Accelerometer Signal Processing for User Activity Detection

Jonghun Baek[1], Geehyuk Lee[2], Wonbae Park[1], and Byoung-Ju Yun[1]

[1] Dept. of Information and Communications, Kyungpook National University, Daegu 702-701, South Korea
afqb@korea.com

[2] School of Engineering, Information and Communications University, Daejeon 305-714, South Korea

Abstract. Estimation of human motion states is important enabling technologies for realizing a pervasive computing environment. In this paper, an improved method for estimating human states from accelerometer data is introduced. Our method for estimating human motion state utilizes various statistics of accelerometer data, such as mean, standard variation, skewness, kurtosis, eccentricity, as features for classification, and is expected to be more robust than other existing methods that rely on only a few simple statistics. A series of experiments for testing the effectiveness of the proposed method has been performed, and its result is presented.

1 Introduction

The concept of a wearable computer was invented to offer the user a portable and personalized user interface to computing resources, such as multimedia services and home automation services [1][2]. One of the most distinguishing features of a wear-able computer is that it should not expect to be attended to but should attend to the user. As a result, any sensible wearable computer should have the skill for sensing the user's states and intentions. In this paper, we propose an improved method for probing the user's activities by using an accelerometer. Information on the user's activities can help a wearable computer provide a suitable service to the user at the right time. For instance, a PDA, which can provide a multimedia service, may pause and wait while the user is running [3]. In addition to such a purpose, the same method can be used to estimate energy expenditure [4], or, by sensor fusion with other data, for estimation of the location and the health condition of the user.

Some of the related researches are Randell & Muller [3], Farringdon, et al., [5], and Schmidt, et al., [6]. Most of the cases they used 1- or 2-axis accelerometers for sensing movements, average, RMS(Root Mean Square) and integrated values for feature values, and a neural network for classification. The accuracy of the activity estimators in their studies was around $85 \sim 90\%$, which may be good enough for some applications, but may not for others. Clearly there is

M.Gh. Negoita et al. (Eds.): KES 2004, LNAI 3215, pp. 610–617, 2004.

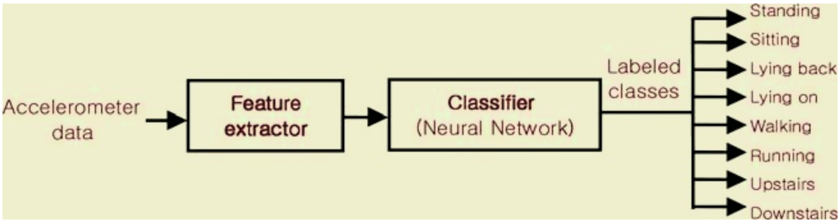

Fig. 1. Signal processing steps for motion state estimation

room for improvement in their results because they made use of the low-order statistics only. We began our research in the hope to enhance the accuracy of an activity detector by including higher order statistics of accelerometer signals than RMS and integrated values. We investigated the characteristics of the output from a two-axis accelerometer in different activity conditions by calculating a histogram, and determined which features to use for the classification of the states of the user. In the classification step, we used a feed-forward neural network that accepts a set of statistics of an accelerometer signal and outputs a motion state of the user. An accelerometer signal is thereby classified into one of the eight motion states; standing, sitting, lying-back, lying-on, walking, running, upstairs, and downstairs.

2 Signal Processing Steps

A single run of accelerometer data is a two-dimensional time series collected for about two seconds at the sampling rate of 15 samples/s from the outputs of a two-axis accelerometer (ADXL202EB) worn by the user on the waist. The X and Y axes of the accelerometer are pointing the upward and forward direction, respectively. As shown in Fig. 1, 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 shown in the figure.

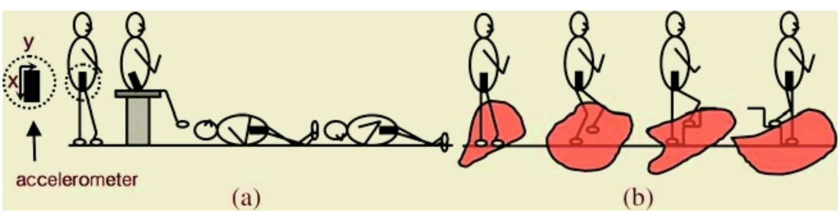

Fig. 2. (a) Orientation of the accelerometer in the four static states (standing, sitting, lying back, and lying on), and (b) typical distribution of accelerometer data in the four dynamic states (walking, running, upstairs, and downstairs)

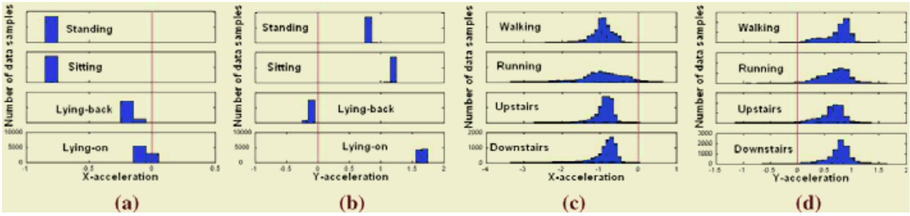

Fig. 3. The histograms of the accelerometer data; (a) X– and (b) Y–axis acceleration in the four static states, (c) X– and (d) Y–axis acceleration in the four dynamic states

3 Five Pairs of Features

As shown in Fig. 2a, the four static states can be easily distinguished because the orientation of an accelerometer is different. On the other hand, it is not easy to classify the dynamic states by using only the direction of the accelerometer because the orientations of the accelerometer are almost the same. As shown in Fig. 3, the histograms of acceleration data belonging to different classes exhibit unique characteristics in their shapes. From the observations, we selected the following statistics as signal features: mean, standard deviation, skewness, kurtosis, and eccentricity.

Mean and standard deviation are simple but the most useful features for distinguishing static states from dynamic states and also for the classification of static states from each other as shown in Fig. 4. The last two plots in Fig. 4 assert the difficulty of classifying dynamic states by using means and standard deviations alone.

Skewness is the degree of asymmetry in the distribution of acceleration data, and kurtosis is a measure that reflects how much a distribution is peaked at the center of a distribution.

As shown in Fig. 5, the skewness in X-acceleration can distinguish walking/running states from upstairs/downstairs states, the skewness in Y-acceleration can distinguish among walking/upstairs states from running state, and the kurtosis in X-acceleration can distinguish upstairs/downstairs states from walk-

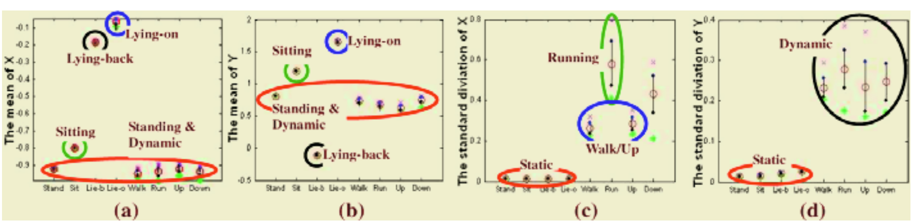

Fig. 4. Distribution of the mean for (a) X, (b) Y and standard deviation for (c) X, (d) Y

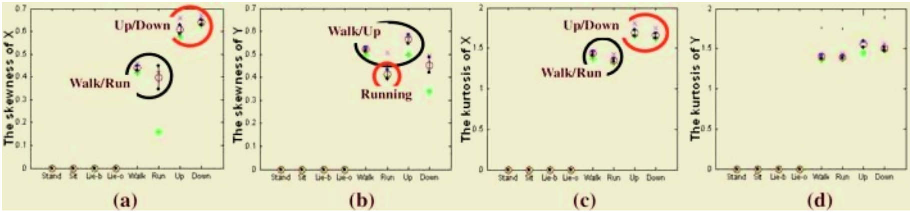

Fig. 5. Distribution of the skewness for (a) X, (b) Y and kurtosis for (c) X, (d) Y

ing/running states. It is not clear whether the kurtosis in Y-acceleration will be effective in classifying any states.

The statistics discussed so far are calculated for each of X and Y acceleration data independently while eccentricity is the feature of vector accelerations in the X-Y plane. As shown in Fig. 6, each of dynamic states exhibits different degree of eccentricity and also different major axes. As a means of expressing eccentricity mathematically, one can calculate the covariance matrix of X & Y acceleration data and use the two eigenvalues of the matrix, e_1 and e_2.

Eccentricity in the case of static states is not very meaningful because the trajectory of vector accelerations forms a point in the X-Y plane. As shown in Fig. 6b and c, eccentricity is expected to be effective in distinguishing walking/upstairs states from running states. Contrary to our expectation, eccentricity is not as useful as other simple statistics. We expect that eccentricity may be proved to be more useful in identifying walkers rather than distinguishing different states of the same user.

4 Multi-layer Perceptron Classifier

Figure 7 summarizes the expected role of the five pairs of features in the classification of acceleration signals into eight different classes. Although we used a neural network for classification in the current work, Fig. 7 suggests a possibility for a more efficient method for classification. For instance, a standard deviation

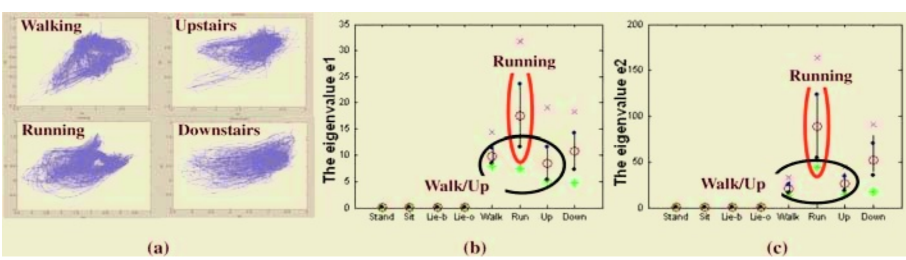

Fig. 6. (a) Trajectories of vector acceleration data for the four dynamic states, and the distribution of the eigenvalues: (b) e_1 and e_2

Table 1. Definitions of features: N is a total number of data samples, c_i is the center value for interval i of the histogram, n_i is the number of data samples in interval i, k is the number of intervals, x and y are the output values of the accelerometer, m_x and m_y are the means of X and Y acceleration, respectively

Features	Definitions
Mean	$m = \frac{1}{N}\sum_{i=1}^{k} c_i \cdot n_i$
Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{k}(c_i - m)^2 \cdot n_i}$
Skewness	$Skewness = \frac{1}{N\sigma^3}\sum_{i=1}^{k}(c_i - m)^3 \cdot n_i$
Kurtosis	$Kurtosis = \frac{1}{N\sigma^4}\sum_{i=1}^{k}(c_i - m)^4 \cdot n_i$
Eccentricity	Represented by the two eigenvalues of covariance matrix $\mathbf{C}$: $\mathbf{C} = \begin{bmatrix} \sum_{i=1}^{N}(x_i - m_x)^2 & \sum_{i=1}^{N}(x_i - m_x)(y_i - m_y) \\ \sum_{i=1}^{N}(x_i - m_x)(y_i - m_y) & \sum_{i=1}^{N}(y_i - m_y)^2 \end{bmatrix}$

is all that is needed to distinguish static states from dynamic states. If a standard deviation indicates the user is in a static state, there is no need to calculate any other statistics except a mean. This kind of reasoning leads naturally to a simple decision tree, which will be obviously more efficient but is less robust than the neural network classifier. Combination of a decision tree approach and a neural network approach may give a better solution but is not pursued in the current work.

The classifier is a multi-layer perceptron with 10 input nodes (5 pairs of features), a single hidden layer of 12 sigmoidal units, and an output layer of 8 sigmoidal units (8 activity states). The number of hidden layers and the number of units in the hidden layers were determined by a series of experiments. As usual, we had to consider trade-off between a training error and an overfitting problem in the determination of the number of units in the hidden layer.

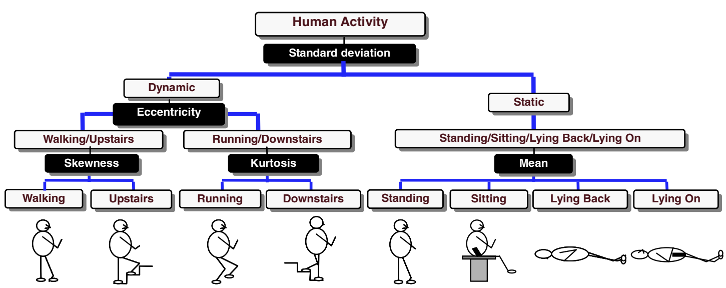

Fig. 7. Classification into the eight activity states by the five pairs of features

Table 2. Tabular representation of the input and output relationship of the MLP classifier: Features are the input of the classifier, and user motion states are the output of the classifier, respectively. Numbers are mean feature values of the training data in the respective motion states

MLP Classifier		User Motion States							
		Stand	Sit	Lying-back	Lying-on	Walk	Run	Upstairs	Downstairs
F	Mean X	-0.92	-0.8	-0.19	-0.06	-0.94	-0.94	-0.92	-0.94
e	Mean Y	0.8	1.2	-0.1	1.65	0.74	0.67	0.62	0.76
a	Standard Variation X	0.01	0.01	0.01	0.01	0.26	0.57	0.28	0.43
t	Standard Variation Y	0.01	0.01	0.02	0.02	0.23	0.28	0.24	0.24
u	Skewness X	0	0	0	0	0.44	0.4	0.61	0.64
r	Skewness Y	0	0	0	0	0.52	0.41	0.57	0.45
e	Kurtosis X	0	0	0	0	1.43	1.35	1.69	1.65
s	Kurtosis Y	0	0	0	0	1.4	1.39	1.56	1.5
	Eccentricity e1	0.02	0.03	0.05	0.05	9.84	17.2	8.65	10.8
	Eccentricity e2	0.24	0.1	0.28	0.19	20.4	85.7	26.5	51.7

5 Experimental Results

We restricted the goal of the proposed method to person-dependent estimation of activity, and gathered all the acceleration data from a single subject. We collected 30 runs of training data for each of the eight activity states, and 30 runs of testing data also for each of the eight activity states. Each run of data consists of a series of X and Y acceleration data recorded for two seconds. Training of the network with the training data was done without any problem (in 300 epochs), and the classification of the test data by so trained network was quite successful. As shown in Table 3a, the classification results were perfect; there was no misclassification.

Of course, we are aware of the limitation of the results. First of all, all the data for training and testing were from a single subject. Moreover, the data were collected on the same day and at the same place. In order to show the robustness of the proposed scheme, we had to collect more diverse data from different days and different places. As the minimal efforts to supplement the results, we collected another set of test data recently (about half a year after the first experiment) in a different building, and tested the same network that was used in the previous experiment (the network trained by the previous training data). The results are summarized in Table. 3b. The correct classification rate was 100% for static, walking, and running states, and dropped to 87% and to 93% for downstairs and upstairs, respectively. The classifier misclassified upstairs cases as running cases possibly because the subject was moving upstairs faster than before.

In spite of such misclassifications, the overall rate of correct classification was about 97.5%. This is a clear improvement on the previous results by other research groups; the accuracy of inference for motion states of the user using a 2-axis accelerometer was around 85 $\sim$ 90%.

Table 3. Classification results by the proposed scheme: (a) results from the first experiment and (b) results form the second experiment using the same network that was trained in the first experiment but using a new set of test data obtained in a different building about half an year later. Symbols in the table: S1 for standing, S2 for sitting, S3 for lying-back, S4 for lying-on, S5 for walking, S6 for running, S7 for upstairs, and S8 for downstairs

(a)		Classification							
		S1	S2	S3	S4	S5	S6	S7	S8
O	S1	30	0	0	0	0	0	0	0
r	S2	0	30	0	0	0	0	0	0
i	S3	0	0	30	0	0	0	0	0
g	S4	0	0	0	30	0	0	0	0
i	S5	0	0	0	0	30	0	0	0
n	S6	0	0	0	0	0	30	0	0
a	S7	0	0	0	0	0	0	30	0
l	S8	0	0	0	0	0	0	0	30

(b)		Classification							
		S1	S2	S3	S4	S5	S6	S7	S8
O	S1	30	0	0	0	0	0	0	0
r	S2	0	30	0	0	0	0	0	0
i	S3	0	0	30	0	0	0	0	0
g	S4	0	0	0	30	0	0	0	0
i	S5	0	0	0	0	30	0	0	0
n	S6	0	0	0	0	0	30	0	0
a	S7	0	0	0	0	2	0	28	0
l	S8	0	0	0	0	0	3	1	26

6 Conclusion

We designed a user activity estimator that can classify acceleration data into eight motion states; standing, sitting, lying back, lying on, walking, running, upstairs, and downstairs. In the first experiment, we used data collected from a single subject on the same day and at the same place, and the classification results were perfect. In the second experiment performed about a half year later in a different building, the results were quite satisfactory though not perfect. Although more extensive and objective comparison is still desired, the results indicated an improvement on the other schemes proposed by other research groups. We believe that the use of higher order statistics such as skewness and kurtosis must have been the main reason for the improved performance.

Obviously, the current scheme has a lot of limitations that need further endeavors. First of all, the current experiments were aimed at person-dependent activity detection. Second, the second experiment revealed the fact that the acceleration data even from the same person can vary over time and at varying places. Third, the ideal assumption that the user will wear an accelerometer on the waist is not realistic or practical in the real application settings. We are currently working on improving the proposed scheme to better deal with such problems, and at the same time on practical implementation of the same scheme for use with small computers with limited computing resources.

References

1. S. Lee, A ubiquitous IT revolution strategy of a foreign country, http://www.etimesi.com, KOREA IT NEWS, 2002
2. Wearable computer, http://korea.internet.com, Korea.internet.com, 2001

3. C. Randell and H. Muller, Context awareness by analyzing accelerometer data, The Metadata International Symposium on Wearable Computers, 2000, pp. 175–176
4. M. Sekine, T. Tamura, T. Fujimoto and Y. Fukui, Classification of walking pattern using acceleration waveform in elderly people, Annual EMBS International Conference, In Engineering in Medicine and Biology Society, 2000, pp. 1356–1359
5. J. Farringdon, A.J. Moore, N. Tilbury, J. Church and P.D. Biemond, Wearable sensor badge & sensor jacket for context awareness. In Proceedings of The Third Interantional Symposium on Wearable Computers, 1999, pp. 107–113
6. A. Schmidt, H.W. Gellersen and M. Beigi, A wearable context-awareness component. Proceedings of The Third International Symposium on Wearable Computers, 1999, pp. 176–177