# A Threshold-based Algorithm of Fall Detection Using a Wearable Device with Tri-axial Accelerometer and Gyroscope

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***Abstract*—Fall events are the external causes of injury in the elderly adults, even leading to disability and death. In this study, we used a weightless and wearable device with built-in tri-axial accelerometer and gyroscope to record 8 types of stimulated-falls and 6 types of different activities of daily living (ADL) preformed by 6 health young subjects. A threshold-based algorithm using our device was developed to determine a fall event. Using our fall detection system, falls could be distinguished from ADL successfully for a total data set.**

***Keywords*—fall detection; accelerometer; gyroscopes; wearable system**

## I. INTRODUCTION

Fall events are the external causes of injury in the elderly adults. According the WHO report, approximately 28-35% of people aged of 65 and over fall each year increasing to 32-42% for those over 70 years of age [1]. Fall events cause not only severe injury but also disability for elderly adults. In 2000, the relative financial costs of fall event were estimated to be approximately $20 billion and increase to $54.9 billion by 2020 [2]. An emergency response system has been developed to facilitate calling for help after a fall event. However, in some severe case of emergency cases, the emergency response system may not be able to active [3, 4]. Hence, reliable and automatic fall detection became more important for aging society.

In recent years, numerous approaches by using portable sensors were developed for the automatic detection of falls. Many stragies utilized the change in aceleration magnitude to determine falls. However, focusing on large acceleration result only in many false positiving as other activities such as sitting and running. [5, 6] Other fall detections rely on detection of body orientation after a fall. These methods may be affected by activities with similar posture and are less effective when the falling posture is not horizontal.

Using both accelerometer and gyroscope sensor for the fall detection was demostrated in the previous studies [7, 8]. When fall event occuring, the accelerometer provides valuable information of body inertial change due to the impact. Simultaneously, the gyroscope provides the unique information of body's rotational velocity during a fall event. A fall event produces both large change of acceleration and angular velocity. These changes are not observed during normal daily activities [8]. Thus, several thresholds of acceleration and angular velocity were set to distinigh between fall event and ADL.

In this study, we developed a weightless and wearable device with built-in tri-axial accelerometer and gyroscope to record 8 types of stimulated-falls and 6 types of different ADL preformed by 6 health young subjects. A threshold-based algorithm using our device was developed to determine a fall event. The feasibility of our fall detection system was demonstrated in this work.

## II. MATERIALS AND METHOD

### A. Wearable system and data acquisition

A wearable system (XYZlife Bio-Clothing 1 (BC1), Kinpo Inc, New Taipei City, Taiwan) is composed of a fitting clothing and a wearable device BC1 with built-in tri-axial accelerometer and gyroscope (MPU-6500, InvenSense Inc., San Jose, US) which were used for data acquisition. The sensor signals were recorded at a frequency of 1k Hz and resolution of 16 bits, and saved in a tablet PC via a Bluetooth module.

During recording, subject wears a fitting clothing with BC1 device, which is placed in front of right chest as shown in Fig. 1.

### B. The simulated fall and ADL study

The simulated fall study involved 6 young healthy (<40 years) subjects. The subjects ranged in age from 30 to 39 years (35.2±2.2 years), body mass from 59 to 76 kg (75.2±2.2 kg), and height from 1.68 to 1.76 m (1.75±0.2 m) have been recruited for this study. Subjects performed eight different types of simulated-falls onto large crash mats under supervision condition. Tri-axial accelerometer and gyroscope signal were recorded during each simulated-falls via BC1 device.



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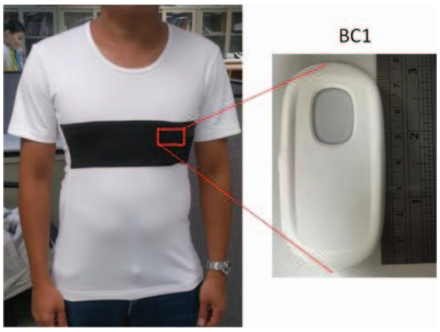


Fig. 1. A fitting clothing with BC1 device, which is placed in front of right chest (red square). Built-in tri-axial accelerometer and gyroscope were used to collect the signal of acceleration and angular velocity.

Standing height occurred most commonly and caused injury to elderly people. Thus, falls from standing height in all directions should be stimulated [9]. Falls with knee flexion were also examined, similar to those observed in previous studies [10, 11]. The simulated-falls performed were: stand foreword fall (F fall), stand back fall (B fall), stand left lateral (SL fall), stand right lateral fall (SR fall), stand foreword fall with keen flexion (F fall_KF), stand back fall with keen flexion (B fall_KF), stand left lateral with keen flexion (SL fall_KF), and stand right lateral fall with keen flexion (SR fall_KF).

The second of this study involved the same subjects performing ADL after stimulated-falls. The ADL chosen were the actives that may cause the large change of acceleration and angular velocity and carried out during normal daily life for elderly adults. Thus, the activities performed as follows:

1. Waking 8 m.
2. Stooping down and touching the ground.
3. Sitting down and standing up from a chair (height, 45 cm).
4. Lying down and getting up from a bed (height, 15 cm).

*C. The fall algorithm*

The parameters used in analyses are similar to the previous studies [1,8]. The total sum acceleration vector, *Acc*, containing both static and dynamic acceleration componets, is caculated from sampled data using

$$Acc = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2},$$

where $A_x$, $A_y$, and $A_z$ are the accelerations (g) in the $x$, $y$, and $z$ direstions. Also, angular velocity is calculated from sampled data as indicated in the following:

$$gyro = \sqrt{(\omega_x)^2 + (\omega_y)^2 + (\omega_z)^2},$$

Where $\omega_x$, $\omega_y$, and $\omega_z$ are angular velocities in $x$, $y$, and $z$ directions.

When the subject falls, the acceleration is changing rapidly and the angular velocity is also increasing along fall direction. Critical threshold in the acceleration and angular velocity are used to determining a fall event. These critical thresholds are defined and derived as follows:

1. FT1 (lower acceleration fall threshold): local minima for the *Acc* signal of each recorded activity are referred to as the signal lower peak values (LPVs). The FT1 for the acceleration signals is set for the smallest upper fall peak recorded.
2. FT2 (upper acceleration fall threshold): local maxima for the *Acc* signal of each recorded activity are referred to as the signal upper peak values (UPVs). The FT2 for the acceleration signals is set for the largest upper fall peak recorded.
3. FT3 (lower angular velocity fall threshold): local maxima for the *gyro* signal of each recorded activity are referred to as the signal UPVs. The FT3 for the angular velocity signals is set for the largest upper fall peak recorded.

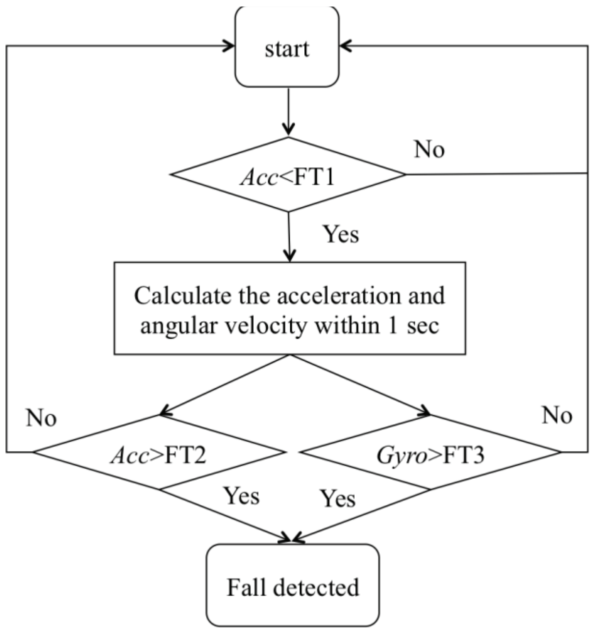


Fig. 2. The flow chart of fall algorithm using these threshold sets.

In this study, we use both FT1 and FT2 in combination with FT3 to detect fall event. All thresholds were determined by the the average values of all simulated falls and ADLs. Our proposed algorithm is shown in Fig. 2. When *Acc* value falls below the FT1 threshold, data from the next 1 sec are compared to FT2 and FT3 for *Acc* and *gyro* values, respectively. Within this period, if both *Acc* and *gyro* values are higher than FT2 and FT3, a fall event was detected. If only one or neither is observed, a fall event is not indicated.



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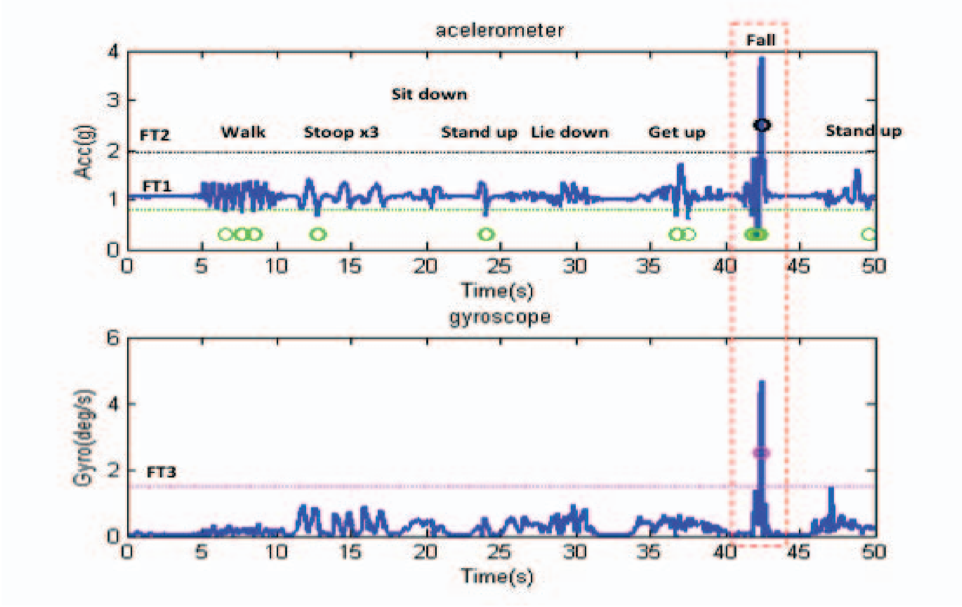


Fig. 3. Display of *Acc* and *gyro* for various activities: walking, stooping, sitting down, standing up, lying down, getting up, and forward falling. Also the thresholds of FT1 (green line), FT2 (block line), and FT3 (purple line) were set to determinate a fall event. Corresponding circle dots are the data points that upper and lower than thresholds. A fall event is indicated when FT2 and FT3 are detected within 1 sec after FT1 was detected (red square).

## III. RESULTS AND DISCUSSION

Fig. 3 shows a typical example of *Acc* and *gyro* signals while wearing BC1 device and performing different daily activites and forword fall sequentially. Corresponding indications (circle) pointed out the *Acc* and *gyro* signals exceeds FT1, FT2, and FT3 during subjects performed different ADLs and simulated-fall. When the fall event occuring (at ~42 sec after recording), the Acc signal decreases from ~1 g to ~0.3 g to cross below FT1 (0.71 g). Then, whitin 1 sec, *Acc* and *gyro* signals increase to ~2.7 g and ~2.3 deg/s, respectively, to cross above FT2 (1.95 g) and FT3 (1.52 deg/s).

The *Acc* signal of some ADLs decresed below FT1 easily, such as stooping down, lying down, and getting up. The LPVs of *Acc* signal records from 6 subjects also indicated these (Fig. 4). However, the confirmatory FT2 are never reached at all ADL (Fig. 5). As previous studies, increasing acceleration was observed during a fall event because of the sudden body inertial changes [8]. We also found that the largely increasing acceleration at 8 simulated-falls. At the angular velocity, only the movement of lying down leaded to increasing angular velocity and crossing above FT3. (Fig. 6) The increasing angular velocity during lie down is possible due to the height of our bed is only 15 cm, and then result in subject's movement similar to fall.

Although using acceleration magnitude alone is available to distinguish falls and ADL in our simulated conditions, using three thresholds to distinguish falls and ADL have been demonstrated higher specificity in many previous studies [8]. Herein, by combining FT1, FT2, and FT3, 100% specificity was obtained in our testing conditions.

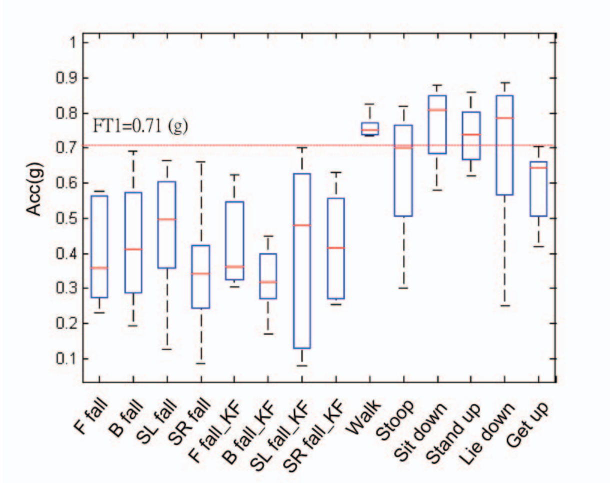


Fig. 4 Boxplot of LPVs for 8 types of simulated-fall and 6 types of different ADL. The red dot line is the FT1 value.

## IV. CONCULSION AND FUTURE WORK

We have demonstrated that our wearable BC1 system is capable to detect falls automatically via this threshold-based algorithm. Currently, limited subjects were recruited and limited ADLs were performed in this work. For the optimization of this algorithm, a large number of subjects will be involved and analyzed. Also, different ADLs are also considered in the future.



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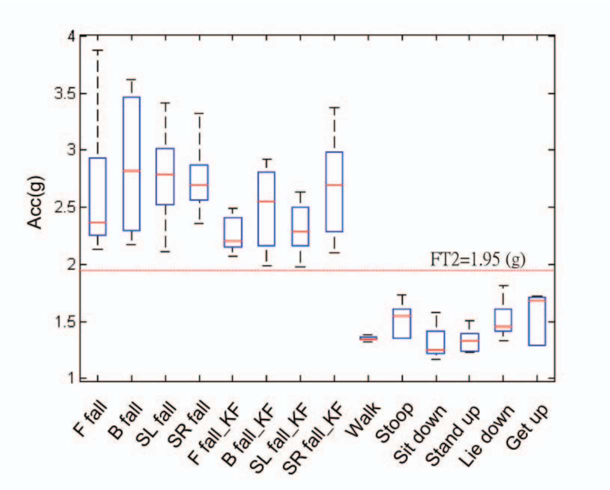


Fig. 5 Boxplot of LPVs for 8 types of simulated-fall and 6 types of different ADL. The red dot line is the FT2 value.

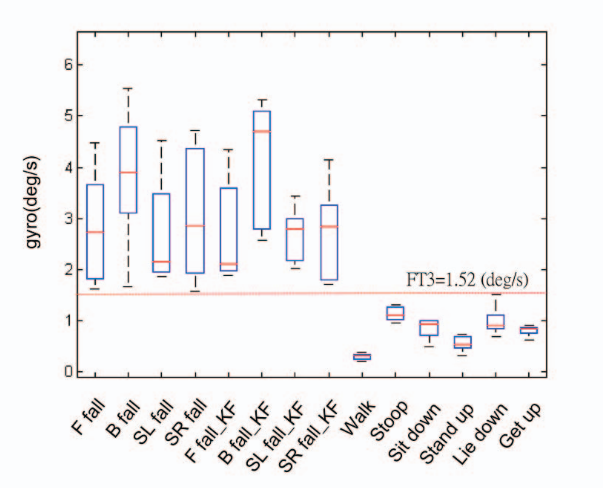


Fig. 6 Boxplot of LPVs for 8 types of simulated-fall and 6 types of different ADL. The red dot line is the FT3 value.

## References

[1] J. Y. Hwang, J. M. Kang, and H. C. Kim J. Y. Hwang, J. M. Kang, and H. C. Kim, "Development of novel algorithm and real-time monitoring ambulatory system using bluetooth module for fall detection in the elderly," IEEE Engineering in Medicine and Biology Society, vol. 1, pp. 2204–2207, September 2004.

[2] National Center for Injury Prevention and Control and Centers for Disease Control and Prevention, *Cost of Falls among Older Adults*, National Center for Injury Prevention and Control, Centers for Disease Control and Prevention, 2013.

[3] J. Fleming and C. Brayne, "Inability to get up after falling, subsequent time on floor, and summoning help: prospective cohort study in people over 90," BritishMedical Journal, vol. 337, no. 7681, pp. 1279–1282, 2008.

[4] D. Kunkel, R. M. Pickering, and A. M. Ashburn, "Comparison of retrospective interviews and prospective diaries to facilitate fall reports among people with stroke," Age and Ageing, vol. 40, no. 2, pp. 277–280, 2011.

[5] E. M. Bertera, B. Q. Tran, E. M. Wuertz, and A. Bonner, "A study of the receptivity to telecare technology in a communitybased elderly minority population," Journal of Telemedicine and Telecare, vol. 13, no. 7, pp. 327–332, 2007.

[6] N. Farber, D. Shinkle, J. Lynott, W. Fox-Grage, and R. Harrell, Aging in Place: A State Survey of Livability-Policies and Practices, AARP Public Policy Institute,Washington, DC, USA, 2011.

[7] L. Qiang, J. A. Stankovic, M. A. Hanson, A. T. Barth, J. Lach, and G. Zhou, "Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information," Wearable and Implantable Body Sensor Networks. Sixth International Workshop on pp.138,143, 3-5 June 2009.

[8] Quoc T. Huynh, Uyen D. Nguyen, Lucia B. Irazabal, Nazanin Ghassemian, and Binh Q. Tran, "Optimization of an Accelerometer and Gyroscope-Based Fall Detection Algorithm," Journal of Sensors, vol. 2015.

[9] B. J. Vellas, S. J. Wayne, P. J. Garry, and R. N. Baumgartner. "Atwo-year longitudinal study of falls in 482 community-dwelling elderly adults." J Gerontol A Biol Sci Med Sci 53(4):M264–74, 1998.

[10] C. Smeesters,W. C Hayes, and T. A. McMahon. "Disturbance type and gait speed affect fall direction and impact location." J Biomech 2001;34(3):309–17.

[11] A.K. Bourke, and G.M. Lyons, "A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor," Medical Engineering & Physics 30:84–90, 2008.



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