Comparison of Recognition Accuracy of ADL with Sensor Wearing Positions using 3-Axis Accelerometer

D. I. Shin[1], S. K. Joo[2] and S. J. Huh[2]
[1]Department of Biomedical Engineering, Asan Medical Center, Seoul, Korea
[2]Department of Biomedical Engineering, University of Ulsan College of Medicine, Seoul, Korea

Keywords: Accuracy, Activity, Daily Life, Sensor, Position, Accelerometer.

Abstract: The monitoring of single elderly is being more important due to rapid transition to aging society. There are many bio-signals to monitor the emergent state of elderly. In this paper we propose new criteria to classify daily life activities using accelerometer and pulse oximeter. We categorized activities with the motility of real action. The upper most criteria are normal and abnormal activity. The lower criteria are 'small or large movement', 'periodic or random movement', 'no movement or shock'. Then we derive some parameters to get thresholds to classify these activities according to our new criteria. The main parameters are entropy, energy and autocorrelation. Some experiments were carried out to determine classifying thresholds. Finally we got results of classified activities such as 'no movements', 'small movements', 'large movements', 'periodic movements' and 'falls'. We got nearly 100% of classifying result for falls and no movements. In this case of 'quasi-emergency state' our developing device investigates further status of elderly by measuring of heart rate and oxygen saturation (SpO_2) using pulse oximeter. Finally the device decides in emergency, it sends a short message to server and then connects to the u-Healthcare centre or emergency centre and one's family.

1 INTRODUCTION

According to the data from Statistics Korea, the aging index will increase rapidly from 9.5% (2006) to 14.3% (2018) and 20.8% (2026). With this trend, the number of single elderly increases too. Knowing the emergency status of these single elderly is a critical issue in the emergency monitoring system. So we have been developing a monitoring device, which can be easily worn on an elders' body. The wearing position is very important because it must be very convenient for the elderly. And in the case of an emergency, the reaction of elderly is also important for the decision whether he or she is serious. There were many researches for monitoring devices(Boo-Ho Yang, Sokwoo Rhee, 2000, P. Mendoza, P. Gonzalez, B. Villanueva, E. Haltiwanger, H. Nazeran, 2004, Giuseppe Anastasi, Marco Conti, Mario Di Francesco, Andrea Passarell, 2009, Francis E.H. Tay, D.G. Guo, L. Xu, M.N. Nyan, K.L. Yap, 2009, Prajakta Kulkarni, Yusuf Ozlurk, 2010, Amr Amin Hafez, Mohamed Amin Dessouky, Hani Fikri Ragai, 2011). In these researches, there are many considerations about monitoring devices and systems with respect to u-Healthcare Monitoring. After all, we conclude that the ideal wearing position is wrist for now. With the progress of technology, the device may be the shape of hearing aid in the future.

In this research, we classified the activity type of elderly in daily life. Recent researches classified the activity type with the real action such as walking, standing, sitting, lying etc.(Arunkumar Pennathur, Rohini Magham, Luis Rene Contreras, Winifred Dowling, 2003, A. Mannini, A.M. Sabatini, 2009, G.M. Lyons, K.M. Culhane, D. Hilton, P.A. Grace, D. Lyons, 2005, Marcia Finlayson, Trudy Mallinson, Vanessa M. Barbosa, 2005, Angela L. Jefferson, Robert H. Paul, Al Ozonoff, Ronald A. Cohen, 2006, A. Godfrey, A.K. Bourke, G.M. Ólaighin, P. van de Ven, J. Nelson, 2011). But in fact this kind of classification is not helpful for the decision of emergency status of an elderly. So we suggest new concept of classification criteria. We categorized activities with the motility of real action. The upper most criteria will be normal and abnormal activity. The lower criteria may be 'small or large movement', 'periodic or random movement', 'no movement or

Shin D., Joo S. and Huh S..
Comparison of Recognition Accuracy of ADL with Sensor Wearing Positions using 3-Axis Accelerometer.
DOI: 10.5220/0005279901800184
In *Proceedings of the International Conference on Biomedical Electronics and Devices* (BIODEVICES-2015), pages 180-184
ISBN: 978-989-758-071-0

shock'.

Once we classify the elderly activity to abnormal we can further investigate the accurate status with the reaction button or pulse oximeter, which will be adopted by our monitoring device. The clinical importance of oxygen saturation of blood (SpO_2) is mentioned on many articles (Barker SJ, Morgan S., 2004, Anna Letterstål, Fredrik Larsson, 2007, Gülendam Hakverdioğlu Yönt, Esra Akin Korhan, Leyla Khorshid, 2010, Elif Derya Ubeyli, Dean Cvetkovic, Irena Cosic, 2010)

If we can classify a person's status by normal or abnormal, we can make more concrete speculation in case of abnormal status. As a result, we may reduce processing resource, power and finally physical size of the sensor. The more compact size and reduced processing power will be more convenient in wearing it.

2 MATERIALS AND METHODS

2.1 System Overview

We extracted acceleration data and oxygen saturation data from our monitoring device in developing. Data was moved from the memory of monitoring device to PC via USB port. Sampling rate is 10ms/sample and converted by 12bits depth.

Fig. 1 shows the illustration of our monitoring device. Figure 2 illustrates our processing system. Personal computer (Pentium V) is used to process and analyse activities. The LabView™ software from National Instruments is used to acquire and display the acceleration data from monitoring device. The Matlab™ software is used to process and analyse the acceleration data.

Figure 1: The illustration of our monitoring device.

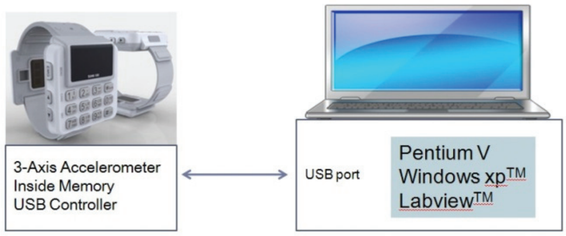

Figure 2: The overall processing system.

2.2 Activity Classification

In this research, we classified the activity type of elderly in daily life. Recent researches classified the activity type with the real action such as walking, standing, sitting, lying etc. But in fact this kind of classification is not helpful for the decision of emergency status of an elderly. So we suggest new concept of classification criteria. We categorized activities with the motility of real action. The upper most criteria will be normal and abnormal activity. The lower criteria may be 'small or large movement', 'periodic or random movement', 'no movement or shock'. Figure 3 shows the classification criteria of our new concept.

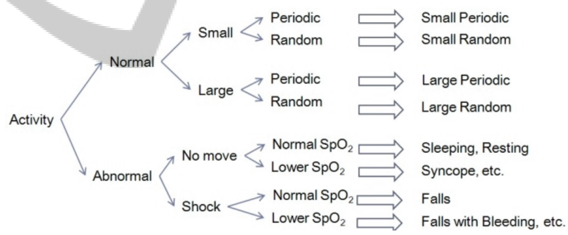

Figure 3: Classification criteria of activities.

The 3-axis acceleration data were pre-processed like below.

$$A_o = \mathrm{sqrt}(a_x^2 + a_y^2 + a_z^2) \quad (1)$$

$$A_{os} = \mathrm{LPF}(A_o) \quad (2)$$

A_o is root-mean-square of original 3-axis acceleration data and A_{os} is low pass filtered data with 5Hz cutoff frequency.

To classify activities, we calculate some parameters and define threshold of classification. First, the entropy is measured like below,

$$\mathrm{Entropy} = \nabla a / \nabla t \quad (3)$$

Entropy is the ratio of acceleration change per unit time. And the energy is defined like this,

$$\mathrm{Energy} = \sum a \quad (4)$$

It can be interpreted as speed. The autocorrelation is calculated for the grade of periodicity.

$$\text{Autocorrelation} = \text{Periodicity (a)} \quad (5)$$

2.2.1 Normal Activity Classification

Normal activity is classified with two categories. The first is the magnitude of movements. This is judged by the threshold of entropy and energy. The judge function is described like this.

$$J_{mov} = a{*}\text{Entropy} + b{*}\text{Energy} \quad (6)$$

The second category is periodicity and judge function for this is,

$$J_{per} = c{*}\text{Entropy} + d{*}\text{Autocorrelation} \quad (7)$$

2.2.2 Abnormal Activity Classification

Abnormal state is categorized into two classes. One is 'no movements', the other is 'falls'. When in 'no movements' there might be two situation which are "in sleep" and "in emergency". In these situations our monitoring device will check heart rate and O2 saturation in blood using pulse oximeter.

To determine whether falls or not, we use the entropy for the threshold function.

$$J_{fall} = e{*}\text{Entropy} \quad (8)$$

To determine whether no movements or not, we use the entropy and the energy for the threshold function.

$$J_{nmov} = f{*}\text{Entropy} + g{*}\text{Energy} \quad (9)$$

2.3 Classifying Algorithm

Figure 4 shows the flowchart of activity classifying algorithm. Once we start the algorithm, the accelerometer in the device is powered on. The acceleration data is acquired with the speed of 100 samples/sec. And then the acceleration data is low-pass filtered with the 5Hz cut-off frequency. We call these procedures 'Pre-processing' and equation (1) and (2) show these procedures. Next, we calculate parameters on equations (3) to (5). Using the entropy and energy we can calculate the parameter J_{nmov}. If J_{nmov} is less than the threshold T_{nmov}, we can judge there are no movements such as resting or sleeping state. If J_{nmov} is great than the threshold T_{nmov}, we can judge that there are some movements that include some kind of falls.

The next stage we investigate the parameter J_{fall} according to the equation (8). If this is greater than T_{fall}, a kind of fall must have happened. Once the state is classified to normal movement, we can classify to lower categories as shown in figure 3.

In real world, situations are more complex and ambiguous. So, the classification algorithm is difficult. But as we refine the algorithm more accurately, the result will be more realistic.

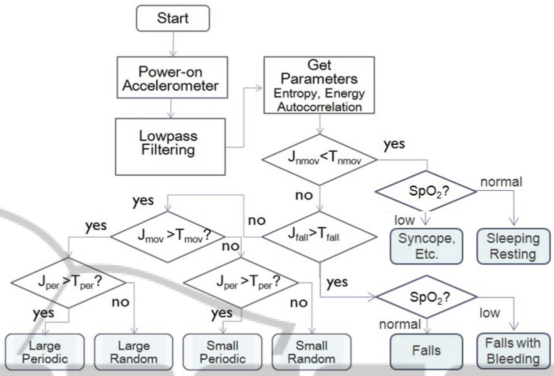

Figure 4: Flowchart of activity classifying algorithm.

3 RESULT

Figure 5 shows the low-pass filtered acceleration data. It includes various activities. Small movements

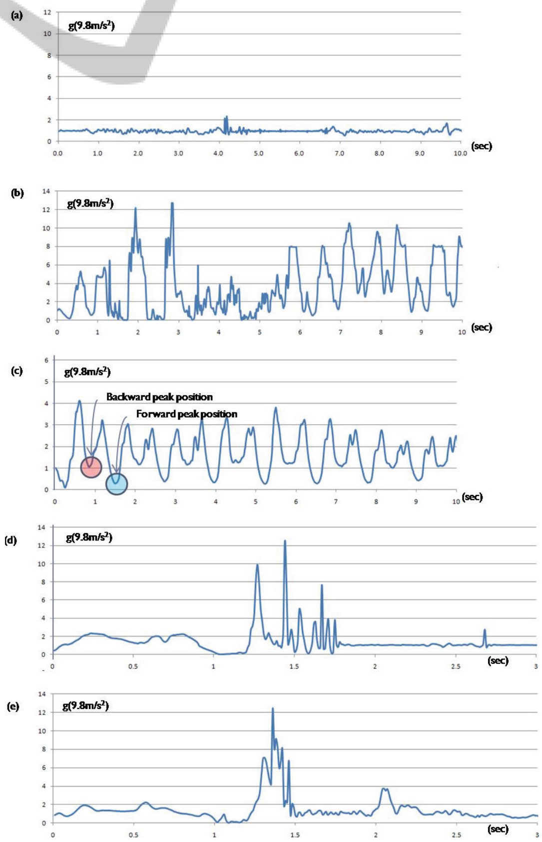

Figure 5: Acceleration data from various activities.

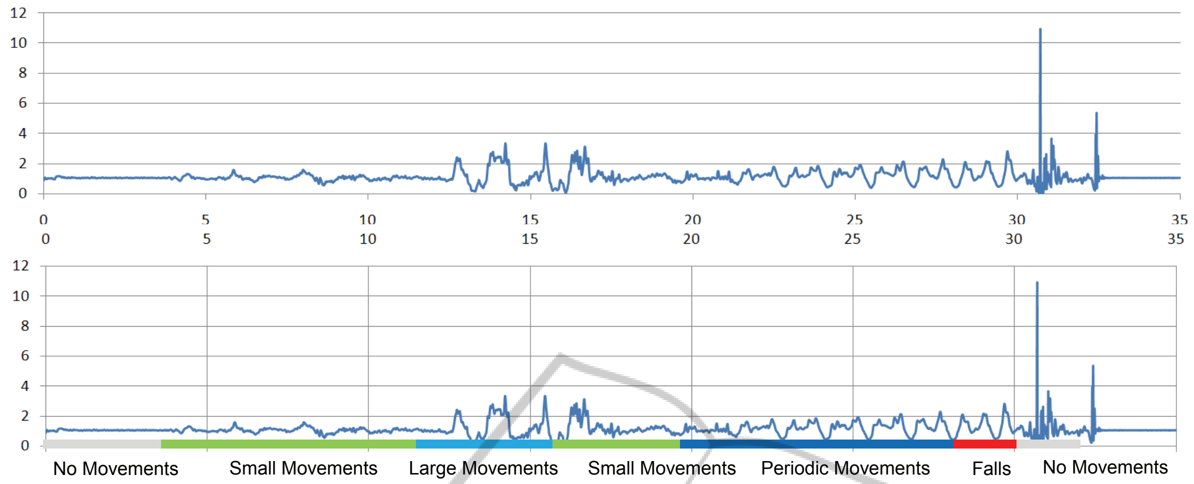

Figure 6: Classified results for successive various activities.

can be showed in Figure 5(a). These movements include gripping a pen, writing, moving a paper, scratching one's skin, removing glasses etc. In small movements, it shows small accelerations under 2g ($1g=9.8m/s^2$). On the other hand, Figure 5(b) shows large movements such as stretching, doing gymnastics, standing up suddenly etc. It shows large acceleration of 5g or more. Sometimes it exceeds 10g but its slope is rather than gradual. Figure 5(c) shows a typical periodic movement which is walking. There are two levels of valley, the upper valley represents backward peak position of hand and the lower valley represents forward peak position of hand.

Figure 6 shows classified results for successive various activities according to our algorithm. The color bar denotes the class of activity. Data from monitoring device is transmitted to personal computer and are processed with Labview™ and Matlab™ software to verify our algorithm.

4 CONCLUSIONS

Knowing the emergency status of these single elderly is a critical issue in the emergency monitoring system. So we have been developing a monitoring device, which can be easily worn on an elders' body. The wearing position is very important because it must be very convenient for the elderly. And in the case of emergency, the reaction of the elderly is also important for the decision whether he or she is serious. After all, we conclude that the ideal wearing position is wrist for now. With the progress of technology, the device may be the shape of hearing aid in the future.

In this research, we classified the activity type of an elderly in daily life. Recent researches classified the activity type with the real action such as walking, standing, sitting, lying etc. But actually this kind of classification is not helpful for the decision of emergency status of an elderly. So we suggest new concept of classification criteria. We categorized activities with the motility of real action. The upper most criteria will be normal and abnormal activity. The lower criteria may be 'small or large movement', 'periodic or random movement', 'no movement or shock'. Once we classify the elders' activity to abnormal we further investigate the accurate status with the reaction button or pulse oximeter, which is already adopted, in our monitoring device. If we can classify a person's status to normal or abnormal, we can make more concrete speculation in case of abnormal status. As a result, we may reduce processing resource, power and finally physical size of the sensor. The more compact size and reduced processing power will be more convenient in wearing it.

REFERENCES

Boo-Ho Yang, Sokwoo Rhee, *Development of the ring sensor for healthcare automation, Robotics and Autonomous Systems* 30 (2000) 273–281

P. Mendoza, P. Gonzalez, B. Villanueva, E. Haltiwanger, H. Nazeran, A Web-based Vital Sign Telemonitor and Recorder for Telemedicine Applications, *in Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA*, September 1-5, 2004, pp. 2196-2199.

Giuseppe Anastasi, Marco Conti, Mario Di Francesco, Andrea Passarell, Energy conservation in wireless sensor networks: A survey, *Ad Hoc Networks 7 (2009)* 537-568

Francis E.H. Tay, D.G. Guo, L. Xu, M.N. Nyan, K.L. Yap, MEMSWear-biomonitoring system for remote vital signs monitoring, Journal of the Franklin Institute 346 (2009) 531–542

Prajakta Kulkarni, Yusuf Ozlurk, mPHASiS: Mobile patient healthcare and sensor information system, *Journal of Network and Computer Applications,* 2010

Amr Amin Hafez, Mohamed Amin Dessouky, Hani Fikri Ragai, Design of a low-power ZigBee receiver front-end for wireless sensors, Micro Electronics Journal 40 (2011) 1561-1568

Arunkumar Pennathur, Rohini Magham, Luis Rene Contreras, Winifred Dowling, Daily living activities in older adults:Part II—effect of age on physical activity patterns in older Mexican American adults, *International Journal of Industrial Ergonomics* 32 (2003) 405–418

G.M. Lyons, K.M. Culhane, D. Hilton, P.A. Grace, D. Lyons, A description of an accelerometer-based mobility monitoring technique, Medical Engineering & Physics 27 (2005) 497–504

Marcia Finlayson, Trudy Mallinson, Vanessa M. Barbosa, Activities of daily living (ADL) and instrumental activities of daily living (IADL) items were stable over time in a longitudinal study on aging, Journal of Clinical Epidemiology 58 (2005) 338–349

A. Mannini, A.M. Sabatini, Computational methods for the automatic classification of postures and movements from acceleration data, *Gait & Posture 30S (2009) S26–S74*

A. Godfrey, A.K. Bourke, G.M. Ólaighin, P. van de Ven, J. Nelson, Activity classification using a single chest mounted tri-axial accelerometer, Medical Engineering & Physics, in Press (2011)

Angela L. Jefferson, Robert H. Paul, Al Ozonoff, Ronald A. Cohen, Evaluating elements of executive functioning as predictors of instrumental activities of daily living (IADLs), Archives of Clinical Neuropsychology 21 (2006) 311–320

Thessa I.M. Hilgenkamp, Ruud van Wijck, Heleen M. Evenhuis, (Instrumental) activities of daily living in older adults with intellectual disabilities, Research in Developmental Disabilities 32 (2011) 1977–1987

Barker SJ, Morgan S., A Laboratory Comparison of the Newest “Motion-Resistant” Pulse Oximeters During Motion and Hypoxemia, *Anesthesia and Analgesia* 2004;98(55),S2:A6

Anna Letterstål, Fredrik Larsson, Assessment of vital signs on admission to short time emergency wards improves patient safety and cost-effectiveness, *Australasian Emergency Nursing Journal, Volume 10, Issue 4*, November 2007, Page 191

Gülendam Hakverdioğlu Yönt, Esra Akin Korhan, Leyla Khorshid, Comparison of oxygen saturation values and measurement times by pulse oximetry in various parts of the body, Applied Nursing Research, 2010

Elif Derya Ubeyli, Dean Cvetkovic, Irena Cosic, Analysis of human PPG, ECG and EEG signals by eigenvector methods, Digital Signal Processing 20 (2010) 956–963