# Wearable Airbags

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Fall-related injury is a common cause of mortality among the elderly. Hip fractures are especially dangerous and can even be fatal. In this study, a threshold-based preimpact fall detection algorithm was developed for wearable airbags that minimize the impact of falls on the user's body. Acceleration sum vector magnitude (SVM), angular velocity SVM, and vertical angle, calculated using inertial data captured from an inertial measurement unit were used to develop the algorithm. To calculate the vertical angle accurately, a complementary filter with a proportional integral controller was used to minimize integration errors and the effect of external impacts. In total, 30 healthy young men were recruited to simulate 6 types of falls and 14 activities of daily life. The developed algorithm achieved 100% sensitivity, 97.54% specificity, 98.33% accuracy, and an average lead time (i.e., the time between the fall detection and the collision) of 280.25 ± 10.29 ms with our experimental data, whereas it achieved 96.1% sensitivity, 90.5% specificity, and 92.4% accuracy with the SisFall public dataset. This paper demonstrates that the algorithm achieved a high accuracy using our experimental data, which included some highly dynamic motions that had not been tested previously.

Keywords: falls ; airbag ; threshold-based ; IMU ; complementary filter

## 1. Introduction

With the world's population ageing, there is an increasing focus on age-related health issues. Fall-related injuries are the primary cause of injury and mortality in the elderly. According to the WHO, every year, 37.3 million people are injured severely enough to receive medical treatment, and 646,000 people die due to falls. Adults over 65 years of age suffer the greatest number of fatal falls [[1]]. Reduced levels of bone density, decreased muscle mass, as well as slow reflexes increase the risk of fall-related injuries in the elderly [[2][3]]. Hip fractures are considered the most dangerous among various injuries, as they can reduce mobility and lead to many complications, and even death [[4]]. In addition, there is a social dimension to this issue, because it mandates special care for the elderly. From an economic perspective, fall-related medical expenses in the elderly were reported to have accounted for as much as USD 50 billion for nonfatal falls and 754 million for fatal falls in the year 2015 alone [[5]]. Therefore, falls and fall-related injuries are major sources of physical, social, and economic problems among the elderly.

In the past, many studies have tried to improve the physical performance of the elderly by implementing exercise programs to help prevent falls. Lord et al. [[6]] conducted a fall prevention exercise program based on physiological profile assessments and sit-to-stand tests. They found that while the program improved knee flexion and visual ability, there was no significant reduction in fall risk. Røyset et al. [[7]] also conducted a fall prevention program using the Norwegian version of the fall risk assessment method, "STRATIRY" (score 0–5), but achieved no significant improvement statistically when compared to the control group.

## 2. Enhanced Algorithm for Detection of Preimpact Fall for Wearable Airbags

There are many commercially available hip protection pads that help mitigate the impact of a fall, but they are inconvenient to use in daily life as they must be worn under the clothes. Additionally, their performance varies, as they tend to slide away from the correct position when worn over time [[8][9]]. To ensure better impact attenuation during falls, some researchers have also developed wearable airbags [[10][11][12]]. Jeong et al. [[13]] developed a hip impact simulator and compared the impact attenuation performance of hip protection pads with a wearable airbag. Their results showed that the wearable airbag did a better job of cushioning the impact from a fall because of its deformation at the time of impact, which increased the contact time and area involved during the impact. However, to successfully utilize a wearable airbag, a fall detection algorithm with a high level of accuracy and sufficient lead time to inflate the airbag before the impact must be used.

Falls can be detected either through stationary devices, such as cameras, or wearable sensors. Rougier et al. [[14]] used a particle filter to track human head position in three dimensions with a single camera, and detected falls using the vertical displacement and velocity of the head. Bian et al. [[15]] tracked the head and waist using a depth camera to detect falls. They applied a support vector machine classifier and achieved 95.8% sensitivity, 100% specificity, and 97.9% accuracy. Wang et al. [[16]] created a surveillance video–based fall detection system using PCANet and a linear support vector machine classifier that achieved 88.87% sensitivity and 98.9% specificity. Li et al. [[17]] used Kinect sensors to distinguish falls based on whether the zero moment point was within the dynamic supporting area or not; they obtained 100% sensitivity, 81.3% specificity, and 91.7% accuracy. However, detecting falls using such stationary camera devices has some drawbacks, including limited coverage area and privacy issues.

In contrast, many fall detection systems have been developed that use wearable sensors, such as inertial measurement unit (IMU) and electromyography (EMG) sensors, based on machine learning (ML) and threshold-based approaches. Rescio et al. [[18]] attached an EMG sensor to the soleus muscle to detect falls and selected the optimal feature among ten types of time-domain features using a Markov random field-based Fisher-Markov selector. They achieved 89.5% sensitivity and 91.9% specificity. Yoo et al. [[19]] obtained acceleration properties from an IMU positioned on the wrist that detects falls using an artificial neural network, and achieved 100% accuracy. Aziz et al. [[20]] used 3-axis acceleration data from an IMU attached on the waist, and compared its performance between logistic regression, decision tree, Naïve Bayes, K-nearest neighbor, and support vector machine. Among them, the support vector machine showed the best performance, with 96% sensitivity and 96% specificity. In general, ML-based fall detection algorithms show good performance, but it takes considerable time to extract features and train classifiers. Therefore, ML-based algorithms are not appropriate for preimpact fall detection where a rapid detection time is required. Therefore, threshold-based fall detection algorithms would be more suitable for predicting falls because of their low computational requirements and quick response time.

Thanh et al. [[10]] captured 3-axis acceleration data from the waist position, to which they applied a Kalman filter to reduce measurement and sensor errors. Their threshold-based fall detection algorithm used the root mean square of acceleration, vertical angle, and vertical velocity, and achieved 100% fall detection accuracy. Zhong et al. [[11]] proposed a threshold-based fall detection algorithm using vertical displacement and vertical velocity from an IMU sensor on the front waist. They obtained 93.6% sensitivity and 95.6% specificity with an average lead time of 363 ms. Nyan et al. [[21]] developed a preimpact fall detection algorithm that used angles calculated from the torso and thigh (with the help of 2 IMUs), as well as the correlation coefficients of the torso and thigh angles. The algorithm achieved 100% specificity, 95.2% specificity, and a lead time of 700 ms. Wang et al. [[22]] calculated acceleration magnitude, acceleration cubic-product-root magnitude, and angular velocity cubic-product-root magnitude from the acceleration and angular velocity data obtained from an IMU placed on the front chest to develop a threshold-based fall detection algorithm. In the study, the algorithm was evaluated using their experimental data and two different public datasets (Cogent Labs and UMAFall). They achieved 98.9%, 98.0%, and 96.6% sensitivity and 100%, 96.6%, and 83.2% specificity based on their experimental data, cogent labs dataset, and UMAFall dataset, respectively. Ahn et al. [[23]] developed a threshold-based fall detection algorithm based on acceleration SVM, angular velocity SVM, and triangle feature calculated from acceleration and angular velocity data from a sensor placed on the front waist. They reported 100% sensitivity and 83.9% specificity using the SisFall public dataset. While some of the previously discussed threshold-based fall detection algorithms showed high detection accuracies, they would not be practical in real-life applications because only less-dynamic (walking, standing, sitting, etc.) or typical motions (climbing upstairs/downstairs, etc.) were included in these studies.

In this study, 6 types of simulated falls and 14 activities of daily life (ADLs), including some highly dynamic motions, were selected to simulate real-life situations. To capture inertial data, an IMU was used. From the captured inertial data, acceleration SVM, angular velocity SVM, and vertical angle were calculated using complementary filter with a proportional integral (PI) controller. Subsequently, a threshold-based preimpact fall detection algorithm was developed based on these parameters. The algorithm's performance was evaluated in a lab experiment involving 30 research participants. For an objective evaluation, we evaluated the algorithm using the SisFall public dataset as well [[24]].

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