Recognition of User Activity for User Interface on a Mobile Device

Jonghun Baek
Dept. of Information and Communication
Kyungpook National University, Daegu, South Korea

Sang Tae Kim
School of Electrical Engineering and Computer Science
Kyungpook National University, Daegu, South Korea

Hyun Deok Kim
School of Electrical Engineering and Computer Science
Kyungpook National University, Daegu, South Korea

Jae-Soo Cho
School of Internet-Media Engineering
Korea University of Technology and Education, Cheonan, South Korea

Byoung-Ju Yun
School of Electrical Engineering and Computer Science
Kyungpook National University, Daegu, South Korea

E-mail: afqb@korea.com

Abstract

This paper presents a novel user interface that recognizes a user physical activity to supplement the lacking user interface of mobile devices. The interfaces of mobile applications are often un-natural due to limited resources and miniaturized input/output controls. In particular, users may encounter such problem in applications like eLearning. Therefore, we developed novel user interaction to complement the poor user interface of mobile devices when a student studies on it through the network.

1. Introduction

Advances in mobile computing and MEMS (Micro-Electro-Mechanical Systems) enable us to embed various sensors into handheld device such as cellular phones, PDAs (Personal Digital Assistants), PMP (Portable Media Player), and other portable devices. Therefore, contextual information can be captured through various sensors and recognition technologies. Specifically, an accelerometer can be easily embedded in a handheld device because an accelerometer has advantages such as being lightweight, small, and inexpensive. For this reason an accelerometer is one of the most widely used sensors in diverse areas, such as counting steps [1], medical engineering [2], novel user interface [3], and context awareness computing [4]. Many new applications for an accelerometer are now being considered by handheld device designers, and in fact handheld device models with an accelerometer are

Proceedings of the 24th South East Asia Regional Computer Conference, November 18-19, 2007, Bangkok, Thailand

available in the market. A handheld device, though its computing power is increasing, provides a limited computing environment when compared with a PC or an embedded system with a digital signal processor. In addition, a handheld device cannot dedicate its full computing power to auxiliary applications when its primary role is a communications device. In particular, an accelerometer application to estimate user activity estimation, which should run all the time, cannot demand too much CPU time. This is not only a matter of saving computing power but also a matter of preserving the limited battery power in a handheld device. Therefore, it is beneficial to develop a light-weight signal processing algorithm in order to estimate user's activity.

Many research groups have tried to estimate a user's activity as context information. Most studies use a signal accelerometer attached to the specific part of a user's body (e.g., waist, wrist, thigh, ankle, and spine) or multiple accelerometers [5]-[10]. This might, however, make it difficult to estimate the user's activity as well as inconveniencing a user in real life, because an accelerometer is fixed on part of the body [11]. In contrast, this paper attempts to minimize inconveniencing the user and to create a more practical, real life, implementation. An accelerometer was embedded in a handheld device and the various positions in which it can be carried by a user in their daily life: front pocket, hip pocket, shirt pocket, backpack, waist, handhold, and so on, were considered. In this case, the gravity acceleration component of an accelerometer's signal varies with the handheld's position and orientation and thus the user activity cannot be easily estimated. In an effort to design a light-weight and effective signal processing method for eliminating the gravity acceleration, we found that a second-order Butterworth high-pass filter (SHPF) was appropriate and efficiently estimated the user activity in various positions by using it. A series of experiment for testing the effectiveness of the proposed method have been performed and the results are presented.

In this paper, the aim is to implement the accelerometer application such as an intelligent multimedia control interface (e.g., static: audio/video, walking: audio, and running: pause) for a handheld device. Such the accelerometer application can be used in ubiquitous learning environments that provide education information at the right time by estimating activity of a user (student) who uses a handheld device. We, therefore, try to estimate if the user is in a static, walking, or running states.

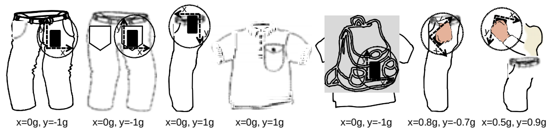


Fig. 1. Data collection protocol: (a) front pocket, (b) hip pocket, (c) waist, (d) shirt pocket, (e) backpack, (f) handhold in the standing and walking, running, respectively.

2. Data collection protocol

Various positions and orientations of an accelerometer are shown in Fig. 1. A different initial orientation of the accelerometer in each position was used to assess the usability of the SHPF for estimating the user activity, regardless of the orientation of the accelerometer or individual's characteristics. The training data set is collected from a single run of accelerometer data, which is a two-dimensional time series collected for about 1 minute from 2 subjects (2 males, age 25 to 34) at a sampling rate of 100 samples/s from the accelerometer when it is in three activities, such as standing, walking, and running, of a user at the various positions of an accelerometer.

Fig. 1 shows the initial directions of an accelerometer at the various positions of a handheld device in three activities of a user. The numbers in Fig. 1 are the average of the output signal for X- and Y-axis of the accelerometer measured during 1 minute for each orientation of an accelerometer in three activities of a user.

3. Acceleration time-series normalization

The existing method for estimating a user's activity is as follows: a feature extractor calculates a set of statistics of the data, which in turn forms a feature vector to be input to a classifier. The output of the classifier is one of the labeled classes, as shown in Fig. 2.

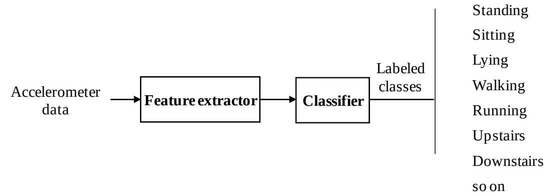
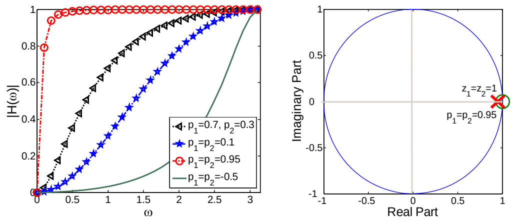


Fig. 2. Traditional signal processing steps for estimating a user activity.

The selection of good features from time series data is a fundamental step in statistical pattern recognition and is a very important task, because if the selected features are extracted based on individual's characteristics and individual's specific situation, the addition of a new person would necessitate more training by designing a new model or by extracting a new feature. In this study, the orientations of an accelerometer are different from each other in various positions of an accelerometer and an individual's characteristics such as body, clothe, and bag. In addition, the orientation of an accelerometer is continuously changing while walking and running. For these reasons, the gravity acceleration component of the accelerometer's signal is also changing and we cannot apply it to the same feature in all positions and orientations of a handheld device. In order to minimize these effects, the acceleration time-series is normalized by the SHPF.

An accelerometer signal, a, can be written as, $a = a_g + a_m$, where, a_g and a_m are the gravity and motion acceleration components, respectively. In the dynamic states, we define gravity acceleration, which is a low-frequency signal, as noise (DC signal) because gravity acceleration is not the same in all positions and orientations of a handheld device. In other words, to classify the user's activity at the various positions of a handheld device, we should implement a filter which completely eliminates the noise component and has no effect on the motion acceleration component.

To develop a light-weight signal processing algorithm for estimating user activity on a handheld device, we used a SHPF and investigated its frequency characteristics. Fig. 3a shows the frequency response of the SHPF, and Fig. 3b shows the pole-zero plot in the z-plane. We observed the frequency response by moving the poles. The frequency response curve had its peak value at a specific frequency component when the pole vale was a complex number. If the pole value was a real number and the pole was moved to the left half plane in the z-plane, then the gain of the SHPF was decreased. For these reasons, the SHPF had an effect on the motion acceleration component and the noise was also not eliminated. However, when the pole was moved to right plane, the skirt characteristic of the SHPF was better and had a maximum flat response at the pass band. Thus, the SHPF can eliminate only the gravity acceleration component (see Fig. 3). We selected $p_1 = p_2 = 0.95$ as the value for both the poles. These vales were selected through the experimentation for the threshold analyses to classify a user's activity. Fig. 3b shows all poles inside the unit circle and therefore, implies a stable filter.



(a) (b)

Fig. 3. Characteristics of the SHPF: (a) frequency response curve and (b) pole-zero plot on the z-plane.

The transfer function and gain (K) of the SHPF are given by:

$$H\left(z=e^{j\omega}\right)=K\frac{(z-z_1)(z-z_2)}{(z-p_1)(z-p_2)},\qquad K=\frac{(1+p_1)(1+p_2)}{4} \tag{1}$$

This transfer function is transformed the following recurrence equation:

$$a_f[n]=(p_1+p_2)a_f[n-1]-p_1p_2a_f[n-2] + K\left(a[n]-2a[n-1]+a[n-2]\right) \tag{2}$$

where, a is the raw signal of the accelerometer and a_f is the signal after filtering.

An experiment was conducted to assess the usability of the SHPF by equation (2). Fig. 4 contains the training data set and shows the experiments results for the representative 3 of 18 contexts (3 activity levels of a user × 6 position levels of a handheld device). In the Fig. 4, all the acceleration time-series data filtered by the SHPF were distributed at near zero g in all the contexts. Therefore, the SHPF eliminated only the gravity acceleration component and very nearly had no effect on the motion acceleration component in all the contexts. As a result, the acceleration time-series was normalized by the SHPF, and the three activities of a user can be classified by their handheld device.

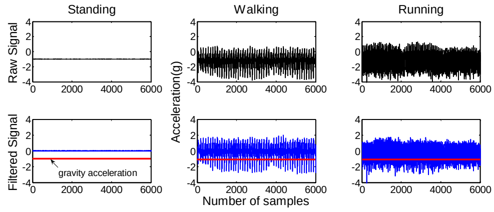


Fig. 4. Raw signal and filtered signal for Y-axis of the accelerometer in the front pocket.

4. User activity estimation

Fig. 5 shows the proposed algorithm in order to estimate a user's activity in various contexts. We investigated the parameters, such as the estimation time and overlapping proportion of acceleration time-series data for the window lengths, for classifying the activity using the training data set. All acceleration features were computed on windows of 100, 200, 300, 400, and 500 samples. The windows corresponded to 1, 2, 3, 4, and 5 seconds, respectively. As a result of the experiments, the performance of the classification was found to be relatively insensitive to variations in time interval. For the overlapping proportion (0%, 25%, 50%, and 75%) at all estimation time, the non-overlapping was easier to classify, therefore, we selected the window size of 200 samples.

To find generic threshold values, a series of

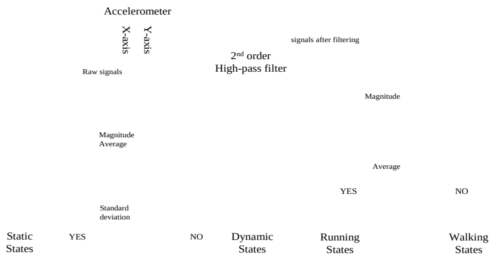


Fig. 5. Raw signal and filtered signal for Y-axis of the accelerometer in the front pocket.

threshold analyses tests were done by using the training data set. From the results of the threshold analyses, the thresholds for differentiating among static, walking and running activities were found, and annotated on the plot in Fig. 6.

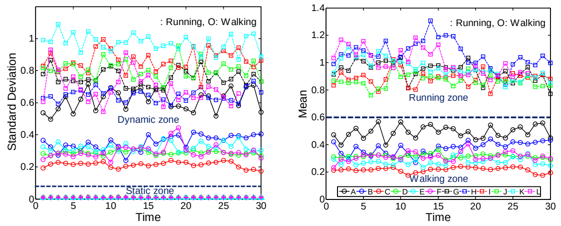


Fig. 6. Thresholds for classifying activity state: (a) distinguish static from dynamic states and (b) distinguish walking from running. Symbols in the figure: A and G for front pocket, B and H for hip pocket, C and I for shirt pocket, D and J for waist, E and K for backpack, F and L for handhold in walking and running, respectively.

Ten subjects participated in evaluating the classification accuracy of the generic threshold values found by the training data set. Two methods were used to collect the test data. The first method was using the data collection protocol. The second method was by freely carrying a handheld device in various positions and orientations. Each method had 5 test subjects (10 males, age 22 to 35). A subject conducted each activity in various contexts for 1 minute in a linear hallway.

The experimental results are summarized in Table 1. There are two numbers in parentheses; the first number is the estimated number of times by the proposed algorithm whereas the second number is actual number of times observed by the supervisor. The results were good enough to demonstrate the effectiveness of the SHPF to estimate user activity in various contexts.

5. Conclusion

To estimate a user's activity in real life, we attached an accelerometer to a handheld device and considered the various positions in which a user could carry it. In an effort to implement a user activity estimation system, we studied the method normalizing the acceleration time-series from an accelerometer and found that the SHPF was appropriate, and developed the user activity estimation system on the PDA which is usable in real life. The proposed algorithm, which is very light-weight, can estimate the user's activity regardless of the orientation of the accelerometer or different test user's and is shown to be as effective as a tried-and-true method.

TABLE I

Classification results: results from using data collection protocol and freely carrying a handheld device in various contexts.

Subject			Data Collection Protocol (%)					Freely Carrying (%)					Averag (%)
			A	B	C	D	E	F	G	H	I	J	
Activity	Static		100	100	100	100	100	100	100	100	100	100	100
	Walking	S1	100	100	100	100	100	100	100	100	100	100	100
		S2	100	100	100	100	100	100	100	100	100	100	100
		S3	100	100	100	100	100	100	100	100	100	100	100
		S4	100	100	100	100	100	100	100	100	100	100	100
		S5	100	100	100	100	100	100	100	100	100	100	100
		S6	100	100	100	100	100	100	100	100	100	100	100
	Running	S1	100	100	100	100	100	100	100	100	100	100	100
		S2	100	100	100	100	100	100	100	100	100	100	100
		S3	100	100	100	100	100	100	100	97	92	100	98.9
		S4	100	100	100	100	100	100	100	100	100	100	100
		S5	100	100	97	63	97	100	100	100	100	100	95.7
		S6	100	100	100	100	100	100	100	100	97	100	99.7

Symbols in the table: S1 for front pocket, S2 for hip pocket, S3 for shirt pocket, S4 for backpack, S6 for handhold, A ~ J for 10 subjects participated in this study, respectively.

Reference

[1] Lee, G., and Baek, J. (2006): "Counting steps using impact oscillator", *Electronics Letters*, 42, (17), pp. 960-961

[2] Bazzarelli, M., et al.. (2003): "A wearable computer for physiotherapeutic scoliosis treatment", *IEEE Transactions on Instrumentation and measurement*, 52, (1), pp. 126 – 129

[3] Baek, J., Jang, I., and Yun, B (2006): "Recognizing and analyzing of user's continuous action in mobile systems", *IEICE Transactions on Information and System*, E89-D, (12), pp. 2957 – 2963

[4] Siewiorek, D., et al. (2005): "SenSay: a context-aware mobile phone", *Proc. of IEEE Int. Sym. Wearable Computers*, pp. 248 – 249

[5] Parkka, J., et al. (2006) : "Activity classification using realistic data from wearable sensors", *IEEE Transactions on Information Technology in biomedicine*, 53, (1), pp. 133-139

[6] Bao, L., and Intille, S. S. (2004): "Activity recognition from user-annotated acceleration data", *Proc. Int. Conf. Pervasive Computing*, LNCS 3001, pp. 1-14

[7] Mantyjarvi, J., Himberg, J., and Seppanen, T. (2001): "Recognizing human motion with multiple acceleration sensors", *Proc. of the IEEE Int. Conf. Systems, Man, and Cybernetics*, 2, pp. 747-752

[8] Lee, S. W., and Mase, K (2002): "Activity and location recognition using wearable sensors", *IEEE Pervasive Computing*, 1, (3), pp. 24-32

[9] Baek, J., et al. (2004): "Accelerometer signal processing for user activity detection", *Knowledge-Based Intelligent Information and Engineering Systems*, LNAI 3215, pp. 610-617

[10] Farringdon, J., et al. (1999): "Wearable sensor badge and sensor jacket for context awareness", *Proc. Int. Sym. Wearable Computers*, pp. 107-113

[11] Yi, J. S., et al. (2005): "Context awareness via a single device-attached accelerometer during mobile computing", *Proc. MobileHCI* 2005, pp. 303-306