S & M 1631

Optimization of a Pre-impact Fall Detection Algorithm and Development of Hip Protection Airbag System

Soonjae Ahn, Dagyeong Choi, Jongman Kim, Seongjung Kim, Youngjae Jeong, Min Jo, and Youngho Kim*

Department of Biomedical Engineering and Institute of Medical Engineering, Yonsei University, 1, Yeonsedae-gil, Maeji-ri, Heungeop-myeon, Wonju-si, Gangwon-do 26493, Republic of Korea

(Received March 31, 2017 accepted February 16, 2018)

Keywords: pre-impact fall detection, airbag, inertial sensor unit, optimization

In this study, a pre-impact fall detection algorithm using a custom-made inertial sensor was optimized, and a spring-trigger airbag system was developed for preventing injuries from falls. Four different types of simulated falls were performed by 20 healthy volunteers (age 23.4 \pm 4.4 years), and six different daily activities were tested in 14 elderly subjects (age 71.8 \pm 4.0 years). An inertial sensor unit was used to measure acceleration, angular velocity, and vertical angle during all activities. Thresholds of 0.9 g acceleration, 47.3°/s angular velocity, and 24.7° vertical angle were determined on the basis of optimizing lead time and accuracy in pre-impact fall detection. A belt-type airbag system consisted of a polyurethane inner skin, an artificial leather outer shell, and a spring-trigger inflator. To evaluate the accuracy of the airbag system, 10 healthy adult males (age 28.5 \pm 2.7 years) wore the system and performed three sets of simulated falls. Fall detection was achieved 401.9 \pm 46.9 ms before impact on average, and the airbag inflated without fail during the falls (100% sensitivity). In all daily activities, no airbag inflation occurred (100% specificity).

1. Introduction

Falls are a significant cause of injury and death in older adults.⁽¹⁾ The frequency and impact of falls are increasing as the elderly population increases in many countries. Approximately 35% of community-dwelling older adults and 50% of those residing in long-term care facilities fall at least once per year.^(2,3) Many suffer moderate to severe injuries that require hospitalization and increase the risk of death. Developing fall prevention systems for older adults is thus a major healthcare priority.

Fall prevention strategies involve identifying individuals with an increased risk of falling and implementing the appropriate prevention mechanism. This includes physical restraints, ⁽⁴⁾ fall-related fracture prevention strategies, ^(5–7) study of risk factors related to syncope, ^(8,9) and multifactorial risk assessment and management. ⁽¹⁰⁾ One strategy to prevent or reduce injury due to falls is to detect falls during descent (pre-impact fall detection) and mitigate the impact.

^{*}Corresponding author: e-mail: younghokim@yonsei.ac.kr http://dx.doi.org/10.18494/SAM.2018.1876

Several groups have developed methods to detect falls before impact. Wu implemented a pre-impact fall detection algorithm using thresholds for horizontal and vertical trunk velocity based on 3D motion capture measurements. She showed that falls could be distinguished from activities of daily living (ADL) with a 300–400 ms lead time before impact. However, such a video-based approach is limited in application by cost and portability.

Recently, a portable wearable sensor was used in a large study to measure inertial properties during falls.⁽¹¹⁾ In that study, Bourke *et al.* developed a pre-impact fall detection algorithm based on a threshold of vertical trunk velocity. A motion capture system and an inertial sensor on the chest consisting of a triaxial accelerometer and a triaxial gyroscope were used. Falls were distinguished from ADLs with 100% accuracy and were detected an average of 323 ms before trunk impact and 140 ms before knee impact. Other studies have used algorithms such as support vector machines (SVMs)⁽¹⁴⁾ and Markov models⁽¹⁵⁾ to detect falls. Thus far, these systems cannot respond to falls in real time. If a fall can be detected in its earliest stage during descent, a more efficient impact reduction system can be implemented using a longer lead time.⁽¹⁾ One such impact reduction system involves using airbags.^(16,17) Previous attempts to implement airbags have been limited by the poor effectiveness of the fall detection algorithm and the use of gunpowder for the airbag inflator, which is an explosion hazard and prevents the use of the device in hospitals and airports. It is necessary to develop an inflator that is both fast and safe.

In this study, a pre-impact fall detection algorithm was implemented using a sensor wearable at the waist, and a spring-trigger airbag system was developed to prevent injury from falls. To verify both the fall detection algorithm and the airbag system, four different types of falls and six types of ADLs were performed.

2. Methods

2.1 Subjects and experiments

Forty healthy male volunteers (age 23.4 ± 4.4 years, weight 68.7 ± 8.9 kg, height 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 on the floor beside a soft foam mattress, then to fall (as if fainting) forward, backward (with and without a twist), or laterally (Table 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.

Table 1 Description of fall types.

Fall type	Description
Forward fall	Faint fall in the forward direction
Backward fall	Faint fall in the backward direction
Side fall	Faint fall in the lateral direction
Twist fall	Rotation on the vertical axis during a backward fall

An MPU-9150 motion-tracking device (InvenSense, San Diego, CA, USA) containing a 3-axis accelerometer and a 3-axis gyrosensor 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 recorded using a Bonita motion capture camera (Vicon Motion Systems Ltd., Oxford, UK) at 340 frames/s.

2.2 Pre-impact fall detection algorithm

The pre-impact fall detection algorithm was applied to falls and ADLs performed by 20 subjects. Data analysis was performed using MATLAB R2010a (MathWorks Inc., Natick, MA, USA). All data were low-pass filtered at 10 Hz. Acceleration, angular velocity, and tilt angle were used as threshold values to define falls in the algorithm. The thresholds in the algorithm were optimized using an interior-point algorithm⁽¹⁸⁾ to maximize the accuracy and lead time. This algorithm solves linear and nonlinear convex optimization problems. Accuracy was defined as the mean of sensitivity and specificity.⁽¹⁹⁾ Lead time was defined as the time between fall detection and impact (Fig. 1). Impact was defined as the collision of the hip with the ground. The impact time was determined as the time when the hips reached the ground. The airbag inflation time was also measured using a high-speed camera.

Sensitivity and specificity were defined as

$$Sensitivity (\%) = \frac{True \ positives}{True \ positives + False \ negatives} \times 100, \tag{1}$$

$$Specificity (\%) = \frac{True \ negatives}{True \ negatives + False \ positives} \times 100 \ , \tag{2}$$

where

- (i) True positive: fall occurs; device detects it.
- (ii) False positive: normal movement (no fall); device detects a fall.

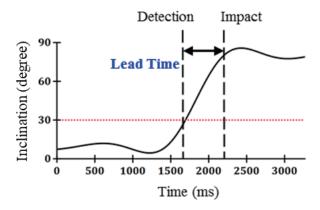


Fig. 1. (Color online) Lead time.

- (iii) True negative: normal movement (no fall); device does not detect a fall.
- (iv) False negative: fall occurs; device does not detect it.

A schematic of the pre-impact detection algorithm is shown in Fig. 2. The thresholds for acceleration, angular velocity, and vertical angle were set to $0.9 \, g$, $47.3^{\circ}/s$, and 24.7° , respectively. When the vector sum of acceleration was less than $0.9 \, g$, the angular velocity was greater than $47.3^{\circ}/s$, and the vertical angle was greater than $24.7 \, deg$, a fall was detected. To prevent misdetection while lying down, the algorithm only worked when the vertical angle was less than 60° . Acceleration data was transformed into trunk inclinations in sagittal and lateral 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°), using the following equations.

$$Deg_{Saggital} = \tan^{-1} \frac{Z_{acc}}{Y_{acc}} \times \frac{180}{\pi}$$
 (3)

$$Deg_{Frontal} = \tan^{-1} \frac{x_{acc}}{Y_{acc}} \times \frac{180}{\pi}$$
 (4)

2.3 Airbag system

The airbag system consisted of an airbag and sensor. The sensor was composed of a CPU and an inertial sensor with a built-in pre-impact fall detection algorithm. If the sensor detected a fall, the airbag inflated (Fig. 3).

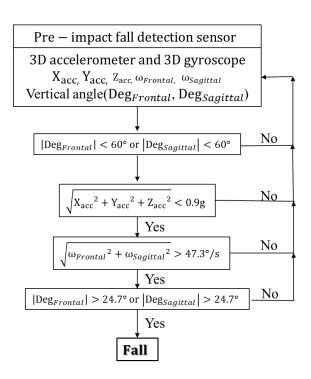


Fig. 2. Pre-impact fall detection algorithm.

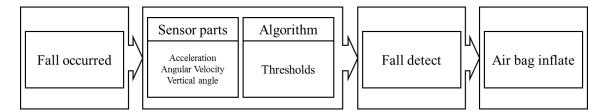


Fig. 3. Flowchart of airbag system.

The airbag consisted of an inner and outer skin. The inner skin was composed of polyurethane and nylon taffeta, and the outer skin of soft artificial leather. The airbag had a built-in spring-trigger inflator. The inflator was designed to eject helium gas from the cartridge when the loaded beads hit the needle as the sensor detected a fall (Fig. 4). A gas cartridge containing 2.5 g of helium was used, and the airbag was 12 L when fully inflated. The airbag system weighed 954.3 g.

2.4 Verification of airbag system

Ten healthy male volunteers (age 28.5 ± 2.7 years, height 173.2 ± 6.7 cm, weight 71.4 ± 8.4 kg) participated in the airbag system verification experiment. They wore airbags and performed the same actions as described in Sect. 2.1. Each activity was performed three times, and sensitivity, specificity, and lead time were calculated.

3. Results

3.1 Inertial measurement unit signal in falls and ADLs

Inertial measurements for falls are shown in Fig. 5. The thresholds selected for acceleration, angular velocity, and trunk inclination were 0.9 g, $47.3^{\circ}/s$, and 24.7° , respectively, indicated in red. Measurements for ADLs (not shown) indicated that no ADL surpassed all three thresholds. Acceleration and angular velocity were greater than 0.9 g and $47.3^{\circ}/s$, respectively, during several ADLs with trunk inclination $<24.7^{\circ}$; trunk inclination exceeded 24.7° only in the sit-to-lie activity.

3.2 Sensitivity and specificity

The airbag system was verified using 10 subjects. No failed inflation occurred for the four types of falls (100% sensitivity), and no incorrect inflation occurred for the six different types of ADLs (100% specificity).



Fig. 4. (Color online) (a) Airbag system and (b) spring-trigger inflator.

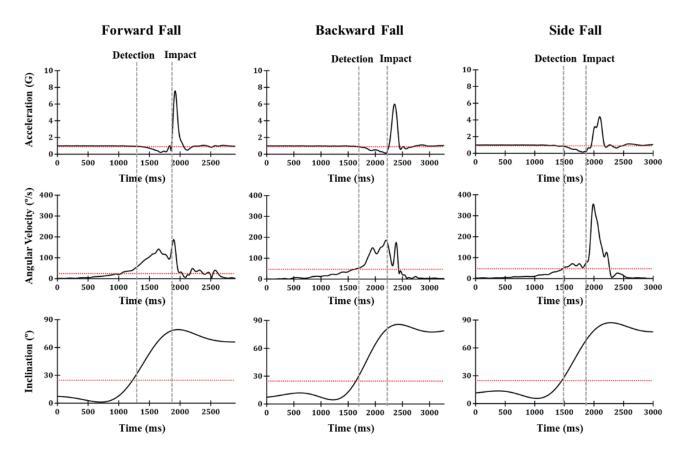


Fig. 5. (Color online) Acceleration, angular velocity, and angle during falls.

3.3 Lead time

Lead times for the four different types of falls are shown in Fig. 6 (mean and standard deviation for individual subjects). Average lead times were 403 ± 32.7 , 422 ± 42.3 , 402 ± 33.1 , and 381 ± 19.0 ms for forward, lateral (side), backward, and twist falls, respectively. The airbag inflation time was 245.43 ± 5.4 ms.

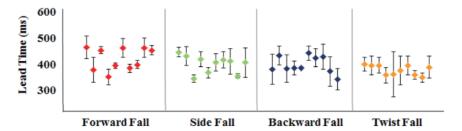


Fig. 6. (Color online) Lead time.

4. Discussion

In this study, a pre-impact fall detection algorithm was developed using an inertial sensor unit. We aimed to detect falls before impact using measurements of acceleration, angular velocity, and trunk inclination. Thresholds for acceleration, angular velocity, and trunk inclination were set to 0.9 g, 47.3%, and 24.7°, respectively. The algorithm was verified by a blind test using four different types of simulated falls and six types of normal activities (ADLs). Using these parameters, we achieved a lead time of 402 ms and 100% accuracy.

Many studies have used pre-impact fall detection algorithms that trigger wearable fall-injury minimization systems. (13,20,21) However, the accuracy of these algorithms has been low. Some studies have shown 100% specificity but without 100% sensitivity. (11,13) In particular, these 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 algorithm used trunk inclination as a threshold in addition to acceleration and angular velocity to avoid such mistakes.

While investigating balance recovery from loss of balance in a fall, Thelen *et al.* found that the maximum lean angle from which subjects could recover balance with a single forward step averaged 32.5° for young men and 23.9° for older men. (22) In comparison, our threshold of 24.7° trunk inclination is well within the limit for balance recovery by young men and close to the limit for older men.

For lying activities in ADLs, in our study, there was only a small variation in acceleration; as a result, no incorrect fall detection was observed. Mistakes in fall detection can occur when subjects are moving while lying down (for example, while watching TV or reading). To avoid these mistakes, we added a threshold of 60° trunk inclination to the beginning of the algorithm.

In this study, we achieved a lead time of approximately 402 ms. A previous study achieved a longer lead time of roughly 700 ms. (23) However, the algorithm required using two inertial sensors, had lower accuracy, and did not detect falls in real time and thus cannot be applied to fall protection. Previous studies have attempted to prevent injuries from falls using airbags. (16,17) However, these studies have been limited by the effectiveness of the detection algorithm (lead time and accuracy). In this study, we developed a pre-impact fall detection algorithm with a long lead time and 100% accuracy, integrated it with an airbag system, and confirmed that the airbag system protects the body when the fall occurs.

A major problem with existing airbag systems is the use of gunpowder in the airbag inflator, which is an explosion hazard. The spring-trigger inflator we developed is safe while being fast enough to deploy the airbag before impact given the long lead time provided by the fall detection system.

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 elderly subjects who are at greater risk of injury. The movement of younger subjects is bound to differ from that of the elderly population, who likely have a slower reaction time and less ability to rescue the body from falling. In addition, our airbag system was tested using a small range of fall types and ADLs. Further tests are needed for other types of falls such as tripping and slipping.

5. Conclusions

In this study, a pre-impact fall detection algorithm was developed using an inertial sensor unit and hip protection airbag system. Thresholds for acceleration, angular velocity, and trunk inclination were set to 0.9 g, 47.3°/s, and 24.7°, respectively. Our pre-impact fall detection algorithm showed a lead time of approximately 402 ms and 100% accuracy. The fall detection algorithm can be improved by applying it to more types of falls and activities of daily living. The inflator and airbag developed in this study can be applied to other fall protection systems. Improved fall detection and prevention devices will be of great help in protecting the elderly from injuries sustained during falls.

Acknowledgments

This research was supported by the Leading Human Resource Training Program of Regional Neo Industry (No. 2016H1D5A1909760) and the Bio & Medical Technology Development Program (No. 2017M3A9E2063270) through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT

References

- 1 R. A. Kenny and D. O'Shea: Clin. Geriatr. Med. 18 (2002) xiii.
- 2 M. C. Nevitt, S. R. Cummings, and E. S. Hudes: J. Gerontol. 46 (1991) M164.
- 3 M. E. Tinetti, J. Doucette, E. Claus, and R. Marottoli: J. Am. Geriatr. Soc. 43 (1995) 1214.
- 4 Y. T. Gross, Y. Shimamoto, C. L. Rose, and B. Frank: J. Gerontol. Nurs. 16 (1990) 20.
- 5 C. Smeesters, W. C. Hayes, and T. A. McMahon: J. Biomech. 34 (2001) 309.
- 6 A. J. van den Kroonenberg, W. C. Hayes, and T. A. McMahon: J. Biomech. 29 (1996) 807.
- 7 S. Yamamoto, E. Tanaka, T. Ikeda, Y. Kubouchi, A. Harada, and H. Okuizumi: J. Biomech. 39 (2006) S89.
- 8 R. A. Kenny, D. O'Shea, and H. F. Walker: Age Ageing 31 (2002) 272.
- 9 K. Peczalski, D. Wojciechowski, P. Sionek, Z. Dunajski, and T. Palko: J. Biomech. 39 (2006) S453.
- 10 M. Weatherall: Evidence-based Healthcare Public Health 8 (2004) 270.
- 11 A. K. Bourke, K. J. O'Donovan, and G. Ó Laighin: Med. Eng. Phys. 30 (2008) 937.
- 12 M. N. Nyan, F. E. H. Tay, A. W. Y. Tan, and K. H. W. Seah: Med. Eng. Phys. 28 (2006) 842.
- 13 G. Wu: J. Biomech. **33** (2000) 1497.
- 14 T. Zhang, J. Wang, L. Xu, and P. Liu: Proc. ICIC2006, Eds. D. Huang, K. Li, and G. Irwin (Springer, Berlin, 2006) 858–863.

- 15 R. K. Ganti, P. Jayachandran, T. F. Abdelzaher, and J. A. Stankovic: Proc. 4th Int. Conf. Mobile Systems, Applications and Services (ACM, 2006) 110–123.
- 16 T. Tamura, T. Yoshimura, and M. Sekine: Proc. 2007 IEEE Engineering in Medicine and Biology Society, 29th Annu. Int. Conf. (IEEE, 2007) 3833–3835.
- 17 T. Tamura, T. Yoshimura, M. Sekine, M. Uchida, and O. Tanaka: IEEE Trans. Inf. Technol. Biomed. 13 (2009) 910.
- 18 M. H. Wright: Bull. Am. Math. Soc. 42 (2005) 39.
- 19 N Noury, A. Fleury, A. K. Bourke, G. Ó Laighin, V. Rialle, and J. E. Lundy: Proc. 2007 IEEE Engineering in Medicine and Biology Society, 29th Annu. Int. Conf. (IEEE, 2007) 1663–1666.
- 20 M. Davidson: US Patents No. 20040003455 (2004).
- 21 T. Lockhart: US Patents No. 20060049950 (2005).
- 22 D. G. Thelen, L. A. Wojcik, A. B. Schultz, J. A. Ashton-Miller, and N. B. Alexander: J. Gerontol. A Biol. Sci. Med. Sci. 52 (1997) M8.
- 23 M. N. Nyan, F. E. H. Tay, and E. Murugasu: J. Biomech. 41 (2008) 3475.

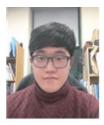
About the Authors



Soonjae Ahn received his B.S. and M.S. degrees in Biomedical Engineering from Yonsei University in 2011 and 2013, respectively. He is currently a Ph.D. student in the Department of Biomedical Engineering at Yonsei University, Korea. His research interests are in the areas of rehabilitation engineering, falls, and fall prevention.



Dagyeong Choi received her B.S. degree in Biomedical Engineering from Konyang University in 2014. She is currently an M.S. student in the Department of Biomedical Engineering at Yonsei University, Korea. Her research interests are in the areas of rehabilitation engineering, sensors, and signal analysis.



Jongman Kim received his B.S. degree in Biomedical Engineering from Yonsei University in 2015. He is currently an M.S. student in the Department of Biomedical Engineering at Yonsei University, Korea. His research interests are in the areas of rehabilitation engineering, motion analysis, and sensors.



Seongjung Kim received his B.S degree in Biomedical Engineering from Yonsei University in 2017. He is currently an M.S. student in the Department of Biomedical Engineering at Yonsei University, Korea. His research interests are in the areas of rehabilitation engineering, signal processing, and sensors.



Youngjae Jeong received his B.S. degree in Biomedical Engineering from Konyang University in 2016. He is currently an M.S. student in the Department of Biomedical Engineering at Yonsei University, Korea. His research interests are in the areas of rehabilitation engineering and motion analysis.



Min Jo received his B.S. degree from Sejong University, Korea, in 2014. He is currently an M.S. student in the Department of Biomedical Engineering at Yonsei University, Korea. His research interests are on muscle fatigue and signal analysis during electrical stimulation.



Youngho Kim received his B.S. degree in Mechanical Engineering from Hanyang University in 1982. He received his M.S. and Ph.D. degrees in Biomedical Engineering from the University of Iowa in 1989 and 1991, respectively. He is currently a Professor in the Department of Biomedical Engineering at Yonsei University, Korea. His research interests are in the areas of human movement, rehabilitation engineering, and biomechanics.