Garment-based detection of falls and activities of daily living using 3-axis MEMS accelerometer

M. N. Nyan; 1Francis E. H. TAY; 2M. Manimaran; 1K. H. W. Seah

1Department of Mechanical Engineering, National University of Singapore

10 Kent Ridge Crescent, Singapore 119260. engp2492@nus.edu.sg

2Institute of Bioengineering and Nanotechnology

Abstract

This paper studied the detection of falls and activities of daily living (ADL) with two objectives: (1) minimum number of sensors for a broad range of activities and (2) maximize the comfort of the wearer for long term use. We used a garment to provide long term comfort for the wearer, with a 3-axis MEMS accelerometer on the shoulder position, as a wearable platform. ADL were detected in time-frequency domain and summation of absolute peak values of 3-D acceleration signals was used as feature in fall detection. 6 male and female subjects performed approximately five-hour long experiment. Sensitivity of 94.98% and specificity of 98.83% for altogether 1495 activities were achieved. Our garment-based detection system fulfilled the objective of providing the comfort of the wearer in long term monitoring of falls and ADL with high sensitivity. In fall detection, our device can summon medical assistances via SMS (Short Message Service). This detection system can raise fall alarm (fall SMS) automatically to individuals to get a shortened interval of the arrival of assistance.

Index terms: falls, activities of daily living, wavelet transform

1. Introduction

Physical activity is defined as any bodily movement produced by the contraction of skeletal muscle and is comprised of numerous diverse components that present a challenge in terms of accurate and reliable assessment of the activity of interest. In activity assessment, fall incidence detection is one of the major health care issues in the elderly because an undetected fall in an older person, especially for the elderly living in solitary lives, can result in a person lying conscious and uncomfortable for hours before being saved. The consequences of falls may lead to institutionalization, restricted activity, other minor injuries, fear of falling, or death. Therefore, prevention/detection of falls and minimizing the severity of fall-related injuries has been an important research area since two decades ago [1-3]. In
this context, monitoring of different movements and postures involved in the daily routine of older persons who are living alone may help to pave the way for identifying persons who have fallen or are at risk of falling. Such an ability may also allow a better assessment of activities of daily living (ADL) and the effects of numerous medical conditions and treatments [4], thus paving the way for planning interventions aimed at maintaining independence and enhancing safety of older persons.

The quantitative assessment of ADL in humans requires an objective and reliable technique to be used under free-living conditions. Several studies have been performed for activities of daily living (ADL) detection using different types of sensors and different detection algorithms [4-7]. However, more studies need to be conducted in view of the need for comfort in activity assessment of the elderly for long-term use. This paper studied the detection of falls and ADL with two objectives: (1) minimize the number of sensors for a broad range of activities and (2) maximize the comfort of the wearer for long-term use. We used a garment as a wearable platform to provide long-term comfort for the wearer. A MEMS technology-based triaxial accelerometer measuring in the lateral, antero-posterior and vertical directions was attached at the shoulder position of the garment. The activities included in our detection system are normal ADL and falls. Normal ADL includes level walking, sitting down, standing up, lying down, getting up, ascending stairs and descending stairs. Instead of detecting sitting down, standing up, and lying down static posture activities, sit-stand/stand-sit, and lie-sit/sit-lie posture transition activities are detected. Moreover, we implemented a new fall notification system to send fall alarms, without user intervention, not only to the health care center but also to individuals to get a shortened interval before the arrival of assistance.

2. Subjects and Materials

In view of the need for safety and comfort, a monitoring system, MEMS Wear as we called it, that can be worn on the body was developed that involved the attachment of MEMS sensors to a garment (Fig.1). In the experimental setup, MMA7260Q (±1.5g - 6g Triaxial Low-g Micromachined Accelerometer, 300mV/g) accelerometer was located on the shoulder location of the garment. Shoulder location was chosen to avoid the injury caused by the sensors during the severe incidents such as falls. The sensor’s sensitivity axes were arranged in lateral, vertical and antero-posterior directions. In detection of falls and activities, the acceleration signals sampled at 50 samples/second sampling rate were processed in the processing unit consisting of MCF5282 ColdFire® Microcontroller (32 bit, 80MHz, 512KB Internal Flash, 64KB Internal SRAM and 16MB external SDRAM), Bluetooth™ transmitter, and 7.6V battery power supply. The processing unit was located in the pocket of the garment. The information of the detected activities was sent to a display unit, Notebook™, through Bluetooth™ wireless communication. In our prototype, ten-meter data transmission range Bluetooth chips were used for less power consumption.

The experiments were performed on 6 male and female subjects (age ranged between 30 and 49 years, height between 152.5cm and 172.7cm, and weight between 49kg and 75kg). Two different experimental settings (Fig.2) were used for two different groups, i.e. group 1 at setting-a (Fig.2(a)) includes subject1, subject 4, subject 5, and subject 6 and group 2 setting-b (Fig.2(b)) includes subject 2 and subject 3. Each subject executed the approximately five-hour-long experiment. During the experiment, all subjects performed the predefined ADL of sit-stand/stand-sit transition, lie-sit/sit-lie
transition, level walking, stairs up, and stairs down. However, the sequence of the activities was not restricted. An observer was together with the subject during the experiment and recorded when the error occurred. Informed consent was obtained from each of the subjects.

3. Signal processing

3.1. Wavelet transform

In discrete wavelet transformation (DWT), a signal $f(n)$ passes through two complementary filters, low-pass filter $g$ and high-pass filter $h$, and is split into approximation coefficients $V_1$ and detail coefficients $W_1$ [8]. The approximation is the high-scale, low-frequency component and the detail is the low-scale, high-frequency component. The approximation coefficients are then split into second level approximation coefficients $V_2$ and detail coefficients $W_2$. The coefficient $g$ associates with the scaling function $\phi$ and the coefficients $h$ associates with the wavelet function $\psi$. The functions are defined as

$$\phi_{j,m}(n) = 2^{-j/2} \phi(2^{-j} n - m), \quad (1)$$

and

$$\psi_{j,m}(n) = 2^{-j/2} \psi(2^{-j} n - m). \quad (2)$$

In wavelet multiresolution analysis, the signal can be reconstructed from the approximation and the detail coefficients. This is the extraction of a signal component in a certain frequency range [8]. The $J$th detail signal $D_J$ is obtained by taking the inverse transformation of $0_{1},\ldots,0_{J-1},W_J$ and $0_J$. Similarly, the approximate signal $S_J$ can be obtained by applying the inverse transformation to $0_{1},0_{2},\ldots,0_J$, and $V_J$. In this way, only the desired frequency band of the original signal is reconstructed and the other frequency components are rejected.

3.2. Falls and activities of daily living detection (ADL)

The flow diagram of falls and ADL detection system is shown in Fig.3. In the algorithm, fall detection, sit-stand/stand-sit transition detection, lie-sit/sit-lie transition detection, and level walking detection were done for all 350-sample segments. The 350-sample data was segmented with 40% overlapping. If fall incident happens, daily activities were not detected for that segment and next 350-sample segment was proceeded. If sit-stand/stand-sit and lie-sit/sit-lie transition activities were
detected, data in both 350-sample segment and 2660-sample segment were replaced with zeros before next processing steps were carried out. 2660 data length was chosen not to miss any sample in segmentation, i.e. 
\[(350-350 \times 0.4) \times 11 + 350 = 2660.\]
Lie-sit/sit-lie transition, sit-stand/stand-sit transition, level walking, ascending stairs and descending stairs activities detections are discussed as follows.

### 3.2.1 Lie-sit/sit-lie detection

The lie-sit/sit-lie posture transition is detected by considering the orientation of the accelerometer with respect to the gravitational axis. In the lying posture, the vertical accelerometer measures almost 0 g, while in sitting and standing posture the accelerometer measures approximately 1 g. Therefore, detection of transition between 0 g and 1 g can be used to detect lie-sit/sit-lie transition [6]. In detection, the DWT was applied to vertical acceleration signal with decomposition into level \( J = 4 \) by “Daubechies order 5 (db5)” mother wavelet [9]. The reconstructed vertical acceleration signal \((<1.5\text{Hz}, S^4)\) was applied to cancel additional peaks with different frequency components (sit-lie/sit transition in Fig.4(b)). A Daubechies mother wavelet (db5) was used in decomposition and reconstruction. The corresponding low pass and high pass filters are finite impulse response (FIR) filters with lengths of ten. After reconstruction, sit-lie/sit-lie transitions were detected using a predefined threshold value (0.8 g). There is no 0.8 g difference in reconstructed vertical acceleration signals in ADL except lie-sit/sit-lie transition (Fig.4).

### 3.2.2 Sit-stand/stand-sit transitions detection

There are two steps in sit-stand/stand-sit transitions detection, namely, transition segment extraction and classification of extracted segment [10].

**Transition segments extraction from the continuous acceleration signals**

Two steps procedure, (1) detection of the location of transition segments (point P) and (2) detection of start/end points of transition segments (points S and E) was performed in segment extraction (Fig.5). In order to detect the locations of transition segments, the DWT was applied to
antero-posterior acceleration signal with decomposition into level $J=4$ by “Daubechies order 5 (db5)” mother wavelet [9]. The approximation signal corresponding to level $J=4$ ($<1.5\text{Hz}, S_4$) was reconstructed in which the amplitudes of other signals (level walking in Fig.5), which have higher frequency than the transition segments, were reduced. In location detection, threshold value was defined as half of the global minimum (threshold value=$\text{global minimum} / 2$). The global minimum value ($g_{th}$) should be less than or equal to -0.3g. All minimum points lower than the threshold level were considered as the locations of sit-stand and stand-sit transitions (Fig.5). In processing the second step, the transition segment was determined by an interval between the beginning of the leaning forward phase (point S) of the transition to the end of the leaning backward phase (point E) (Fig.5). These two points were detected using gradient thresholding approach. The transition segments were confirmed by rest states with 1-second time duration in 4-second time interval before or after the posture transition point (P) or both (Fig.5). The rest state is the rest period during which the variance of the acceleration signal was less than a predefined value ($<0.0005g$). Therefore, the segment of time duration between 0.7-2 seconds (>35 samples) with 1-second long rest state before or after was taken as a true transition segment. Using these start point (S) and end point (E), the segments related to transition activities from the vertical acceleration signal were extracted and used in classification.

Sit-stand and stand-sit classification using features from time-frequency domain

After extracting the transition segments from vertical acceleration signals, classification was implemented using DWT coefficients (the coefficients of $W$ and $V$). In feature extraction, the extracted segment was decomposed to level $J=1$ by “Daubechies order 5 (db5)” mother wavelet and coefficients were arranged as $V^1, W^1$. The first twenty-five wavelet coefficients were used as features. In order to reduce the number of wavelet coefficients to be used as features representing each segment, every five successive components were averaged. Therefore, the feature vector size was reduced to 25/5=5 components for every sit-stand or stand-sit transition signal (Fig.6). In classification, Euclidean distance ($\sqrt{\sum_{k=1}^{n} (u_k - x_{ik})^2}$) between a vector to be identified and the standard data set was used, where $u=\text{standard data set}$, $n=\text{total number of components in a vector (n=5)}$ and $i=\text{index of vectors to be identified}$. 

Fig.4. Reconstructed vertical acceleration signals for fall, sit-stand/stand-sit transition, sit-lie/lie-sit transition, level walking, ascending stairs and descending stairs activities.
3.2.3 Level walking, ascending stairs and descending stairs activities detection

Level walking was detected for every 350-sample segment unless a fall event was detected. To identify the level walking patterns, positive peaks of vertical acceleration signal above the predefined threshold level (0.1g) were detected. Numbers of successive peaks greater than five were chosen as level walking steps. Therefore, all gait activities, level walking, ascending stairs and descending stairs, were detected as level walking before spatial filtration was applied for 2660-sample segment (Fig.3) [11].

In detection of ascending stairs and descending stairs activities, spatial filtration of wavelet coefficients decomposed by discrete dyadic wavelet decomposition was applied to 2660-sample segment in separation of the segments of gait patterns in the continuous accelerometer record [11]. After segment separation process, power of coefficients of separated segments ($P_{coefy} = \frac{1}{N} \|d_y\|_2^2$ and $P_{coefs} = \frac{1}{N} \|d_z\|_2^2$, where $N$ is the number of samples and $d_y$ and $d_z$ represent extracted coefficients of vertical and antero-posterior acceleration signal), were used as features in classification among these three activities [12].

3.2.4 Fall detection

In fall detection, 350-sample long data was normalized and absolute peak value from each dimension was calculated. Summation of absolute peak values greater than a predefined threshold value (1.2 V, 4.8g) was determined as a fall event [13]. In notification of fall events without user intervention, the processing unit on the garment is connected to a mobile phone through Bluetooth wireless communication (Fig.7). When a fall is detected, it sends a pre-defined code to the mobile phone. Apart from the fall, the user can generate ‘Emergency Help’ event by pressing a button on the wearable node. Upon receiving a ‘fall code’ or ‘emergency help code’ from the wearable module, the Python SMS script inside the phone sends out SMS to a predefined group of mobile numbers. For the script, the Python interpreter natively interacts with the Symbian operating system of the phone. The script is implemented as a background process, no interference with the normal application, in the mobile phone.
### 4. Results and discussions

Table 1 The sensitivity and specificity of activities in approximately five-hour long experiment

| Age | Sex   | Height | Weight | Duration of monitoring | Total number of activities |
|-----|-------|--------|--------|------------------------|---------------------------|
| 32  | Male  | 165.1  | 65kg   | 300.4min               | 131                       |
| 49  | Female| 157cm  | 50kg   | 303.05min              | 84                        |
| 45  | Female| 152.5cm| 49kg   | 302.18min              | 204                       |
| 30  | Male  | 172.7cm| 51kg   | 303.1min               | 586                       |
| 29  | Female| 150cm  | 75kg   | 286.7min               | 263                       |
| 30  | Male  | 172.7cm| 50kg   | 279.62min              | 227                       |

| 1   | 2    | 3    | 4    | 5    | 6    |
|-----|------|------|------|------|------|
| Age | 32   | 49   | 45   | 30   | 29   |
| Sex | Male | Female | Female | Male | Female | Male |
| Height | 165.1 | 157cm | 152.5cm | 172.7cm | 160cm | 172.7cm |
| Weight | 65kg | 50kg | 49kg | 51kg | 50kg | 75kg |
| Duration of monitoring | 300.4min | 303.05min | 302.18min | 303.1min | 286.7min | 279.62min |
| Total number of activities | 131 | 84 | 204 | 586 | 263 | 227 |

| Activity   | 1  | 2  | 3  | 4  | 5  | 6  |
|------------|----|----|----|----|----|----|
| Level walking | 32 | 100 | 100 | 39 | 100 | 100 |
| Sit-stand   | 28 | 100 | 100 | 39 | 100 | 100 |
| Stand-sit   | 28 | 100 | 100 | 39 | 100 | 100 |
| Lie-sit     | 28 | 100 | 100 | 39 | 100 | 100 |
| Sit-lie     | 28 | 100 | 100 | 39 | 100 | 100 |

Overall sensitivity for 1495 activities: 1420/1495 = 94.98%

Overall specificity for 1495 activities: 1437/(1437+17) = 98.83%

Even though the system can detect fall, according to the experimental results presented in our previous publication [13], it was not included in the activity detection experiment. The sensitivity and specificity of each subject is presented in Table 1. Sensitivities (defined as the ability of the system to correctly identify the true activities) and specificities (defined as the ability of the system not to generate false detection) were calculated as sensitivity = (true positives/(true positives+false negatives)) and specificity = (true negatives/(true negatives+false positives)). True positives, false negatives, true negatives and false positives of one type of activities, e.g., sit-stand transition, were estimated as follows:

- True positives were equal to the number of true sit-stand transitions, correctly detected by the system.
- False negatives were equal to the number of sit-stand transitions, not detected or wrongly detected by the system.
- True negatives were equal to the number of other types of activities detected by the system, which were not true sit-stand transitions.
- False positives were equal to the number of other types of activities wrongly detected as sit-stand transitions.
Our new detection approach interferes minimally with the usual activity of the subject. The sensor and the casing (20mmx30mmx10mm) are light weight and attached to the shirt using Velcro™ at the inner side of the shirt. The casing (50mmx80mmx25mm) for the microcontroller, rechargeable flat Lithium-ion battery, and Bluetooth™ transmitter are inside the pocket. The cable connecting the sensor and the microcontroller casing is between the two layers of cloths, near the zipper, of the shirt. Then, the two layers are fastened using Velcro™. For washing the shirt, the cable, sensor casing, and microcontroller casing, can be easily dismantled from the shirt. Therefore, monitoring the falls and ADL in the living environment with minimal interference is possible using the system we developed.

The place of attachment of sensors on the human body is an important issue. Shoulder position is chosen for three considerations. First, the sensor on the body will be least interfered by the subject's activities. Second, the sensor will cause minimal discomfort to the subject and third, the sensor will not injure the wearer during the severe incidents such as falls. In activity detection, the sensors are mostly attached to the body directly using adhesive tape or elastic straps to avoid the artifacts due to the movements of clothes. According to our experimental results (Fig.4, and Fig.5), even the signals from gait activities did not interfere to detection of sit-stand/stand-sit and sit-lie/lie-sit transitions. Therefore, the artifacts caused by the movements of the clothes are not a serious issue in our detection method.

In conclusion, our detection methods and system, with the sensor on the shoulder part of a garment, fulfilled our objectives of providing comfort to the wearer with high sensitivity in detection compared to other detection systems [4-7]. These objectives are the most important in long term application of in-home health care telemedicine application. In fall detection, our device can summon medical assistances via SMS. This detection system can raise fall alarm (fall SMS) automatically to individuals to get a shortened interval before the arrival of assistance.

References
[1] Kannus, P., Palvanen, M., Niemi, S., Parkkari, J., Natri, A., Vuori, I., Jarvinen, M., 1999. Increasing number and incidence of fall-induced severe head injuries in older adults: nationwide statistics in Finland in 1970-1995 and prediction for the future. Am J Epidemiol, 149, pp 143-50.
[2] Myers, A. H., Young, Y., Langlois, J. A., 1996. Prevention of falls in the elderly. Bone, 18(1), Supplement 1, pp 87-101.
[3] Campbell, A. J., Borrie, M. J., Spears, G. F., 1989. Risk factors for falls in a community-based prospective study of people 70 years and older. J Gerontol, 44, pp 112-117.
[4] Najafi, B., Aminian, K., Paraschiv-Ionescu, A., Loew, F., Bula, C. J., Robert, P., 2003. Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. IEEE Trans Biomed Eng, 50(6), pp 711-723.
[5] Tamura, T., Fujimoto, T., Muramoto, H., Huang, J., Sakaki, H., Togawa, T., 1995. The design of an ambulatory physical activity monitor and it application to the daily activity of the elderly. Engineering in Medicine and Biology Society, IEEE 17th Annual Conference, 2, pp 1591-1592.
[6] Mantyjarvi, J., Himberg, J., Seppanen, T., 2001. Recognizing human motion with multiple acceleration sensors. Systems, Man, and Cybernetics, 2001 IEEE International Conference on, 2, pp 747 - 752.
[7] Mathie, M. J., Celler, B. G., Lovell, N. H., Coster, A. C. F., 2004. Classification of basic daily movements using a triaxial accelerometer. Medical & biological engineering & computing, 42 (5), pp 679-687.
[8] Mallat, S. G., 1989. A theory for multiresolution signal decomposition: the wavelet representation. IEEE Trans Pattern Anal Machine Intell., 11(7), pp 674–693.
[9] Daubechies, I., 1992. Ten Lectures on Wavelets. no. 61 in CBMS-NSF Series in Applied Mathematics, Philadelphia: SIAM.
[10] Nyan, M. N., Tay, E. H. F., Seah, K. H. W., and N. H. Ismail., 2005. Detection of daily physical activities in the time-frequency domain. Submitted for publication to Medical & Biological Eng & Computing.
[11] Nyan, M. N., Tay, E. H. F., Seah, K. H. W., Sitoh, Y. Y., 2005. Classification of gait patterns in
the time–frequency domain. Journal of Biomechanics, In Press, Corrected Proof, Available online.

[12] Nyan, M. N., 2006. Analysis and detection of human motion in time-frequency domain. PhD dissertation, National University of Singapore.

[13] Tay, E. H. F., Nyan, M. N., Koh, T. H. Z., Seah, K. H. W., Sitoh, Y. Y., 2005. Smart Shirt That Can Call for Help after a Fall. International Journal of Software Engineering and Knowledge Engineering, Volume 15 (2), pp 183-188.