Automated Recognition of Human Movement States using Body Acceleration Signals

Md. Rafiul Hassan[1], Rezaul K. Begg[2], Ahsan H. Khandoker[3] and Robert Stokes[2]

[1]Department of Computer Science and Software Engineering
The Unversity of Melbourne, VIC 3010, Australia.
[2]CARES, Victoria University, Melbourne 8001, Australia.
[3]Department of Electrical Engineering
The University of Melbourne, VIC 3010, Australia.

Abstract. Automated recognition of human activity states has many advantages, e.g., applications in the smart home environment for the monitoring of physical activity levels, detection of accidental falls in the older adults in the home environment or assessment of the recovery phase of patients living independently at home. In this paper, we describe an accelerometer-based system to recognize three activity states, e.g., steady state gait or walking, sitting and simulated sudden accidental falls. The recorded 3D movement accelerations of the trunk were processed using wavelets, and the features were extracted for recognition of movement states through the use of a fuzzy inference system. The system was trained and tested using 58 different data segments representing the three states. Cross-validation test results indicated an overall recognition accuracy by the machine classifier to be 89.7% with an ROC area of 0.83. The results suggest good potential for the system to be applied for various situations involving activity monitoring as well as gait and posture recognition. Further tests are required using various population groups.

1 Introduction

Falls in older people during locomotion is a major public health issue, as it leads to injuries, hospitalization and a significant cost to the community. In Australia, falls related injury costs have been estimated to be A$2.4 billions per annum [1]. Researchers around the globe are investigating this subject using various techniques. One methodology involves gait analysis in a laboratory environment to identify the significant changes in gait that occur due to ageing. Some of these changes may be important in the understanding of why people fall and this information may also help us to devise techniques for the prevention of falls. Automated monitoring of gait and posture of an individual within the home environment has recently received significant attention. The main advantage of such monitoring is to identify people at risk of falls and also to assess their overall well-being. For example, such technique could be used for checking the healthy life style of patients recovering at home or to monitor the health risk of an older person living independently at home. In order for a system to be effective in such applications, the system has to be robust enough to differenti-

Rafiul Hassan M., K. Begg R., H. Khandoker A. and Stokes R. (2006).
Automated Recognition of Human Movement States using Body Acceleration Signals.
In *Proceedings of the 2nd International Workshop on Biosignal Processing and Classification*, pages 135-143
DOI: 10.5220/0001225601350143

ate between the various events and activities such as walking, sitting, resting, or accidental falls. In this paper, we attempt to develop an automated system that could be applied to distinguish such sequences of events.

In the past, a number of studies have used accelerometer technology to automate the monitoring of daily activities of humans such as walking, sitting, standing, climbing stairs, walking velocity, etc, classified and recognized by analyzing the various frequency components of the acceleration signals [2-3]. To acquire the useful knowledge from the raw dataset, wavelet analysis was extensively used in some of studies [4-6].

To automate recognition of activities from either pre-processed raw data, various techniques and classifiers have been proposed in several studies, such as Fractal estimation [4], Neural Networks [3,7]. However, these techniques have their own merits and limitations, which depend on the dataset. In our previous work [8], we have successfully applied fuzzy rules to recognize gait changes due to trip-related falls in a laboratory environment. In this study, we apply fuzzy classifier to recognize the daily activities in a home environment.

2 Methods

In this study, data were collected from a simulated home environment. A triaxial accelerometer unit (giving acceleration information in horizontal, vertical and lateral positions) was placed on a subject's body to collect movement data. Acceleration data were pre-processed using wavelet technique and classified using a set of fuzzy rules.

2.1 Description of the System

A schematic diagram of the experimental setup is shown in Figure 1. This measurement system consisted of a Crossbow ±4G triaxial accelerometer unit, a National Instruments 6013 16-bit PCI analog to digital converter interface card, a Labview 7.0 data acquisition program [http://www.ni.com/labview/] and a personal computer. The accelerometer unit was attached to the upper body (trunk) of the subject.

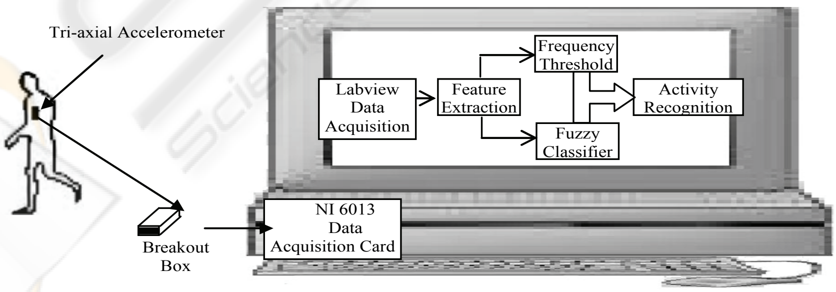

Fig. 1. Activity recognition of individuals in a smart home.

A breakout board was used to connect the accelerometer with the analog to digital converter card such that data could be acquired by the computer. The physical data was digitized using the 16-bit analogue-to-digital (A/D) converter and the LabView program captured and recorded the data signal onto the PC harddrive. In this study, data were collected and digitized at 100 Hz (100 bits/sec) sampling rate.

The experiments were set up in a room of size 3.5m by 3.5m Various items of furniture (chairs, tables, etc) were arranged to mimic an actual home environment. For the purpose of data collection, each subject entered into the room through the only door of the room and walked to the chair, sat on the chair, typed something using the PC keyboard, sometimes suddenly fell (simulated falling) onto the ground and consequently stood up. The experiments were performed on healthy subjects with no known gait problems.

2.2 Feature Extraction

2.2.1 Wavelets and Transformations

Wavelet functions as defined by [15], are constructed from translations and dilations of a single function called the "mother wavelet" $\psi(t)$.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), \qquad a,b \in \Re, a \neq 0 \tag{1}$$

where, the scaling parameter 'a' represents the degree of compression (its value is linked to the frequency of the wavelet), and the translation parameter 'b' represents time location of the wavelet. Higher wavelet frequencies are indicated using 'a' <1, whereas lower frequencies are represented when 'a'>1.

A discrete wavelet transformation of a signal $f(x)$ can be represented using the following equations

$$a_{2^J}(k) = \int f(x)\phi_{J,k}(x)dx \tag{2}$$

$$d_{2^j}(k) = \int f(x)\psi^*_{j,k}(x)dx \tag{3}$$

$$f(x) = \sum_k a_{2^J}(k)\phi_{J,k}(x) + \sum_{j=1}^{J}\sum_k d_{2^j}(k)\psi_{j,k}(x) \tag{4}$$

In equations (2),(3) and (4), 'j' stands for the dilation index, 'k' represents the index in time, 'J' is the depth of the decomposition level and '*' symbolizes complex conjugation [4]. The scaling function coefficient ϕ gives the average value of the signal over the given interval, which is used to calculate the approximation coefficients. The details coefficients obtained using equation 3 keeps the high frequency information while the approximation coefficients in each level contain the low frequency information.

The details coefficients were used in this study to obtain the frequency of a signal in a specific time period. To detect the frequency of a function representing a fixed length signal (length of signal was selected to be 1 second in this research), a wavelet decomposition followed by a translation of scale to frequency was computed. First, the signal was decomposed using wavelets of up to 'n' labels and then the energy of the details coefficients for each of the levels was obtained. The scale value (a_m) related to the maximum energy from the set of energy values was then taken into consideration to dig out the original frequency of the signal. Next step was to find out the frequency of a wavelet for the corresponding scale.

2.2.2 Translation from Scale to Frequency

As the frequencies in a signal predominate the scales chosen in wavelet decomposition, by analyzing the relationships between the scale and frequency the pseudo-frequency of the signal can be obtained. Following the methodology outlined in [16], the pseudo-frequency of a wavelet corresponding to a scale was computed. In doing so, first the center frequency F_c of the wavelet was computed by the following equation [10]:

$$F_a = \frac{F_c}{a.\Delta} \tag{5}$$

where, a = scale, Δ = sampling period,

F_c = center frequency of the wavelet in Hz.

F_a = pseudo-frequency corresponding to the scale a in Hz.

Using this method, the frequency calculated at scale 'a_m' became the pseudo-frequency of the signal. The next step in the recognition system was the inclusion of the fuzzy classifier for the identification of different activities (e.g., walking, sitting or simulated falls) of the subjects using the calculated frequency information of the acquired signals.

2.3 Fuzzy Classifier

Fuzzy logic provides a framework for modeling uncertainty, human way of thinking, reasoning and the perception process, and has been found to be very useful in expressing the nonlinear relationships among the inputs and outputs [11-13]. Conditional statements such as 'if-then' are the linguistic representation of fuzzy rules. Recently, we have applied fuzzy rules to classify gait patterns of healthy adults and adults with balance problems and the gait classification accuracy was found to be over 89% [8]. Here, we propose to apply fuzzy rules to classify movement states using features translated into the various wavelet coefficients.

With our present study, we don't have any prior knowledge about the rules relating to the subject's movement data. So defining rules for these dataset is a problem. However, there are techniques to identify a reasonable number of rules from a given dataset in order to establish a fuzzy system. For example, Chiu [14] has developed a technique based on subtractive clustering to extract rules. This technique has been tested in gait pattern classification for rule generation [8], and was also applied in this research .

2.4 Simulated falls event detection

In order to detect the occurrence of sudden/accidental falls, a signal of a fixed time interval (1 second) was considered. During such events, the movement frequency is expected to be momentarily high. To identify whether there was any instantaneous increase in frequency, the details coefficient D_{coeff} values for the signal were analyzed. As the wavelet transformation provides both the frequency and time information, any sudden increase in frequency can be monitored by studying the details coefficients.

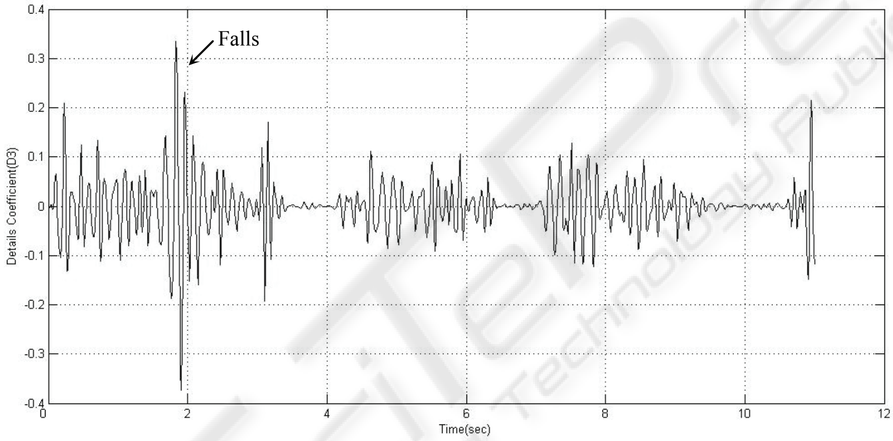

Fig. 2. The details coefficient values at label 3 to detect simulated falls.

Figure 2 shows a plot of the details coefficient and illustrates an abrupt increase in its magnitude during the falls event (~200ms). To automate the system's falls identification capability, a threshold θ was selected and the following threshold logic was applied:

for i=1 to length(signal)
    if $D_{coeff} > \theta$ *then*
        identify sudden fall
    end if
end for

In this study, details coefficient at level 3 (D3) was found to be the most suitable for the problem, especially in the vertical direction.

3 Results

We tested the proposed wavelet-fuzzy method using data related to the 60 state changes (change from one state to another state). As mentioned above, three types of body states were considered: sitting, walking and a sudden simulated fall on the ground). A change in state might take place according to one of the following sequences:

Walking, Sitting, Walking….
Walking, Sudden fall, Standing up and Walking again….
Sitting, Walking…

Figure 3(a-c) shows typical raw acceleration signal recorded during movement representing the various states in the horizontal anterior-posterior, medio-lateral and vertical axes respectively. Figure 4 plots the computed detailed coefficients using equation (3) for a mother coifflet wavelet (at levels 1 to 9) of the acceleration signal displayed in figure 3(a).

For this data, 'coifflet' wavelet was found to be suitable for calculating the pseudo-frequency of the acceleration signals as well as to identify the instantaneous increase in the frequency. During walking task, the major frequency component was close to 4.0 Hz while that for the sitting posture on a chair or on the ground was found to be ~0.14 Hz. There were slight variations in the frequencies along the three axes as can be seen in Figure 5. Therefore, information from more than one source is necessary for correct recognition, and in this case, all three acceleration signals from the tri-axial accelerometer were used for training and testing the fuzzy classifier.

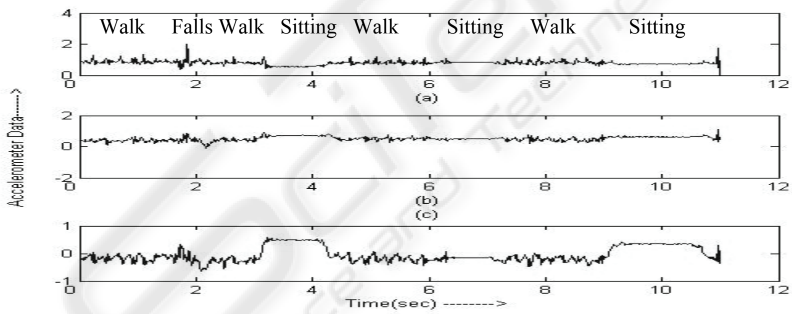

Fig. 3. The collected signal using tri-axial accelerometer a) Horizontal anterior-posterior (a_x), b) Medio-lateral (a_y) and c) vertical(a_z) signals.

Table 1. Classification accuracy of the model (sitting and walking).

Total Activity (Training & Testing)	Accurate classification	Classification accuracy	ROC area
58	52	89.7%	0.83

Table 2. Sensitivity and specificity of the model.

Activity Name	Total activity	Sensitivity	Specificity
Walking	26	0.917	0.833
Sitting	22		
Simulated Falls	10	All the fall events were recognized correctly with 100% accuracy	

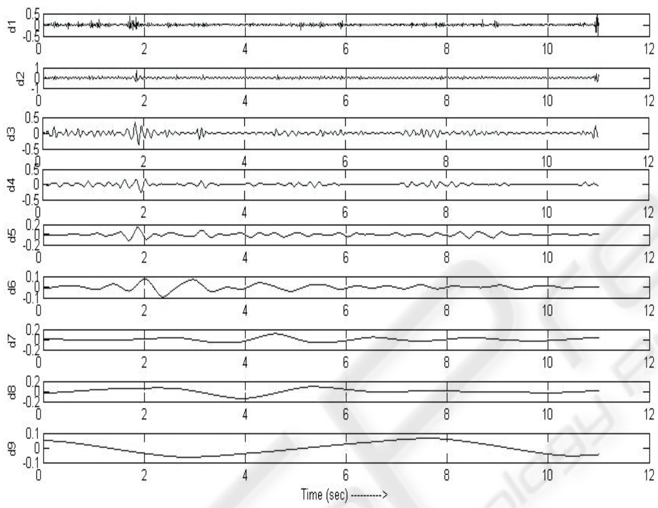

Fig. 4. The details coefficients (d1 to d9) at levels 1-9 of the signal in figure 3(a).

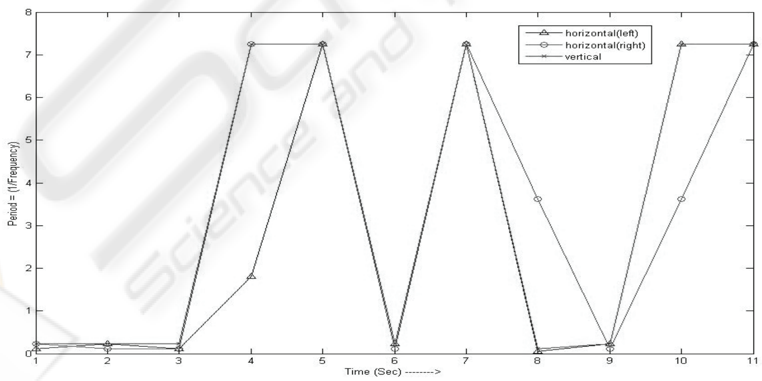

Fig. 5. The frequencies of segmented signal (into 1 second each) of the raw signals presented in figure 3.

Classifier's performance was tested using a four-fold cross validation test. Table 1 illustrates the overall result suggesting an overall accuracy of 89.7% in differentiating walking and sitting. This accuracy is also reflected in the ROC curves that recorded a high area (0.83) (see Figure 6). However, the recognition accuracy for all the simulated falls was found to be 100%.

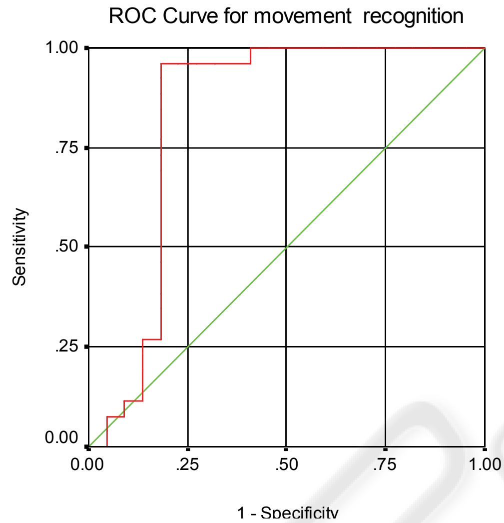

Fig. 6. ROC curve for identifying the two states: sitting and walking.

4 Discussions and Conclusion

Human movement behavior and the associated body positions change continually in reaction to the demands of the environment in which we move. Accordingly, the signal collected for a specific action of the subject was not the same all the time. It might be a difficult task to recognize the subject's current activity with only the application of simple thresholds. Classifying different activities with the application of sensor data on the same ground level (where the value of 'g' is constant) makes the problem more challenging. Most of the previous tasks related to activity identification and classification dealt with movements in different levels (e.g., walking downstairs i.e., 'moving with g' or walking upstairs i.e., 'moving against g') [4- 6]. In this study, as the value of 'g' remained fixed throughout the experiment, movement task differences were reflected only in the acceleration frequencies (see figure 5).

It was observed that signals collected from only one axis could identify some of the activities at times but not always. With the use of 3D accelerations the system was found to identify and recognize the subject's activities more robustly. Moreover, being random in characteristics, fuzzy systems were found particularly suitable for analyzing the in-depth information in the recorded signals. However, for detecting accidental falls event, a threshold level detector might be suitable due to its sudden increase in frequency level.

The benefits of the proposed model are: (1) the accelerometer can be attached to the garments without the complicated setup procedures, (2) activities can be identified on the same floor/level, (3) any accidental falls can be accurately identified.

This specific model could be applied in a smart home to monitor and discriminate any discrepancy in subject's behavior. In particular, this model could potentially help older adults who are living independently in their homes. The usage of garments for recording accelerometer signals, allows a non-intrusive monitoring technique of the subject's gait activities.

References

1. Fildes B. 1994. Injuries among older people. Melbourne: Collins Dove.
2. Fahrenberg, J., Foerster, F., Smeja, M., Muller, W. (1997), "Assessment of posture and motion by multichannel piezoresistive accelerometer recordings" , *Psychophysiology.* Vol : 34(5), pp. 607-612.
3. Mantyjarvi, J., Himberg, J., Seppanen, T. (2001), "Recognizing human motion with multiple acceleration sensors", *Proceedings of IEEE international conference on Systems, Man and Cybernetics*, pp. 747-752.
4. Sekine, M., Tamura, T., Akay, M., Fujimoto, T., Togawa, T., and Fukui, Y. (2002),"Discrimination of Walking Patterns Using Wavelet-Based Fractal Analysis", *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* Vol : 10 (3), pp. 188-196.
5. Cho, S. Y., Park, C.G., and Jee, G.I., (2002),"Measurement system of walking distance using low-cost accelerometers", *Proceedings of the 4th Asian Control Conference*, pp. 1799-1803.
6. M. N. Nyan, Tay, F.E.H., Seah, K.H.W., Sitoh, Y.Y. (2005),"Classification of gait patterns in the time-frequency domain", *Journal of Biomechanics*, (In press).
7. Aminian, K., Robert, P., Jequier, E., and Schutz, Y. (1995), "Estimation of Speed and incline of walking using neural network", *IEEE Transaction on Instrumentation and Measurement*, Vol : 44(3), pp 743-746 .
8. Hassan, M.R., Begg, R., and Taylor, S. (2005), "Fuzzy Logic-based recognition of gait changes due to trip-related falls", *Proceedings of the 2005 IEEE Annual Conference on Engineering in Medicine and Biology(EMBS'05).*
9. Debnath, L. (2001), *Wavelet Transforms & Their Applications*, Birkhäuser , Boston ,USA.
10. Misiti, M., Misiti, Y., Oppenheim, G., Poggi, J-M. (2005), *Wavelet Toolbox User's Guide-For use with Matlab,* The Mathworks Inc.
11. Meunier, B. B, Yager, R. R., and Zadeh, L. A. (Eds)(2000), *Uncertainty in Intelligent and Information Systems*, World Scientific Publishing Company, Singapore.
12. Pedrycz, W. (1995) , *Fuzzy Sets Engineering*, CRC Press.
13. Zadeh, L. A. (1965), *Fuzzy Sets, Information and Control*, Vol : 8, pp. 338-353.
14. Chiu. S.L.(1997), *Extracting Fuzzy Rules from Data for Function Approximation and Pattern Classification*, Chapter 9 in Fuzzy Information Engineering: A guided Tour of Applications (eds) D. Dubois, H. Prade, and R. Yager, John Wiley & Sons.
15. Morlet, J. , Aerens, G., Fourgeau, E., ans Giard, D. (1982) ,"Wave propagation and sampling theory, Part I: Complex signal land scattering in multilayer media", *Journal of Geophysics*, Vol : 47, pp. 203-221.
16. Abry, P. (1997), Ondelettes et turbulence. Multirésolutions,algorithmes de décomposition, invariance d'échelles, Diderot Editeur, Paris.