PRE-IMPACT FALL DETECTION USING VERTICAL ANGLE AND ACCELERATION TRIANGLE FEATURE

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In this study, pre-impact fall detection algorithms were developed using an IMU sensor at the waist. Forty male volunteers participated in the experiments (four types of falls and six types of ADLs). An IMU was used to measure acceleration, angular velocity and vertical angle during all activities. Thresholds of acceleration, angular velocity, and vertical angle were set to 0.9 g, 47.3°/s, and 24.7° respectively for algorithm using vertical angle. Thresholds of acceleration, angular velocity, and triangle feature were set to 0.9 g, 47.3°/s, and 0.19 respectively for pre-impact fall detection algorithm using triagle feature. Pre-impact fall detection algorithms with the vertical angle and the triangle feature resulted in the lead time of 402 ms and 427 ms respectively. Both algorithms showed 100% accuracy to detect falls.

KEYWORDS: Falls; ADLs; IMU; fall detection algorithm; lead time.

INTRODUCTION: Fall is a significant cause of injury and death in the elderly (Kenny & O'Shea, 2002). The frequency of falls are increasing as the elderly population increases in many countries. Approximately 35% of community-dwelling elderly adults and 50% of those residing in long-term care facilities fall at least once per year (Nevitt, Cummings & Hudes, 1991; Tinetti, Doucette, Rose & Marottoli, 1995). Many of them suffer moderate to severe injuries that require hospitalization and increase the risk of death. Therefore, it is a major healthcare priority to develop fall prevention systems for the elderly adults.
Fall prevention strategies involve identifying individuals with an increased risk of falling and implementing the appropriate prevention mechanism. This includes physical restraints (Gross, Shimamoto, Rose & Frank, 1990) fall-related fracture prevention strategies (Smeesters, Heyes & McMahon, 2001; von den Kroonenberg, Hayes & McMahon, 1996; Yamamoto, Tanaka, Ikeda, Kubouchi, Harada & Okuizumi, 2006), study of risk factors related to syncope (Kenny, O'Shea & Walker, 2002) and multi-factorial risk assessment and management (Weatherall, 2004). One strategy to prevent or reduce injury due to falls is to detect falls during descent (pre-impact fall detection) and mitigate the impact (Bourke, O'Donovan & Laighin, 2008; Nyan, Tay, Tan, & Seah, 2006; Wu, 2008; Zhang, Wang, Xu & Liu, 2006; Ganti, Jayachandran, Abdelzaher, & Stankovic, 2006). Recently, a portable wearable sensor was used to measure acceleration and angular velocities during falls. If a fall can be detected in its earliest stage during descent, a more efficient impact reduction system can be implemented with a longer lead time. In this study, two different pre-impact fall detection algorithms were implemented using a sensor wearable at the waist and tested in four different types of falls and six types of ADLs.

METHODS: Forty healthy male volunteers (age 23.4 ± 4.4 years, 68.7 ± 8.9 kg, 172.0 ± 7.1 cm) participated in the study. 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 fall simulations, subjects were told to stand upright on the floor beside a soft foam mattress, then to fall (as if fainting) forward, backward (with and without a twist), or laterally (Figure 1). All falls were performed five times. A chair and mattress were used for ADL trials, which included sit-to-stand transitions, walking, stand-to-sit transitions, sit-to-lie transitions, jumping, and running. Each activity was performed three times.

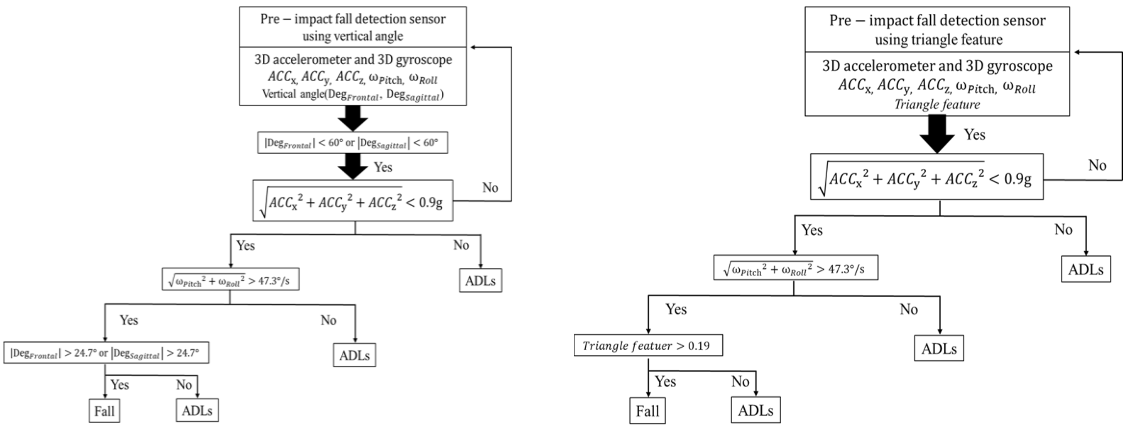
(A) (B) (C) (D)

Figure 1: Falls (A) Forward fall (B) Backward fall (C) Side fall (D) Twist fall

An MPU-9150 motion-tracking device (InvenSense, San Diego, CA, USA) containing a 3-axis accelerometer and a 3-axis gyro sensor was used for pre-impact fall detection. The sensor was attached to the middle of the left and right anterior superior iliac spines. Data were sampled at 100 Hz. All falls and ADLs were also recorded using a Bonita motion capture camera (Vicon Motion Systems Ltd., Oxford, UK) at 340 frames/s.

Data analysis was performed using MATLAB R2010a (MathWorks Inc., Natick, MA, USA). All data were low-pass filtered at 8 Hz. Acceleration data was transformed into the vertical angle in the sagittal and the frontal planes, measuring how many degrees these body segments deviated from the vertical axis (i.e., standing is 0°, and supine on the floor is 90°). The triangle feature was defined by the area of the triangle consisting of the vector sum of the acceleration in the two directions (x-axes, z-axes) and the acceleration in the y-direction.

The thresholds in the algorithm were optimized to maximize both the accuracy and the lead time. (Lead time was defined as the time between fall detection and impact.) Results showed that a fall was detected based on the VA algorithm when the vector sum of acceleration was less than 0.9 g, the angular velocity was greater than 47.3°/s, and the vertical angle was greater than 24.7° (Figure 2 A). Similarly, a fall was detected based on the TF algorithm when the vector sum of acceleration was less than 0.9 g, the angular velocity was greater than 47.3°/s, and the triangle feature was larger than 0.19 (Figure 2 B).



(A) (B)

Figure 2: (A) Pre-impact fall detection algorithm using vertical angle. (B) Pre-impact fall detection algorithm using triangle feature.

RESULTS: The pre-impact fall detection algorithms were tested for ten subjects. No failed detection occurred for four types of falls (100% sensitivity), and no incorrect detection was found for six different types of ADLs (100% specificity). Lead times for four different types of falls are shown in Table 1. Average lead time of the VA algorithm was 403 ± 32.7 ms, 422 ± 42.3 ms, 402 ± 33.1 ms, and 381 ± 19.0 ms for forward, lateral (side), backward, and twist falls, respectively. Average lead time of the FT algorithm were 423 ± 22.8 ms, 422 ± 31.8 ms, 442 ± 47.4 ms, and 397 ± 27.8 ms for forward, lateral (side), backward, and twist falls, respectively. The mean lead time of FT and VA algorithms were 427 ± 45.9 ms and 401.9 ± 46.9 ms respectively

Table 1: Lead times based on VA and TF algorithms.

	VA Algorithm	***TF Algorithm***
Forward Fall	403 ± 32.7 ms	423 ± 22.8 ms
Side Fall	422 ± 42.3 ms	422 ± 31.8 ms
Backward Fall	423 ± 33.1 ms	442 ± 47.4 ms
Twist Fall	381 ± 19.0 ms	397 ± 27.8 ms
Mean ± Std	401 ± 46.9 ms	427 ± 45.9 ms

DISCUSSION: In this study, pre-impact fall detection algorithms were implemented using an IMU sensor positioned at the waist. The algorithms used acceleration, angular velocity and one of the two tilting features (vertical angle or triangle feature).

Many studies have used pre-impact fall detection algorithms. Some studies have shown 100% specificity but without 100% sensitivity (Bourke, O'Donovan & Laighin, 2008; Wu, 2008). In particular, those algorithms produced false-positive errors, mistaking jumps or stand-sit transitions for falls. If acceleration is used as the only threshold, jumping and sitting in a chair can be mistaken for falling. Our algorithms used tilting features (vertical angle or triangle feature) as a threshold in addition to acceleration and angular velocity in order to avoid such mistakes.

A previous study achieved a longer lead time of roughly 700 ms (Nyan, Tay, Tan, & Seah, 2006). However, the algorithm required using two inertial sensors had lower accuracy. The algorithms developed in this study achieved 100% accuracy with only one sensor. The results showed that the lead time was approximately 30ms longer in TF algorithm than in VA algorithm because the triangle feature increases nonlinearly with the vertical angle.

It should be pointed out that all activities tested in this study were performed by healthy volunteers because the experimental procedure was not suited for the elderly subjects who are at higher risk of injury. The movement of younger subjects is bound to differ from that of the elderly population, who likely have slower reaction time and less ability to rescue the body from falling. In addition, the algorithms were tested using a small range of fall types and ADLs. Further studies are needed for other types of falls such as tripping and slipping. However, the present study demonstrated that VA and TF algorithms could improve the efficacy of the fall prevention system before the impact.

CONCLUSION: In this study, VA and TF algorithms were developed for the pre-impact fall detection using an IMU sensor. Both algorithms resulted in 100% accuracy. VA and TF algorithms showed a lead time of approximately 402 ms and 420 ms respectively. The fall detection algorithms can be improved by extending this to other types of falls and ADLs. The present improvement of pre-impact fall detection could be of great help to protect the elderly from fall injuries.

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