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HUMAN ACTIVITY RECOGNITION USING ACCELEROMETER AND BAROMETER IN SMARTPHONE

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Abstract. *People have searched the 3-axes accelerometer in smartphone to recognize human activities, and usually got relatively high accuracy in walking, running, standing and sitting etc., but much lower accuracy in upstairs and downstairs. In the paper, a new scheme combining an accelerometer and a barometer for human activity recognition on smartphone is proposed to solve this problem. In the method, 10 effective features were extracted from accelerometer and barometer data to classify five activities (walking, running, upstairs, downstairs and jumping) combined with an ANN classifier. An Android application was developed to perform the tasks of data collecting and classifying in real-time. We run the app on smartphones, and achieved average accuracies of these five activities above 95.3%. Contrast tests demonstrate that this method enhances the precision of upstairs and downstairs about 23%.*

Keywords: Activity recognition, ANN, Accelerometer, Barometer, Smartphone

1. **Introduction.** Sensors-based human activity recognition, which aims to recognize various human activities using wearable sensors, is one of the research hot spots. It has wide application prospect in many domains, i.e., health care, sport, indoor navigation and smart home etc. [1-4].

Body-worn sensors system is well suited for activity classification in laboratory condition for long periods of time [5-7]. However, for a real user, it can be rather inconvenient to wear multiple sensors devices at specific positions. Currently, smartphones have incorporated a variety of sensors, including accelerometers, gyroscopes, magnetometer, barometers, thermometers, and light sensors etc. Consequently, smartphones became a new platform of activity recognition for their powerful sensory ability. What is more, automatic activity classification using smartphones has gained more research attention compared with recognition based on special wearable devices recently as it allows ubiquitous and unobtrusive activity detection. Most of the previous researchers [8-10] only used the triaxial accelerometer to study PA recognition on smartphone. Typically, the activities recognized on phone are running, walking, jogging, upstairs, downstairs, siting and standing. The accuracy of running, walking, sitting, and standing ranges from 75% to 99%, but the accuracy of upstairs and downstairs is below 80%.

In recent years, the combination of other sensors, like the gyroscope and magnetometer, with an accelerometer has been studied [11,12]. However, it does not obviously improve activity recognition performance. To the best of our knowledge, there is no study investigating the performance of barometer in smartphone. In this paper, a new scheme combining an accelerometer and a barometer for human activity recognition on smartphone is proposed. The activities including walking, running, jumping, ascending stairs and descending stairs were classified. The cellphone was put in the front pants leg pocket when collecting data or taking tests. In this method, only effective time domain features extracted from 3-axes accelerometer and barometer were adopted for decreasing computational complexity as well as energy consumption of mobile phones. Besides, processing one-dimensional data of barometer further reduced the calculated amount and the size of the classification model compared with processing three-dimensional data of gyroscope or magnetometer. The classification results using multilayer neural classifiers demonstrated the effectiveness of our method.

2. **Algorithm.** The whole framework of the system is presented in Figure 1. The framework consists of three units: data acquisition unit, data processing unit, and display unit. In data acquisition unit, a window of raw pressure data and three-axis acceleration are collected. In data processing unit, the raw data are first filtered and feature values are extracted, and then the extracted features are used to train classifier and recognize activities. In addition, we counted steps through zero-crossing detection combining threshold value verification [13]. The recognition results are displayed in display unit.

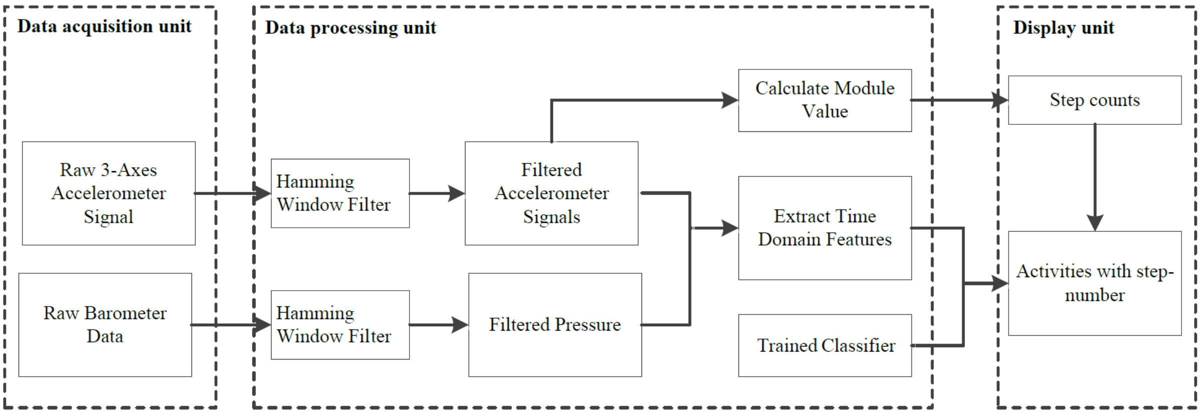

FIGURE 1. The scheme of the system

2.1. **Data collection.** Large amounts of labeled data are essential to train the prediction model for activity recognition. So we created an Android application for recording raw pressure data and triaxial acceleration data. The accelerometer and barometer work in SENSOR-DELAY-GAME mode, and the raw data are recorded every 20ms. We then enlisted the help of 21 volunteer subjects (15 men and 6 women) to carry the smart phones while performing a specific set of activities. The device for collecting data is a SAMSUNG N7508v integrated with an MPU6500 acceleration sensor and a BMP180 barometer. These subjects carried the Android phone in their front pants leg pockets and were asked to perform each activity 60s for three times and save data. These data were named after the subjects' name and the activities they performed.

2.2. **Pre-processing.** The selection of an appropriate window size is important, and different values can be set for it. In principle, the larger the window size is, the more complex activities can be distinguished. We selected a window of two seconds based on previous studies [8-12], since it was shown that a window size of two seconds was an effective and sufficient value for a reasonable activity recognition performance. The pre-processing of the raw signal contains segmentation and filtering. Each segment is a window-size of 2 seconds with 100 data. Since the raw data contains system noise and human body jitter noise, we processed data using Gaussian filtering methods. After the Gaussian filter process, the raw data curve becomes smoother with smaller burr.

2.3. **Features extracted from triaxial acceleration.** Common time domain and frequency domain features extracted from the triaxial acceleration data are mean, max, min, standard deviation, variance correlation between axes, skewness, integration, energy, entropy, and time between peak, etc. Time domain features are generally of low computational amount; on the contrary, frequency domain features based on fast Fourier transform are complex.

Standard deviation, skewness, interquartile range, correlation and M4 (intermediate variable of Hjorth parameters) are a set of efficient features to distinguish these activities [5,6,9,10]. The features are described as below.

(1) Standard deviation: Standard deviation is the square root of variance.

$$Std = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(a_i - a)^2} \tag{1}$$

(2) Skewness : Skewness is the skew direction and extent.

$$Skew = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{a_i - a}{Std}\right)^3 \tag{2}$$

(3) Interquartile range (IQR): Interquartile range reflects the degree of variation. It is the difference between the third quartile Q_3 and the first one Q_1 after the data was sorted by ascending counts. The equation is defined as:

$$IQR = Q_3 - Q_1 \tag{3}$$

(4) Correlation: Correlation is the ratio of the covariance and the product of the standard deviations. The equation is defined as:

$$Corr = \frac{\operatorname{cov}(x, y)}{\sigma_x \sigma_y} \tag{4}$$

$\operatorname{cov}(x, y)$ stands for covariance, and σ_x and σ_y stand for deviations.

$$\operatorname{cov}(x, y) = \sum_{i=1}^{N}(x_i - x)(y_i - y)/(N-1) \tag{5}$$

By comparing the difference degree of all features extracted from accelerometer data of three axes when performing different activities, 8 features are selected. They are the standard deviation from each of the 3 axes, the skewness, IQR of y-axis and z-axis and the correlation between y-axis and z-axis acceleration.

2.4. **Features extracted from pressure.** We found that the pressure data showed pretty increase tendency when ascending stairs, and decrease when descending stairs. In addition, fluctuation of downstairs data is much stronger than that of upstairs data. The problem of confusion between upstairs and downstairs could be solved well if some features which can reflect these tendencies were introduced. Two features we extracted from barometer data are standard deviation and gradient. Standard deviation reflects signal's stability, and gradient stands for direction and degree of slope.

Gradient was calculated using the following formula:

$$Gradient = \Delta x/\Delta y \tag{6}$$

where Δx is the window length, and Δy is the difference between the last pressure value and first pressure value of the window.

Calculations show that the gradient of downstairs ranges from $-1.5*10^{-3}$ to $-0.5*10^{-3}$, and oppositely the gradient of upstairs varies between $0.3 * 10^{-3}$ and $1.4 * 10^{-3}$. The standard deviation of downstairs ranges from $2.6 * 10^{-2}$ to $4 * 10^{-2}$, and the gradient of upstairs ranges from $2.5 * 10^{-2}$ to $5.4 * 10^{-2}$. Figure 2 represents these five activities

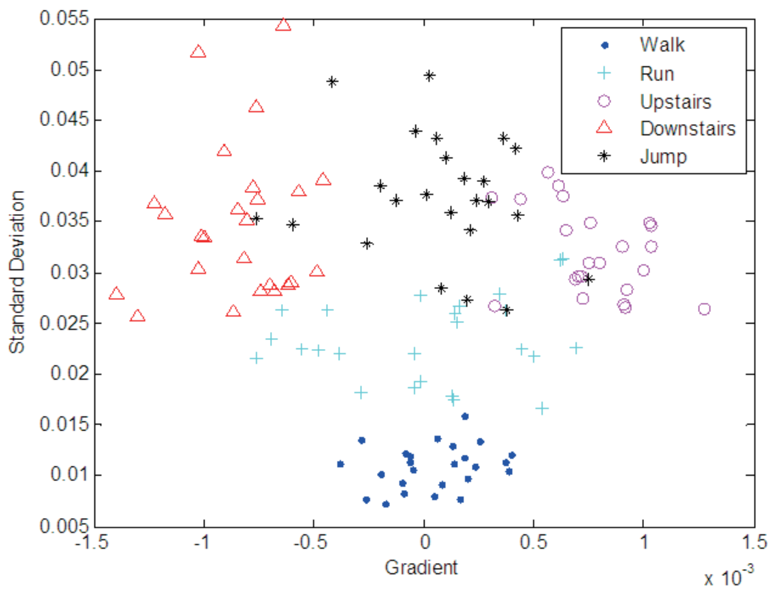

FIGURE 2. 2D feature space of five human motions

in 2D space. Each activity is represented by 25 data points which are sets of standard deviation and gradient. From Figure 2, we verify that points of upstairs and downstairs are obviously distinctive.

3. **Experimental Setup.** The classifier we used is feed forward neural network. ANN is widely adopted by many researchers in human activity recognition research [5-7,12]. Two models were trained to verify the validity of barometer off-line, the first was trained with 8 feathers extracted from 3-axes accelerometer, and the other was trained with all 10 feathers. To design the ANN, we experimented varying the number of hidden layer and the neurons number of hidden layers to get the best network architecture. The structure of the first feed forward artificial neural networks classifier consists of an input layer with 8 neurons, one hidden layer with 6 neurons and an output layer with 5 neurons. Another has 10 inputs, two hidden layers (the first has 8 neurons and the second has 7 neurons).

Then we build an Android application to recognize activities and count step numbers from the continuous data stream provided by the phone and display the name of the recognized activities with steps. We conducted a group contrast experiment on the two models in which 8 testers (did not join in data collection) were asked to perform certain steps of each activity and then conducted a sequence of continuous actions.

4. **Results and Discussion.** In this experiment, each tester completes a set of activities: walks and runs 200 steps, climbs up and down 50 stairs (including turning at stair corners), and jumps 30 times twice carrying respectively the two applications. The results for activity recognition experiment are presented in Table 1 and Table 2.

TABLE 1. Recognition result of single accelerometer

Experiment 1		Recognition Result						
Activity	Step	Total	Walk	Run	Upstairs	Downstairs	Jump	Accuracy
Walk	1600	1634	**1295**	69	153	117	0	**79.2**
Run	1600	1590	63	**1354**	63	99	6	**84.6**
Upstairs	400	379	34	15	**265**	65	0	**66.3**
Downstairs	400	404	19	31	69	**280**	5	**69.3**
Jump	240	241	0	0	0	0	**241**	**99.6**

Table 2. Recognition result of accelerometer and barometer

Experiment 2		Recognition Result						
Activity	Step	Total	Walk	Run	Upstairs	Downstairs	Jump	Accuracy
Walk	1600	1610	**1526**	44	17	13	0	**94.8**
Run	1600	1621	18	**1593**	2	6	2	**98.3**
Upstairs	400	387	15	4	**360**	8	0	**90.0**
Downstairs	400	392	3	10	6	**373**	0	**93.2**
Jump	240	240	0	0	0	0	**240**	**100**

Table 1 demonstrates that the ANN classifier which was trained with 8 feathers extracted from accelerometer data can achieve accuracy of above 80% in recognizing walking, and running, but the accuracy was down to 66.3% and 69.3% when identifying upstairs and downstairs. From Table 2 we can see that the classifier trained with 10 feathers extracted from accelerometer and barometer data performs much better in identifying these two stair climbing activities, and accuracy of these two activities was improved by about 23%; meanwhile, accuracy of other activities also got improved.

In the previous study, we sampled data at 50HZ, but it is necessary to find an appropriate frequency to reduce the power consumption of the mobile phone. So we ran a follow-up experiment. Figure 3 shows the general accuracy at different sampling frequency.

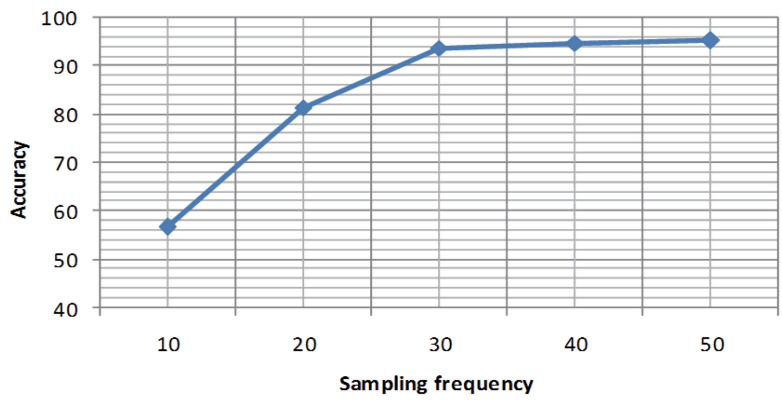

Figure 3. General recognition accuracy at different sampling frequencies

From Figure 3, we can see that the accuracy improves significantly when the frequency is less than 30, but barely increases when the frequency exceeds 30HZ. The result suggests that 30HZ is a much more appropriate sampling frequency.

5. **Conclusion.** This paper implements a real time and high accuracy human activity recognition algorithm based on smartphone accelerometer and barometer. The problem of confusing about upstairs and downstairs is well handled through introducing barometer. Contrast test showed that this method enhances the precision of upstairs and downstairs about 23%. Although, the recognition accuracy on the device is excellent, there are still some remaining issues. For example, in this work, the phone was in the pant pockets. In the future we will search a position – independent algorithm.

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