Pre-impact Fall Detection using Wearable Sensor Unit

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Abstract: In this study, we verified our pre-impact fall detection algorithm through a clinical trials using wearable sensor (accelerometer and gyro sensor) at waist. Forty male volunteers participated in the clinical trial (three types of falls and seven types of ADLs). Results show that falls could be detected with an average lead-time of 530ms before the impact occurs, with no false alarms (100% specificity) and no incorrect detects (100% sensitivity). Our algorithm for pre-impact fall detection with a wearable sensor unit could be very helpful to minimize fall risk.

1 INTRODUCTION

Falls are a major cause of injuries and deaths in older adults (Annekenny and O'shea, 2002). Even though most falls produce no serious injury, 20-30% of fall related patients will suffer moderate to severe injuries. Furthermore, some of them require hospitalization to continue living in community and have an increased risk of death (Nevitt et al., 1991; Tinetti et al., 1995). Approximately 35% of community-dwelling older adults and 50% of older adults residing in long-term care facilities fall at least once per year. The development of system to prevent falls and fall-related injuries in older adults is a major public health priority.

The most promising fall prevention strategy involves the identification of individuals who had increased fall risk and the implementation of the appropriate prevention mechanism. Furthermore, it includes physical restraint (Gross et al., 1990), investigation of fall-related fractures prevention strategies (Smeesters et al., 2001; Van den Kroonenberg et al., 1996; Yamamoto et al., 2006), study of characteristics and risk factors of syncope (Kenny and O'Shea, 2002; Peczalski et al., 2006), and multi-factorial risk assessment and management (Weatherall, 2004).

As for intervention strategies, one of the important problem in preventing or reducing the severity of injury in the elderly is to detect falls in its descending phase before the impact (pre-impact fall detection) (Hayes et al., 1996). A few groups have attempted to detect falls before impact (Bourke et al, 2008; Nyan at al., 2006; Wu, 2000). Wu implemented pre-impact fall detection algorithm using threshold of the horizontal and vertical velocity profiles of the trunk using motion analysis system. He showed that falls can be distinguished from activities of daily living (ADL) with 300–400ms lead-time before the impact (Wu, 2000). Bourke et al. investigated pre-impact detection algorithm of falls using threshold of the vertical velocity of the trunk (Bourke et al., 2008). An optical motion capture system and an inertial sensor consisting of a tri-axial accelerometer and a tri-axial gyroscope were used in their experiments. The inertial sensor was located on the chest of the body. Falls can be distinguished from ADLs, with 100% accuracy and with an average of 323ms prior to trunk impact and 140ms prior to knee impact, in that subject group (Bourke et al., 2008). In pre-impact fall detection, if a fall can be detected in its earliest stage in the descent phase, more efficient impact reduction systems can be implemented with a longer lead-time for injury minimization (Hayes et al., 1996).

In this study, we implemented a pre-impact fall detection algorithm using a wearable sensor positioned at waist. To verify our pre-impact fall detection algorithm, three types of falls and seven types of ADLs were conducted based on the characteristics of angular movements of the sensor.

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2 MATERIALS AND METHODS

2.1 Subjects and Experiments

Forty healthy male volunteers participated in the present study. Subject information in the study was shown in Table 1.

Table 1: Subject information in the study.

n = 40

Subject information	Mean ± SD
Age (year)	23.4 ± 4.4
Weight (kg)	68.7 ± 8.9
Height (cm)	172.0 ± 7.1

The experimental protocol was approved by the Yonsei University Research Ethics Committee (1041849-201308-BM-001-01) and written informed consent was obtained from each subject. In faint falls simulations, the subjects were told to stand on the floor beside the mattress. Then they fell by simply relaxing to the side, back, and front. All falls were conducted on soft foam mattress for five times respectively. A chair and the mattress were used for the ADL trials (sitting, sit–stand transitions, walking, stand–sit transitions, lying, jump, running). Each activity was conducted for three times. The algorithm was determined using experimental data of twenty subjects, and then verified with blind test data of twenty subjects. All clinical trials (falls and ADLs) were recorded by a Bonita camera (Vicon Motion Systems Ltd, UK) at frame rates of 200 frames/s.

MPU-9150 (Invensens®, USA) containing a 3-axis accelerometer and a 3-axis gyro sensor was used for the pre-impact fall detection sensor. The definition of the sensor axis are shown in Figure 1.
The sensor was attached on the middle of the left and the right anterior superior iliac spines. Data was sampled at 100Hz.

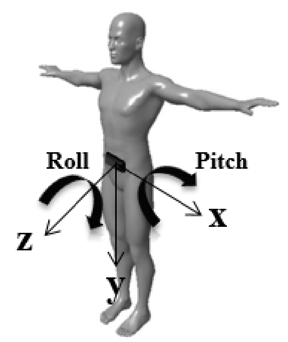

Figure 1: Definition of the sensor axis.

2.2 Pre-impact Fall Detection Algorithm

The algorithm was applied to falls and ADLs for twenty subjects. For rapid detection before the impact, threshold of acceleration and angular velocity was set to 0.8g and 30°/s, respectively. Furthermore, the threshold of vertical angle was set to 30° because the maximum angle in the ADL does not exceed beyond 30°, and we confirmed that the angle during the ADL was not over 30° (Figure 2). Lead time was defined as the time between impact and detection (Figure 3). The process flow of pre-impact detection algorithm in the processing unit is shown in Figure 4. Acceleration data was transformed into angles in sagittal and lateral planes, measuring how many degrees these body segments deviate from the vertical axis (i.e., standing is 0° and supine on the floor is 90°), using the following equations:

$$Deg_{SAG} = \tan^{-1}(Z_{acc} / Y_{acc})*(180/\pi) \quad (1)$$

and

$$Deg_{LAT} = \tan^{-1}(X_{acc} / Y_{acc})*(180/\pi) \quad (2)$$

If sum of acceleration vectors is less than 0.8g and angular velocities ($|\omega_{SAG}|$, $|\omega_{LAT}|$) are larger than the 30°/sec and vertical angles ($|Deg_{SAG}|$, $|Deg_{LAT}|$) larger than 30° threshold level, the sensor detects a fall.

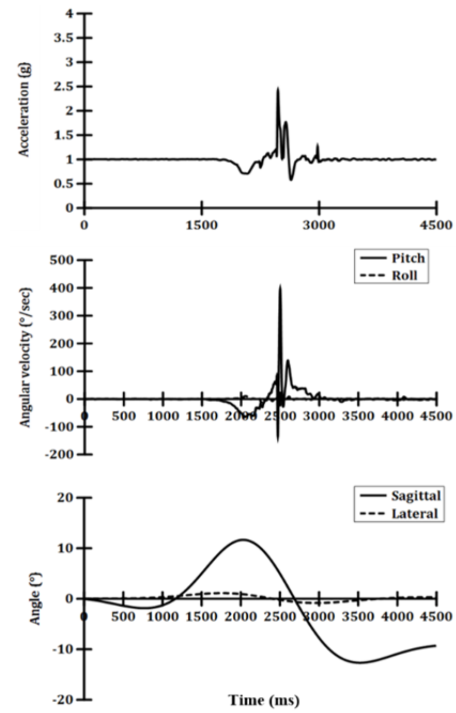

Figure 2: Acceleration, angular velocity and angular data for stand-sit activity.

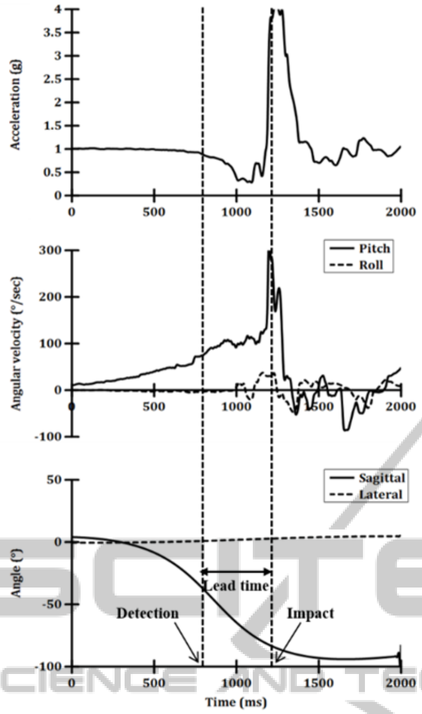

Figure 3: Acceleration, angular velocity and angular data for backward fall.

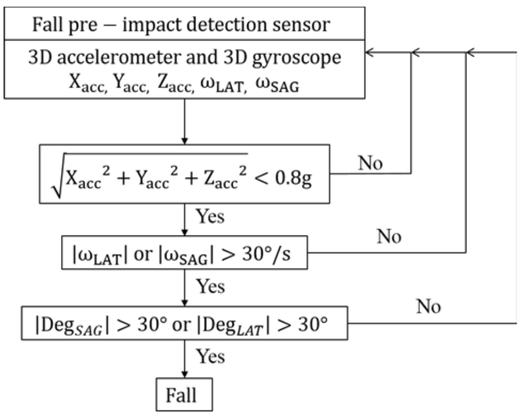

Figure 4: Pre-impact fall detection algorithm.

3 RESULTS

Table 2 showed peak acceleration, angular velocity and angle during falls and ADLs. The results showed that both acceleration and angular velocity were greater than the threshold during several ADLs while the angle did not exceed the threshold. For the angle, it exceeded the threshold during sit-lying activity only, but acceleration did not reach the threshold during sit-lying activity. The algorithm verified with blind test for twenty subjects. In the blind test, no false detects was found in the experiment (100% sensitivity) for all falls. Furthermore, no incorrect detection was found in the experiment (100% specificity) for all ADLs. Means and standard deviations of lead times for the three types of falls were shown in Figure 5. The lead time was 474 ± 38.3ms, 590.3 ± 122.6ms and 527 ± 62.3ms in the backward, the forward and the side falls respectively in order.

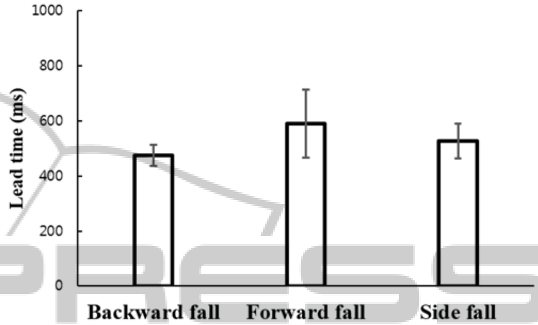

Figure 5: Mean and standard deviations of lead time in backward, forward and side falls.

4 DISCUSSION

As most of the fall-related injuries occur when the body hits the ground, the application of a pre-impact fall detection approach along with fall impact reduction systems for injury minimization will provide useful intervention for elderly people susceptible to faint falls (Wu, 2000; Davidson, 2004; Lockhart, 2006; Ulert, 2002).

This study aimed to detect a fall before impact using acceleration, angular velocity and angular features. In this study, we achieve lead time of approximately 530ms and 100% specificity.

Some previous studies showed 100% specificity. However, they did not show 100% sensitivity (Wu, 2000; Bourke et al., 2008). In particular, sometimes their algorithm made mistakes on jump or stand-sit transition for fall. If using acceleration threshold only, the jump might be mistaken for fall because the variation of the acceleration was large. For the stand-sit transition, especially during sitting to a chair, the pattern of acceleration is similar to the acceleration pattern of fall. Furthermore, there is rapid variation of the acceleration pattern when hip contacts to the chair. However, our algorithm using the threshold of angle could avoid these wrong recognitions.

In the assessment of successful balance recovery from complete loss of balance in fall, Thelen et al.

Table 2: Peak acceleration, angular velocity and vertical angle during falls and ADLs.

Trials		Acceleration (g)	Angular velocity (°/s)		Angle (°)	
			Pitch	Roll	Sagittal	Lateral
Falls	Backward	4.1 ± 0.6	300.3 ± 59.7	45.7 ± 14.2	94.2 ± 4.7	4.7 ± 3.2
	Forward	4.5 ± 0.5	220.6 ± 41.6	75.9 ± 17.2	89.6 ± 9.2	8.4 ± 4.6
	Side	4.4 ± 0.6	121.2 ± 13.7	419.4 ± 61.3	6.69 ± 2.7	75.95 ± 12.4
ADLs	Sit-Stand	1.4 ± 0.2	110 ± 23.1	8.9 ± 7.6	31.1 ± 6.1	2.6 ± 1.3
	Stand-Sit	2.2 ± 0.3	392.3 ± 61.3	11.2 ± 6.1	11.63 ± 3.1	1.12 ± 2.7
	Sit-Lying	1.1 ± 0.1	80.7 ± 31.7	15.3 ± 3.8	90.3 ± 8.3	4.3 ± 2.8
	Walking	2.1 ± 0.2	50.1 ± 10.9	59.3 ± 14.9	1.4 ± 6.2	2.1 ± 3.1
	Jump	7.5 ± 1.1	421.2 ± 149.1	102.3 ± 62.1	27.3 ± 2.1	3.6 ± 3.8
	Running	4.2 ± 0.9	132.8 ± 45.7	98.2 ± 34.9	11.5 ± 9.7	2.6 ± 4.1

(1997) found that the maximum lean angle where subjects could recover balance with a single forward step averaged 32.5° for young men and 23.9° for older men. Therefore, it can be noted that our threshold 30° of sensor angle is very well within the limits of balance recovery during the fall process. For lying activities in ADLs, there was a small variation in acceleration and no wrong recognition was found even though the angle changed to 90°.

It should be pointed out that all activities tested in this study was performed by healthy volunteers aged below 30, since the experimental procedure was not understandably suited for elderly subjects who are at greater risk of suffering injury. The movement of younger subjects is bound to differ from that of the elderly population, who may have as lower reaction time and lesser ability to rescue the body from falling. In addition, our algorithm were tested against a small range of fall types and ADLs. Therefore, further tests are needed for other types of falls such as tripping and slipping.

Nevertheless, our pre-impact fall detection algorithm can be implemented in a wearable fall injury minimization system to track a user's body movement and notify the fall impact reduction device.

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