ON DEVELOPING A REAL-TIME FALL DETECTING AND PROTECTING SYSTEM USING MOBILE DEVICE

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Trip and slip falls frequently cause injuries in workplace and to the elderly during activities of daily living (ADLs). In recent years, several fall detecting algorithms have been developed using inertial measurement units (IMU). Although high sensitivity of fall detections could be reached based on self-initiated or pretending falls, and signals resulting from fall impact, real-time fall detecting, i.e. after fall initiation and before the impact, and hence reducing fall impact or serious injuries, has not been achieved. The goal of this study was to develop an algorithm, using the sensing signals from IMU of mobile devices (smartphones), to identify fall initiation, to provide sufficient lead time to trigger protection devices before impact, and to demonstrate the feasibility of real-time fall detecting and protecting using a mobile device.

Introduction

According to previous research, 15.9% of the elderly over 65 years old and 20.8% of the elderly over 80 years old experienced unexpected falls in 2008 (Stevens *et al.*, 2008). Falling in the elderly could result in variety of physical injuries, such as bruises and strains, and psychological traumas, such as self-restriction of activities due to fear of falling (Arfken *et al.*, 1994; Salkeld *et al.*, 2000). Without doubt, fall-related issues, such as fall detection, prevention, protection…etc. are worthy of attention.

Previous research defined falls as certain part of body, e.g. hand, touches the ground or reaches beneath the level of knees (Zhang *et al.*, 2006). Further research synoptically classified falls into trip, slip, step down and faint, among which trip and slip are the most common (Smeesters *et al.*, 2001). In order to detect falls, several detection methods have been developed. Motion capture systems were extensively utilized in biomechanics fields and early research of fall detections. However, more recent studies substituted motion capture systems for wearable IMU (inertial measurement unit) systems because of their convenience and better feasibility, and analyzed the detection accuracy by the concepts of sensitivity and specificity (Lord & Colvin, 1991). Nowadays, prevalence of commercialized mobile devices, like smartphones and pad computers, have drawn tremendous attention and allowed sensors embedded to be more available with lower cost.

The purpose of this study was to develop an algorithm, using IMU of smartphone, to identify fall initiation and trigger a protecting device to reduce fall injuries and to demonstrate the feasibility of real-time fall detecting and protecting using a mobile device.

Material and Method

Subjects

To develop the detecting algorithm, twelve healthy subjects (height: 1.69 ± 0.03 m; weight: 67.33 ± 7.52 kg; age: 24.30 ± 2.02 yrs.) were recruited to perform ADLs, unexpected slip and trip falls. To verify whether the developed algorithm and threshold were feasible, other thirty healthy subjects (height: 1.69 ± 0.04 m; weight: 63.17 ± 7.37 kg; age: 24.3 6 ± 2.04 yrs) were recruited to perform unexpected slip and trip during level walking. All subjects had no previous history of musculoskeletal injuries that would jeopardize the performance of tasks, and were provided written informed consent to participate in this study, which has been approved by the Institutional Review Board of Mackay Memorial Hospital.

Experimental Environment

All subjects were asked to perform unexpected falls in a designed experimental path, which contains mechanisms on floor to induce trip falls, by wooden plates suddenly popping up from beneath, and oiled floor surface to increase risk of slip falls.

Hardware

The IMU comprise of a triaxial accelerometer (g sensor) and gyroscope embedded in a smartphone (Samsung Galaxy S2 i9100, Samsung, Korea), operating with Android 2.3.3 (Google Inc, USA) system. Due to the combination of different sensors and algorithm requirements, a compromise on sampling rate, 88-95 Hz for triaxial accelerometer and 92-100 Hz for gyroscope, was reached in this study. Middle of chest was chosen to be the location of smartphone in this study, as shown in Figure 1 (Shany *et al.*, 2012).

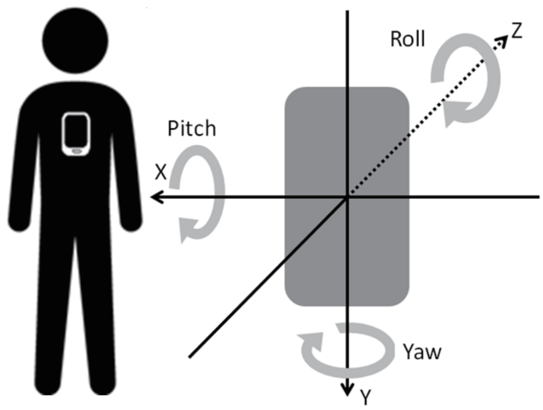

Figure 1. Position and orientation of IMU

ADLs and unexpected falls test

Twelve subjects were asked to perform each group of ADLs in a randomized order, shown in Table 1, for ten times.

Table 1. Tasks of ADLs test

Group 1	Group 2	Group 3
• Seated	• Getting on bed from standing upright	• Walking
• Sit to stand	• Getting on bed with self-selected strategy	• Going upstairs
• Squatting	• Getting up from bed	• Going downstairs
• Squat to stand		• Jogging

For unexpected falls, subjects were asked to perform level walking in designed experiment path with unexpectedly induced slip and trip conditions. To avoid learning effect, each trial would be ceased right after first trip or slip occurred. During the process, 3D accelerations and angular velocities of the body were recorded simultaneously by the smartphone. The data were used for developing the fall detecting algorithm.

Real-time test

Thirty subjects were asked to perform unexpected slip and trip, which induced by the mechanisms and oiled floor surface in designed experiment path, to verify the sensitivity of the algorithm and lead time, defined in data processing below. During the process, acceleration and angular velocity of the body were analyzed by algorithm instantly to detect whether a fall occurred.

Data Processing and Statistical Analysis

Acceleration values of all three directions and angular velocities of pitch and roll were superposed since rotation in vertical axis was not significant when falling. Kinematically, downward movements, like falling, show increasing acceleration, whereas upward movements, like jumping, show decreasing acceleration, in vertical direction. Thus, minimum superposed acceleration of triaxial acceleration in each task was extracted for fall detection.

To assess system accuracy, we quantified *sensitivity*, defined as the probability of an actual fall occurred given that the detector recognized a fall, and *specificity*, defined as the probability of an actual ADL occurred given that the detector recognized an ADL, using the data from the above-described experiment.

Delay time was defined as the allowed duration between threshold detection based on acceleration (minimum superposed acceleration was reached) and threshold detection based on angular velocity (maximum superposed angular velocity was reached).

Lead time, defined as the duration from an actual fall was detected to impact occurred, was taken into account to verify whether protection devices can be activated in time.

Results

For ADLs and unexpected fall test, acceleration and angular velocity in each task of the twelve subjects were shown as box-plot in Figure 2.

The range of trip and slip was 1.90 ± 0.90 m/s^2. Therefore, the threshold between ADLs and detected fall was chosen to be 4.60 m/s^2, which included 99.7% of falls, assuming the probability of falls were normally distributed. The threshold of angular velocity was chose to be 3.6 rad/s^2. If the superposed acceleration or angular velocity exceeded the chosen thresholds during any task, an alarm will be displayed on the smartphone, and a fall was considered identified.

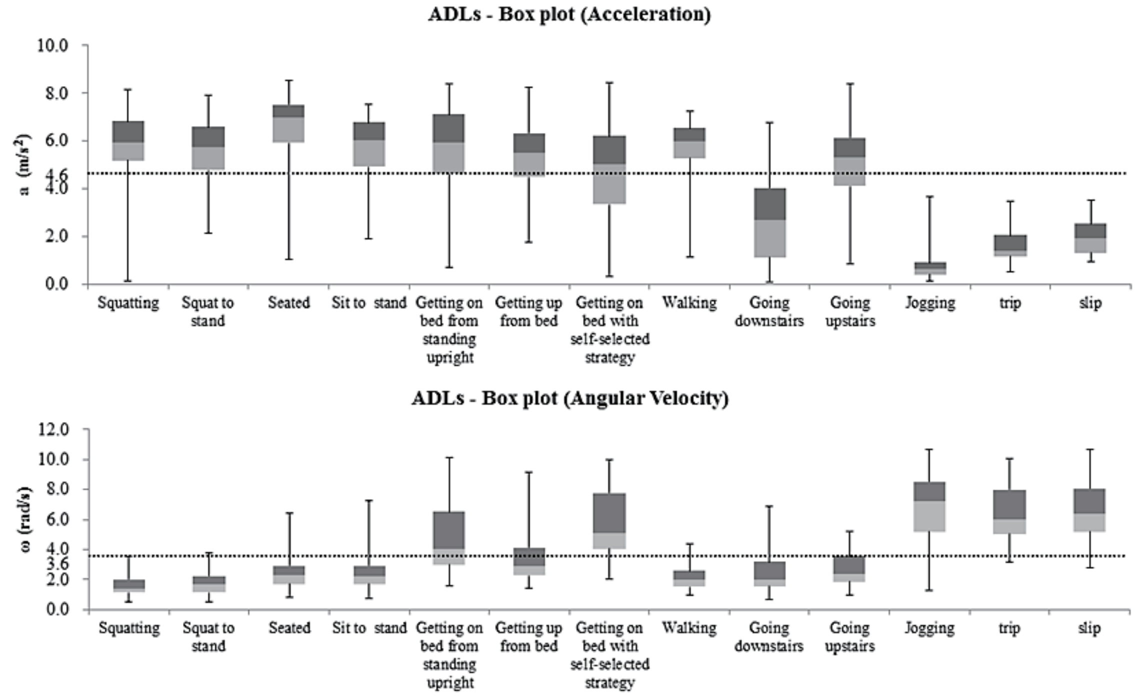

Figure 2. Minimum superposed acceleration and maximum superposed angular velocity of ADLs and unexpected fall test

As shown in Figure 2 acceleration part, going downstairs and jogging, which involved in relatively large motion in the vertical direction, might confuse the algorithm and result in low specificity. However, by using two type of sensors (accelerometer and gyroscope) to detected fall collaboratively with OR logic gate, specificity can be increased significantly as compared to using one type of sensor alone. Table 2 presents the specificity of fall detector during ADLs test with triaxial accelerometer and gyroscope respectively and collaboratively. For collaborative detection using both triaxial accelerometer and gyroscope, a 255ms delay time was chosen according to our previous study (Lin, 2013).

Table 2. Specificity during ADLs test with sensors respectively (Acc: accelerometer only; Gyro: gyroscope only) and collaboratively (Both: using both accelerometer and gyroscope)

Group 1	Acc.	Gyro.	Both
Squatting	79.17%	100.00%	100.00%
Squat to stand	79.17%	99.16%	99.17%
Seated	84.17%	86.67%	98.33%
Sit to stand	83.33%	90.00%	96.67%
Group 2	Acc.	Gyro.	Both
Getting on bed from standing upright	75.83%	38.00%	79.17%
Getting up from bed	73.33%	65.00%	86.33%
Getting up from bed with self-selected strategy	56.67%	17.50%	60.00%
Group 3	Acc.	Gyro.	Both
Walking	84.17%	95.00%	100.00%
Going downstairs	17.50%	84.16%	84.16%
Going upstairs	63.33%	76.67%	82.50%
Jogging	0.00%	6.67%	6.67%

After setting the thresholds and delay time, the establishment of algorithm of our system was completed. Figure 3 illustrates the step-by-step structure of the fall detecting algorithm.

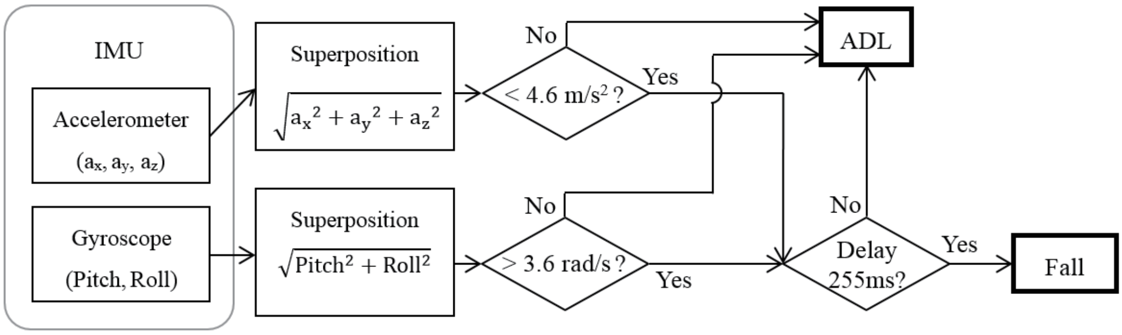

Figure 3. Structure of the algorithm

Sensitivity and specificity of real-time test, which has been performed by thirty subjects, are shown in Table 3. Furthermore, to verify that our system was capable of providing sufficient lead time for protection devices, results are shown in Table 4.

Table 3. Sensitivity, specificity of our system during real-time test

		Actual fall	
		+	-
Detecting results	+	95.24%	5.75%
	-	4.76%	94.25%

Table 4. Lead time of each slip and trip during real-time test

Lead time (ms)	Average	S.D.	Max	Min
Trip	173	53	249	101
Slip (lying down)	157	18	178	135
Slip (sitting)	95	28	132	51

Discussion

This study demonstrated the feasibility of developing a fall detecting system with IMU embedded in smartphones to achieve real-time fall recognition and to provide sufficient lead time to trigger protection devices.

Certain activities in ADLs, such as getting on bed from standing upright and jogging, would significantly confuse the algorithm with falls and lead to low specificity of the system. Furthermore, although high sensitivity and specificity were achieved in this study, various ADLs, which were excluded in this study, might lead to misjudgments.

Commercialized protection devices, such as airbags, need approximate 35ms to achieve full protection function to reduce impact. Our results show sufficient lead time for protection devices to fully activate, if airbags or similar protecting devices are used, in both trip and slip falls, although protecting device has not been integrated into our system yet. Furthermore, with advance of micro-electro-mechanical techniques, high precision and accuracy and, as a result, better sensitivity may be achieved.

Due to safety concerns, elderly subjects were excluded in our experiment during the developing process. Young and healthy subjects might not be able to represent certain group of people who actually need fall detectors. Therefore, our future studies will focus on the individualization of the detecting algorithm to make fall detector more suitable for different users.

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