behaviors. In another words, secondary recognition is another classifier which is different from the classifier of BP artificial neural network. The principle is to take the output of BP artificial neural network as the input of secondary recognition, and misrecognition behaviors can be recognized as the real behaviors in most cases. Fig. 4 shows the distribution of yz_correlation between real behavior of "walking" and misrecognized behavior of "walking" which is recognized as behavior of "upstairs".

In Fig. 4, the behaviors of green point are recognized as "walking" without secondary recognition. The distribution of yz_correlation is different from the real "walking". One or several features will assist yz_correlation in secondary recognition to prevent the yz_correlation of "walking" in the region of "upstairs". Experimental results show that the behaviors of green point are recognized as "upstairs" with secondary recognition.

In Fig. 5, the black data points are recognized as "running" without secondary recognition. The discrimination of three features between real "running" and misrecognized "running" which should be "downstairs" are also presented; Fig. 6 shows the discrimination of the added three features between two kinds of behavior of "running". By observing the Fig. 5 and Fig. 6, the discrimination of the added three features between "running" and "downstairs" is enhanced significantly.

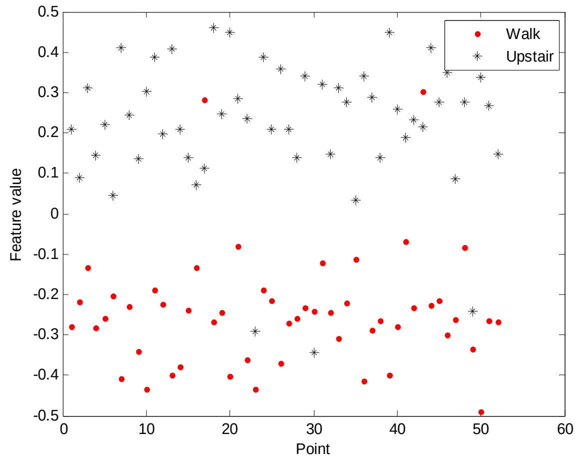

Fig. 4. Distribution of a_hor_m4 in five different patterns.

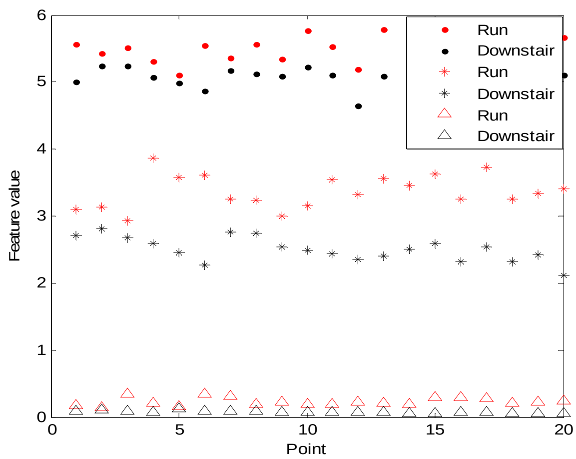

Fig. 5. Distribution of 3 features between "running" and "downstairs".

In summary, the second recognition is based on judgment conditions which can be used to recognize the misrecognized behavior from the real behavior and overcome the weakness of BP artificial neural network in some extent.

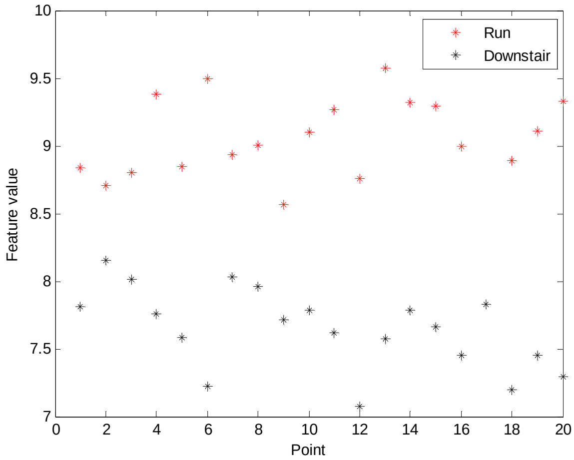

Fig. 6. Synthetic distribution of 3 features between "running" and "downstairs".

For example, "walking" will be recognized as "upstairs" when slow walking or a very light pace of walking is adopted by using BP artificial neural network. However, by analyzing the yz_correlation, a_hm4 and std_yz (the sum of standard deviation of Y-axis and Z-axis within 3 s), it can be found that, for real "upstairs" the yz_correlation is positive; the value of a_hm4 is between 0.02 and 0.1; and the value of std_yz is greater than 5; but for misrecognized "upstairs" which is actually "walking", the situations are different. The yz_correlation is negative, the value of a_hm4 is greater than 0.25; and the value of std_yz is smaller than 5. Therefore, based on these three judgment conditions, the real "walking" can be recognized from misrecognized "upstairs".

To ensure the rigorousness of the secondary recognition, the behavior will be reclassified only when all the conditions are satisfied. In this research, the various behaviors which can be easily recognized as other behaviors are studied, and the proper judgment conditions by analyzing the 12 features are found. Based on these judgment conditions, behaviors can be recognized precisely by secondary recognition. Experimental results show that the accuracy of this model is about 87 % without secondary recognition, and the accuracy is increased to about 95 % with secondary recognition. Table 1 and Table 2 show the test information of five testers, the results shows that the accuracy is improved by more than 8 % with secondary recognition.

Table 1. Accuracy without secondary recognition.

Behavior	Walk	Run	Jump	Up stairs	Down stairs	Accuracy
Walk	133	2	1	14	5	87.5 %
Run	4	91	0	0	5	90.7 %
Jump	0	3	91	0	6	91 %
Upstairs	6	0	0	135	4	84.3 %
Down stairs	5	2	0	6	137	88.7 %

Table 2. Accuracy with secondary recognition.

Behavior	Walk	Run	Jump	Up stairs	Down stairs	Accuracy
Walk	148	0	0	5	2	98.7 %
Run	0	100	0	0	0	100 %
Jump	0	0	100	0	0	100 %
Upstairs	2	0	0	143	0	95.3 %
Down stairs	0	0	0	2	148	98.7 %

7. The Results and Analysis

In this study, the average accuracy is about 95 % of the six types of studied behaviors. The accuracy can be improved when training samples are increased within a certain range, but beyond this range, the accuracy will reduce again. This is because of the over-fitting issue when the amounts of training samples exceed the appropriate number.

From Table 1 and Table 2, it can conclude that some features have high discrimination for "running" and "jumping", so the accuracy of "running" and "jumping" are the best no matter in what kind of testers. For example, when the behavior is "running", the value of per_h3 can distinguish running from other behaviors easily. However the behaviors of "walking", "upstairs" and "downstairs" are different from other behaviors and the accuracy is only about 87 % without secondary recognition.

8. Conclusions

It is proved that the algorithm of behavior recognition in this study is stable, and in addition to the stability, this algorithm also has the advantage of strong expansibility, which can extend to other modules easily. The experimental results show that the rate of error recognition is low (less than 5 %). Comparing with the behavior recognition of the image sensors, the module of this study based on accelerometer has some advantages, such as low cost and simple algorithm. Therefore, this behavior recognition technology based on the Android mobile phone should have good potential for various applications.

Acknowledgements

This work was financially supported by Natural Science Foundation of Chongqing (No. CSTC-2012jj B40003). Open Research Program from Key Laboratory of Optoelectronic Devices and Systems (Education Department / Guangdong Province) of Shenzhen University.

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