Detection of Activities Daily Living and Falls Using Combination Accelerometer and Gyroscope

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Abstract— **This paper studied the detection of falls and activities of daily living (ADLs) with the objective: to automatically monitor health situation and prevent the elder out of injury from fallings. In this study, a wireless sensor system (WSS), based on accelerometer and gyroscope, is placed at the centre of the chest to collect real-time ADLs and fall data. The WSS contains a set of ADXL345 (3-axis digital accelerometer sensor), ITG3200 (3-axis digital gyroscope sensor), MCU LPC17680 (ARM 32-bit cortex M3), and Wi-Fi module RN131. Experiment protocols consisting of four types of falls such as forward fall, backward fall, and side way fall (left and right), and ADLs such as standing, walking, sitting down/ standing up, stepping, running along with normal gait involved 324 tests on 18 human subjects.**

The results from the experiment shows the system and algorithm could distinguish falling and ADLs with high accuracy.

Keywords— **Fall Detection, Activities of daily living, Wireless sensor system.**

I. INTRODUCTION

Activities Daily Living recognition have been receiving increasing attention in recent years. The benefit of automatically recognize different activities of humans activities makes it appealing for healthcare such as monitoring health situation, especially for elder. It provides more information on the patient's day-to-day health for the clinician. Additional, fall is the most significant causes of injury for elderly. These falls are cause many disabling fractures that could eventually lead to death due to complications, such as infection or pneumonia. More than one-third of elderly people, who is over 75 year old, have fallen at least once a year, and 24% of them has serious injuries [2] (J.Y. Hwang, J.M Kang, H.C. Kim, September 1-5, 2004). Because of that, ADLs classification and fall detection is necessary for protecting health of elder.

Most of the research on falls detection and ADLs classification in which accelerometers is used focus on determining the change in magnitude of acceleration. Base on acceleration value thresholds, ADLs or falls are distinguished. [1] (Quoc T. Huynh, Uyen D. Nguyen, Su V. Tran, Afshin Nabili, Binh Q. Tran, 2013) [3](U.Lindeann, A.Hock, M.Stuber, W.Keck, and C.Becker, 2005) [4 - 2] (M. Kangas, A. Konttila,P. Lindgren, I. Winblad, T. Jämsä, 2008 Feb 21) [5] (Ig-Jae Kim, Saemi Im, Eugene Hong, Sang Chul Ahn and Hyoung-Gon Kim, 2007). These systems successfully detect with sensitivities greater than 85% and specificities between 88-94%. However, focusing only on large acceleration can result in many false positives from fall-like activities such as sitting down quickly and running.

Furthermore, previous studies used complex algorithms like Neural Network [6] (Saisakul chernbumroong, Anthony S. Atkins, and Hongnian Yu, 08/11/2011) to classification ADLs or Support Vector Machine (SVM) [7] (Tong Zhang, Jue Wang, Liang Xu, Ping Liu, 2004) and Markov models [8] (R. K. Ganti, 2006) to detect the fall. However, accuracy of these systems has not been proven to be highly effective. They also use excessive amounts of computational resources and cannot respond in real time. In addition, activity patterns are particularly difficult to obtain for training systems.

Some fall detection algorithms also assume falls happen when the body lies prone on the floor. But they are less effective when a person's fall posture is not horizontal, e.g. fall happen on stair.

Unlike other previous researches, this project proposes using both accelerometer and gyroscope sensors to not only detect falls but also to classify ADLs with increasing in sensitivities and specificities of a system.

II. METHODOLOGY

In this study, we developed a wireless sensor system and an algorithm to classify ADLs and fall events. The system includes a Wireless Sensor System (WSS) and a detection algorithm. Figure1 shows the overall schematic of system. The WSS transmits and receives real-time accelerometer and gyro data during ADLs and fall. The detection algorithm is based on a simple threshold method.

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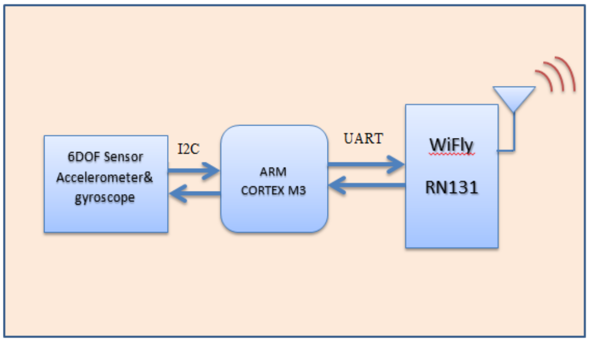

Fig. 1 The schematic of wireless sensors system

A. Wireless Sensor System (WSS)

The wireless sensors system contains a set of Sensor module, Micro Control Unit, and Wi-Fi module. The Sensor Module, the Micro Control Unit, and the Wi-Fi module are used to sense body orientation and activity data, control the flow of data, and transmit/receive data, respectively. The WSS is placed at the center of chest, see Fig 2.c.

Sensor Module

Since our system measures both acceleration and angular velocity to classify ADLs and detect falls, we chose to use the 6-DOF module with small size and power requirements. It includes a tri-axial accelerometer ADXL345 and a tri-axial gyroscope ITG3200 (Fig 2.a). The acceleration measurement range of ADXL345, with a high resolution of 13bit and 4mg/LSB, is up to $\pm$ 16g. This is an important aspect in recognizing the fall. In addition to the accelerometer, the ITG-3200 can capture the angular velocity between ±2000°/sec. The digital data output of these modules is formatted as 16 bits two complements prior to transmitting. The sensor modules are connected with MCU via I2C digital interface port.

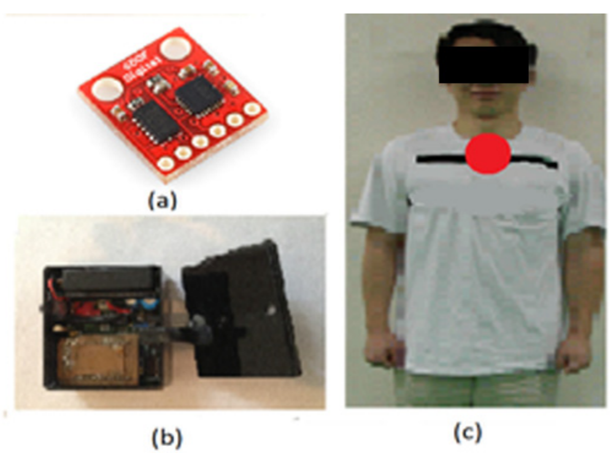

Fig. 2 ADLs classification and fall detection system: (a) sensor module (6 DOF), (b) wireless sensor system (WSS), (c) system attached on center chest.

The Micro Control Unit (MCU) module (ARM 32 bit Cortex M3)

The LPC 1786 (NXP product's) is used to develop the control system. This is an ARM Cortex-M3 32-bit based microcontroller for embedded applications requiring a high level of integration and low power dissipation. The chip can operate up to 100MHz CPU frequency. In addition, the UART interface provides the sampling frequency up to 4Mb/s.

Wireless Module

The Wifly RN131 module is a stand-alone Wi-Fi module, providing a fully integrated 2.4GHz and IP stack with IEEE 802.11 b/g standard. The RN131 can operate with the communication speed up to 11 Mbps. Due to its small form factor and extremely low power consumption; it is perfect for mobile wireless applications with portable battery operated devices. Additionally, its UART hardware interfaces for connecting with MCU can operate up to 1 Mbps data rate.

Collection Data Program

The WSS (Fig.2.b) consists of 6-DOF, MCU and Wi-Fi module. The MCU is connected to wireless module via UART port and 6DOF module via I2C port. The WSS collects the acceleration and angular velocity values. In addition, the WSS sends the real-time data to a computer via 802.11 wireless protocols to be displayed.

The collection data program is written in Matlab (Mathworks, Inc, Natick, MA). The program receives and display real-time data from the WSS. It continuously plots the acceleration and angular velocity values of each fall and saves the data for later analysis. Figure 3 (below) shows a display of the collection data program.

B. Experimental Setup

The experiment is performed on 18 young healthy subjects (age from 19 to 28 years, weight from 50 to 90 kg, and height from 154.5 to 180.0 cm). Experiments were performed at The Catholic University of America (Washington, DC) and approved by the Human Subjects/Institutional Review Board (IRB) Committee. The WSS was attached to the center of the chest (Fig. 1.c.). This is the optimum location to attach sensor for detecting as mentioned in our previous study [9] (Quoc T. Huynh, Uyen D. Nguyen, Su V. Tran, Binh Q. Tran, 2013). In this experiment, subject performs ADL such as standing, walking, sitting down/ standing up, stepping, running, lying down/ sitting up and 4 different kinds of fall tests: forward fall, backward fall, right sideway fall, and left sideway fall.

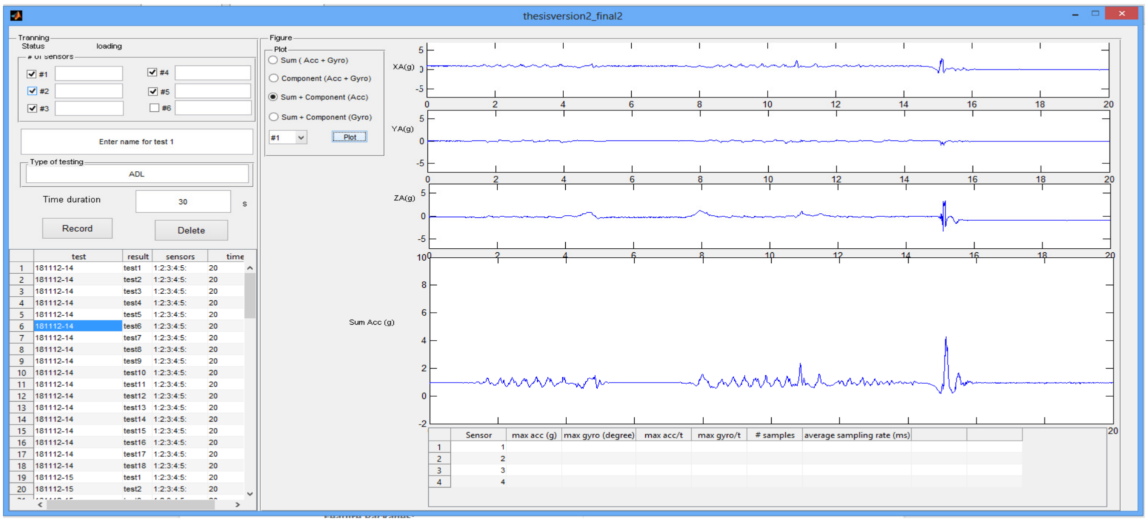

Fig. 3 The collection data program

C. Data Analysis and Algorithm

The parameters used in analyses are similar to previous studies [4](M. Kangas, A. Konttila,P. Lindgren, I. Winblad, T. Jämsä, 2008 Feb 21) [5] (Ig-Jae Kim, Saemi Im, Eugene Hong, Sang Chul Ahn and Hyoung-Gon Kim, 2007) [10](J. Klenk, C. Becker, F. Lieken, S. Nicolai, W. Maetzler, W. Alt, W. Zijlstra, 5 November 2010). The total sum acceleration vector Acc, contain both dynamic and static acceleration components, is calculated from sampled data as indicated in Eq. (1)

$$\mathrm{Acc}=\sqrt{(A_x)^2+(A_y)^2+(A_z)^2} \quad (1)$$

WhereA_x, A_y, A_z is the acceleration (g) in the x, y, z axes, respectively.

Similarly to the acceleration, the angular velocity is calculated from sampled data as indicated in Eq. (2)

$$\omega=\sqrt{(_x)^2+(_y)^2+(_z)^2} \quad (2)$$

Where$_x, _y, _z$ is the acceleration (g) in the x, y, z axes, respectively.

There are 324 tests collected from 18 subjects. Figure 5 shows a typical example of the acceleration (Fig.5a.) and angular velocity signals (Fig5.b) during stand, walk, sit down/stand up, step and fall.

When stationary, the acceleration, from tri-axial accelerometer is approximated +1g, and angular velocity is 0^o/s. When the subject moves, the acceleration is changing and the angular velocity produces a variety of signals along activities. Over all of test, with walking activity, we found that average peak acceleration reached 1.5-1.8 g. and the average peak angular velocity reached 10-50 ^{o}/s. With sitting down/ standing up, the average peak acceleration is same with walking. However, when human sit down, the upper torso bend down and backward, vice versa with standing up. So the average peak angular velocity of sitting down/standing up is higher walking, they reached 80-130 ^{o}/s. Similar with lying back/ sitting up (Fig.7), the average peak acceleration reached 1.4-1.8g, and the average peak angular velocity reached 130-260 ^{o}/s.

However, with high density ADLs such as stepping (Fig.5), the average peak acceleration and angular velocity is higher than walking, 1.8-2.1 g for acceleration and 40-80 ^{o}/s for angular velocity. With running, the average peak acceleration is higher stepping (2.2-2.8 g) and the average peak angular velocity reached 60-120^o/s. Especially, with falling, the both acceleration and angular velocity were received high value. The average peak acceleration for falling is 2.5-5.4 g and the average peak angular velocity for falling is 200-320 ^{o}/s.

The table 1 is shown the summary of acceleration and angular velocity of ADLs and fall of 384 tests.

Table 1 Summary of acceleration and angular velocity of ADLs and fall.

Activities	**Peak acceleration (g)**	**Peak angular velocity (^{0}/s)**
Standing	1	0
Walking	1.5-1.8	10-50
Sitting down/standing up	1.6-2.0	80-130
Lying down/ sitting up	1.4-1.8	130-260
Stepping	1.8-2.1	40-80
Running	2.2-2.8	60-120
Falling	2.5-5.4	200-320

Base on analyzing all of database, we propose a novel algorithm that can classify ADLs such as standing, walking, sitting down/standing up, stepping, running and detect the fall.

The flowchart of our algorithm is summarized in Fig.4.

The algorithm involves the following steps: Firstly, using acceleration thresholds (1g &1.8g) divides the activity to 3 groups: the first is standing, the second is normal ADLs, and the third is high density ADLs (include fall). With case normal ADLs, we can classify activity base on angular velocity thresholds (50^o, 130^o) such as walking, sitting down/standing up, lying down/ sitting up. With case high density ADLs, if average peak angular velocity is above 200^o, the fall is detected. Otherwise, the average peak acceleration threshold (2.1g) is compared for classification between stepping and running.

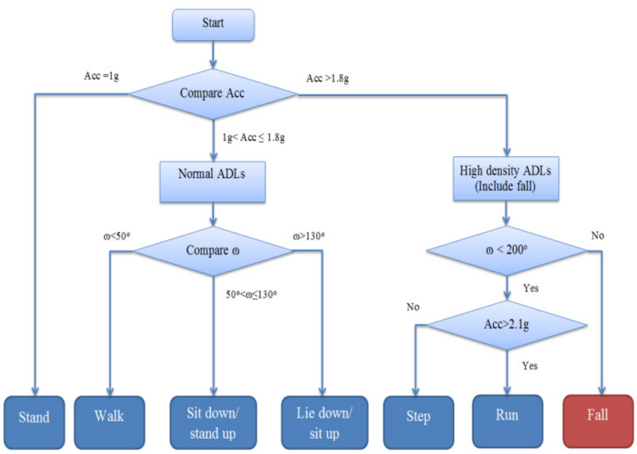

Fig. 4 Fall detection and ADLs classification algorithm schema

III. RESULTS AND DISCUSSION

The sensitive and the specificity of the system are defined as follows:

$$\text{Sensitivity} = \frac{\text{No.TP}}{\text{No.TP+No.FN}} \tag{3}$$

$$\text{Specificity} = \frac{\text{No.TN}}{\text{No.TN+No.FP}} \tag{4}$$

Where:

- Number of True positive (No.TP): an activity occurs, the device detects it.
- Number of False positive (No.FP): the device announces an activity, but it did not occur.
- Number of True negative (No.TN): another activity is performed; the device does not declare a activity.
- Number of False negative (No.FN): an activity occurs but the device does not detect it.

The result of 324 tests shows the sensitivity of the system and the specificity of system on table 2.

Table 2 Summary of sensitivity and specificity system.

Activities	**Sensitivity (%)**	**Specificity (%)**
Standing	100	100
Walking	97.14	95.93
Sitting down /standing up	91.35	94.67
Lying down/ sitting up	95.37	93.59
Stepping	98.75	99.07
Running	95.06	98.45
Falling	100	99.382

Compared to other algorithms, our algorithm not only classifies ADLs but also detect fall. Furthermore, it also has shown to have a higher sensitivity and specificity than previous study such as with 89.14% sensitivity and 89.97% specificity for walking [11] (Bidargaddi, N. ; E-Health Res. Centre, Brisbane ; Sarela, A. ; Klingbeil, L. ; Karunanithi, M., 2007), with 95% sensitivity for stepping [12] (Guillaume thuer and tim verwimp, 2008-2009) and with sensitivities greater than 85% and specificities between 88-94% for falling [3](U.Lindeann, A.Hock, M.Stuber, W.Keck, and C.Becker, 2005) [4] (M. Kangas, A. Konttila,P. Lindgren, I. Winblad, T. Jämsä, 2008 Feb 21) [5] (Ig-Jae Kim, Saemi Im, Eugene Hong, Sang Chul Ahn and Hyoung-Gon Kim, 2007) . The proposed method is a simple threshold method; therefore, it could be easily ported onto an electronic device worn by a person.

One of the limitations of this study is that young subjects performed the tests. Therefore, the young subjects might not be able to simulate the actual ADLs of the elderly. Therefore, the threshold values of the real condition could be significantly different than our findings. Further research is required to actually identify the correct threshold.

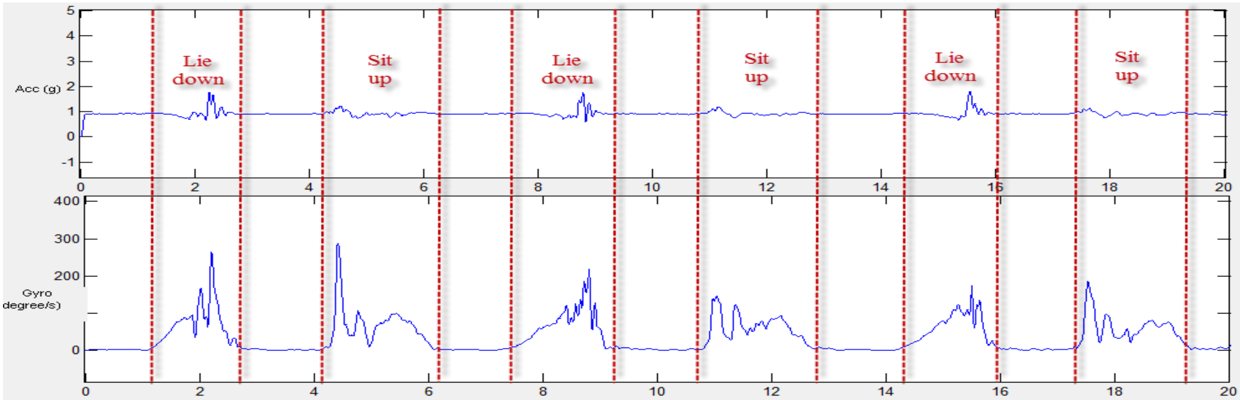

Fig. 5 The signal for standing, walking, sitting down/standing up, stepping and falling. (a)The sum of acceleration Acc.(b)The sum of angular velocity ω.

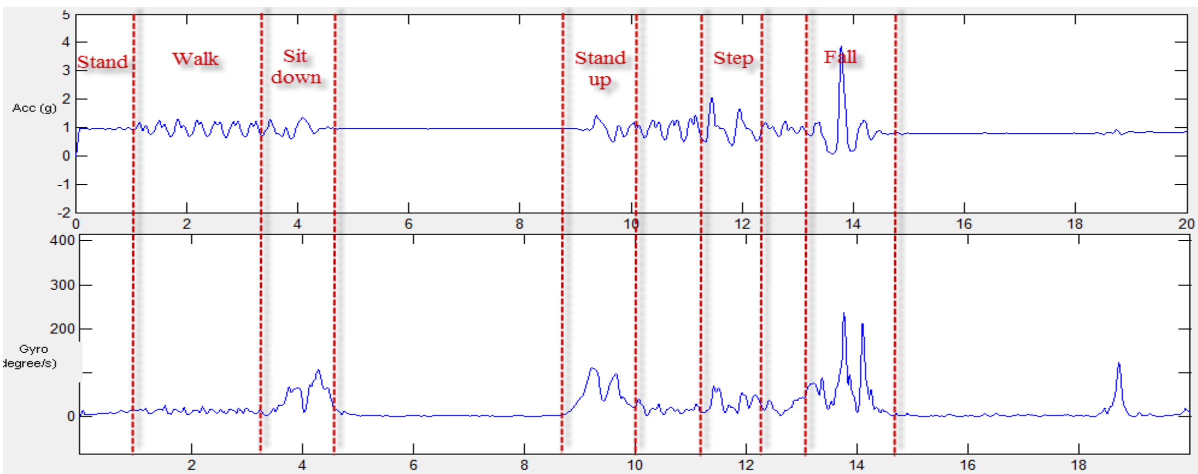

Fig. 6 The signal for running.(a)The sum of acceleration Acc.(b)The sum of angular velocity ω.

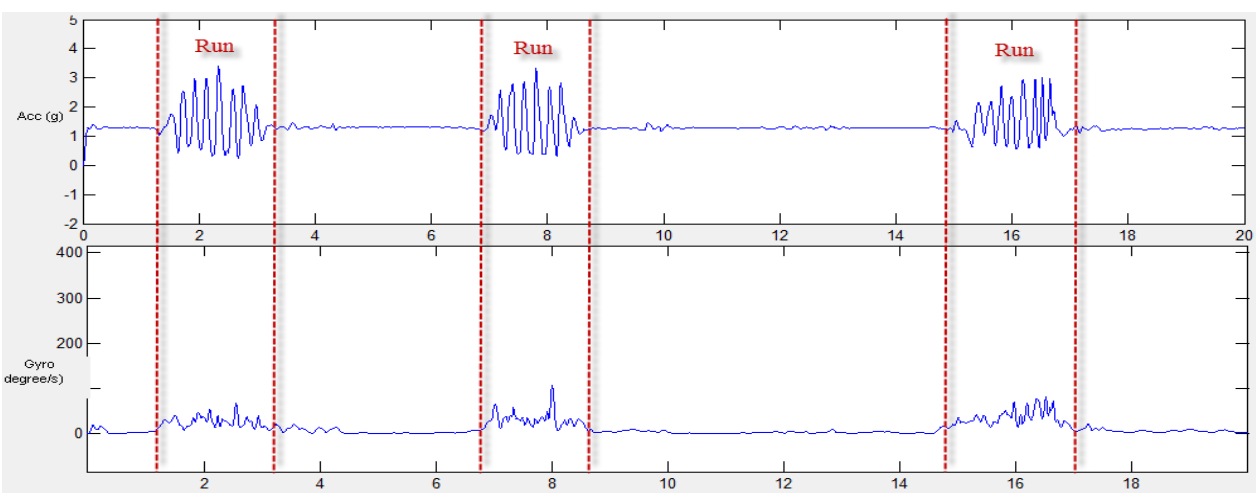

Fig. 7 The signal for lying back, sitting up.(a)The sum of acceleration Acc.(b)The sum of angular velocity ω.

IV. CONCLUSION AND FUTURE WORK

In this study, a wireless sensor system is implemented to measure the acceleration and angular velocity at center chest on the body for ADLs and four different types of fall. The collected data is used to evaluate the performance of the algorithm. There are many fall detections or ADLs classification systems investigated in previous studied. However, to increase the accuracy, we proposed a combination of accelerometer and gyroscope simultaneously. As the results, we have improved the accuracy, specifically the specificity and the sensitivity. We also have used small battery operated devices, which can be easily woven into garments.

In conclusion, fall detection and ADLs classification system has been validated to show high sensitivity and specificity results, using the combination of accelerometer and gyroscope. Future development will investigate a system to include GPS and GPRS to inform medical attention. Furthermore, an air bag is integrated the system for preventing the elder out of injury when they fall.

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