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Body and Fall Detection System with Heart Rate Monitoring

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A B S T R A C T

Falling is a significant cause of catastrophic injuries such hip fractures in the older population. Injury- or unconsciousness-related immobility means that the victim is unable to summon their own assistance. It is fairly usual for older people who live alone to go for hours without being located following a fall, which greatly raises the significance of fall-related injuries. In the coming decades, the number of falls will increase as the Baby Boomer generation ages. This project's goal was to plan and build an elderly fall detection and prevention system. The system comprises of a wirelessly connected laptop and a wearable monitoring device. The gadget can tell the difference between a fall and a non-fall correctly. When a fall is detected, the gadget sends out a loud alarm through the laptop and the device, alerting people of the user's fall. The device may also detect unsafe tilt that indicates a fall, at which point it warns the user to adjust their position to avoid falling minimize the risk of falling. The main goal of this research was to create the best algorithm for identifying falls and separating them from non-falls. A variety of algorithms focused on acceleration magnitude and angle change were explored, merged, and based on both gyroscope and accelerometer platforms. The process of establishing the most successful algorithm involved rigorous testing and data collection.

Keywords: fall detection, acceleration magnitude, angle change, angular velocity, algorithm, threshold, fall prevention, elderly, automatic, wireless, Bluetooth, SVM

Literature Review

Multiple research journals were consulted to find relevant information regarding fall detection. From these journals, information on how to use the acceleration readings along multiple axes from an accelerometer to calculate acceleration magnitude, cross product magnitude, and angle change was found [11]. In addition, information on how to use the output from our gyroscopes to determine angular change, velocity, and acceleration was also found [9]. Several journals also included the approximate values of angle change and acceleration thresholds expected during falls, leading up to falls, and in ADL [11].

INTRODUCTION

Between one-third and fifty percent of those over 65 fall each year [1]. Half of these older people who do fall do so repeatedly [1]. Falls are the leading cause of injury in older adults and the leading cause of accidental death in those 75 years of age and older, accounting for 70% of accidental deaths [2]. Over 90% of hip fractures are caused by falls, and most of these fractures affect those over the age of 70 [3]. The U.S. spends more than $20 billion a year on treating falls-related injuries and complications [4]. After their children have grown up and left the house, many elderly people live alone in a flat or a smaller house. An older person who falls often is unable to get up on their own or call for assistance. Therefore, a system that can automatically detect falls is needed so that patients can call for assistance even if they are unconscious or unable to get up after falling.

There are already several products on the market attempting to address this problem that have reached commercialization [5,6,7]. However, all of these products require the fall detection device to connect (via RF) to a stationary base station, which is often a separately purchased product. This base station, placed centrally in one’s house and hardwired to a phone line, then phones a call centre for help. The disadvantage of these products is that they all require an intermediary call service which amounts to a hefty monthly fee. Also, they are all limited to the range of one’s house because they depend on the central base station for outside contact.

Regarding the non-commercialized side of development, the majority of fall detection research is focused on creating new, more effective algorithms for differentiating falls from non-falls. The work around fall detection is distinguished by the equipment used and by the features extracted from sensor data. The first approach is based on accelerometers. An accelerometer is a device that can detect the magnitude and direction of acceleration along a certain axis; usually three-axis accelerometers are used. Accelerometers can also calculate one’s angle in relation to the Earth by detecting the acceleration due to gravity of the Earth [8]. The second main approach uses gyroscopes, which measure orientation. A spinning wheel with a freely orientable axle makes up a gyroscope [9]. It may measure the orientation along one or more axes, just as an accelerometer. Using gyroscopes, it is possible to determine one's orientation and changes in orientation, which can be used to calculate angular velocity and acceleration [8].

2.Methodology

Using accelerometers, the most common and simple methodology for fall detection is using a tri-axial accelerometer and applying thresholds [9,10]. This means that any motion that exceeds some threshold value of acceleration will be considered a fall. More advanced detection involves taking the dot product or cross product of the axial accelerations to obtain the cross product magnitude and angle change [11]. With this knowledge, new algorithms can be created, such as those that analyse acceleration threshold and post-fall orientation.This is important because often when a person falls, their orientation changes from vertically standing to horizontally lying on the floor.

Researchers using accelerometers give a lot of attention to the optimal sensor placement on the body; researchers generally agree that optimal fall sensor placement is at the waist [10,12]. Using gyroscopes, a similarly-placed gyroscope measures pitch and roll angular velocities. Fall and tilt detection can be successfully accomplished by using a threshold method to measure angular shift, velocity, and acceleration [9].

This project involved testing and devising algorithms for maximum sensitivity and specificity. We tested existing algorithms while using our own ideas to come up with new hybrid algorithms. Different from existing fall detection systems, our device uses both accelerometers and gyroscopes. This opened doors to new algorithms that integrate both components and essentially allowed us to have two stages of detection whereas existing devices only have one.

Testing and data collection involved multiple persons simulating falls and non-falls or Activities of Daily Living (ADL) [10]. We let the device's algorithm distinguish between them, followed by algorithm evaluation. Since asking older people to intentionally fall is unreasonable, the simulated falls were completed by young adults (aged 20-25) in a monitored environment

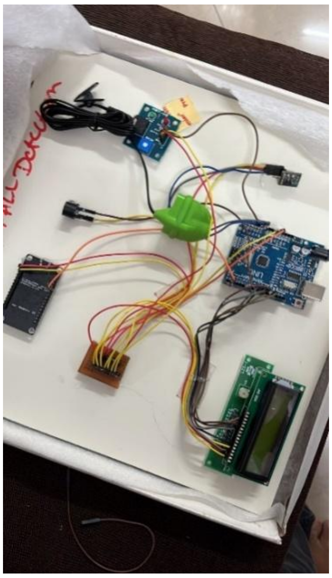
3.Result

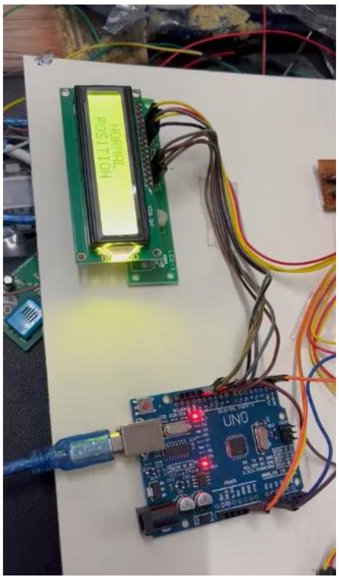
A similar process to the one involving acceleration magnitude described above was completed with the other fall-related parameters of angle change, angular velocity and angular acceleration. For example, using the same test data as above, we also looked at the orientation change involved before and after both falls and non-falls in order to determine our orientation change ranges/thresholds.

Using the values we had determined from both research and our own fall/non-fall data collection and testing above, we established the different thresholds in our algorithms. After setting the threshold variables in our Arduino programs, we began to test the different algorithms. For accuracy and realism, the falls/non-falls were performed on bare ground instead of cushioned mats. Due to the physical demanding nature of the falls, we limited the number of tests to 20 per algorithm. To perform our testing we uploaded each algorithm program to the Arduino one at a time and performed 10 true falls and 10 non-falls and recorded the results. For consistency, only one tester was used for all algorithms and replicated the same style of fall/non-fall for each algorithm as close as possible. The experimental results are seen below in Table 5.1.

Examining these results, we see the SVM designed and trained from test fall data by partner Binh Nguyen performed the best out of the four algorithms. It was able to correctly recognize 10/10 of our real falls (true positives) and 9/10 of our non-falls (true negatives); its only fault was recognizing one non-fall as a fall (false positive). This performance was closely followed by Algorithm 3, which correctly identified 10/10 falls and 8/10 non-falls. Algorithm 1 competed respectfully, identifying 8/10 falls and 8/10 non-falls. Algorithm 2 was least effective of the four algorithms, distinguishing 7/10 falls and 8/10 non-falls.

These results are reasonable and expected. The SVM outperformed the algorithms because it was trained on a wide range of falls and non-falls whereas the regular algorithms focused simply on recognizing falls. In addition, the SVM was trained on data that included specific data from the same person who performed the final testing; it was almost as if the device was customized to the tester's fall characteristics. Algorithm 3 performed very well as it was quite sensitive to all falls; this is because it calculated orientation change only after the person returned to normal acceleration: either standing up or immobilized on the ground. Algorithm 2 performed somewhat poorer than the others as its primary focus was on repetitive impacts and motions. Algorithm 1 relied too much on the negative acceleration before a fall: several types of fall produced minimal freefall effects before impact. Without this initial drop in acceleration, the algorithm did not pass the first decision statement.





4.Conclusions and Recommendations

The objective of this project was to design and create a wearable Fall Detection System for the elderly that can link wirelessly with a pre-programmed laptop computer or Bluetooth-compatible mobile phone. To find the algorithm with the maximum sensitivity and specificity (Algorithm 3), we combined hybrid fall detection techniques developed from existing algorithms. Additionally, we were able to create, train, and deploy a straightforward SVM that beat all conventional algorithms by analysing sensor data and determining if a fall has occurred on a yes-or-no basis. This was possible because to our large test data collection synched with a laptop. Our fall detection system is an improvement over earlier systems and designs when considering the underlying detection process. We incorporated hybrid fall detection algorithms derived from existing algorithms to find the one with the highest sensitivity and specificity (Algorithm 3). In addition, we were able to use our extensive test data set to design, train, and implement a simple SVM able to examine data from sensors and determine if a fall has occurred on a yes/no basis that outperformed any of the regular algorithms.

With this project, there are several areas for the future development. On the more commercial aspect of things, improvements would include: having pre-recorded voice instructions for the user, the addition of a microphone so the user can record their own personal voice messages to be sent to contacts during emergencies, establishing emergency contacts though the PC-side by sending text messages, emails, or Voice over IP (telephoning through the internet), reducing using specialised printed circuit boards, manufacturing techniques, and lithium-ion batteries, the entire size of the device can be made for fully mobile communication by porting PC-side programming to an iPhone, Blackberry, or Google Android phone. On the theoretical development side of things, most apparent is the need for additional testing of our existing algorithms; further tweaking of threshold values and decision/trigger conditions could produce new, even better algorithms. In addition, more test subjects from a wider range of physical categories performing more types of fall/non-fall activities would give a much more complete data set to work from.

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