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A Smartphone Application for a Portable Fall Detection System

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Abstract

When a person, especially an elderly person, falls down, it often results in many complications such as life threatening injuries. In many cases, medical assistance is too late to prevent major complications. Fall sensing devices are being developed and explored to combat this issue. However, at the current stage, a common problem is that manual activation of the device maybe impossible due to injuries. Another problem is that some fall detection systems would require the user to wear uncomfortable equipment. This may cause people to be reluctant to wear the device. Therefore, there is indeed a need for portable and intelligent falling detection systems. In this research, we take a novel look at the detection systems. The aim is a portable, cost efficient, and a user-friendly system that does not interfere with usual habits. Because people normally carry phones and wear watches daily, we adapt a smart phone that includes medical contacts and a fall detector that is a digital watch, EZ430-Chronos provided by Texas Instruments, to detect the falling and to communicate with emergency contacts. We study intelligent algorithms to detect falling by using data sensing technologies that includes the three-axis accelerometer and clock readings, which are recording real-time information from the watch.[1, 2] Our algorithm, embedded in the watch, calculates falling metrics and matches them with falling patterns. Each movement produces a different degree of acceleration and forms a pattern. A fall pattern is unique compared to the patterns of other actions. When there is a matched fall pattern, the watch will send a command through Bluetooth wireless to the smart phone to activate a medical assistance call/message. Our experiments show that our system differentiates falling from sitting, walking, running, and most other normal situations.

Keywords: Fall Detection, Smartphone, Digital Watch

1. Introduction

Major injuries are a complication that elderly or those who have bone degeneration disease encounter after falling. Many who fall may not receive immediate attention after this occurs. According to the data collected from Centers for Disease Control and Prevention, fatal falls have increased substantially in the past decade.[3] To assist those who face these complications we have developed an intelligent fall detection device that is embedded in a watch. The watch is a small portable device that is a common tool in use by many, making it the perfect candidate for this project. While still having all the features of an original watch, the EZ430 Chronos includes a three-axis accelerometer and wireless communication capabilities. This watch allows programming of the embedded system by using a software compiler called Code Compositor Studio. This allows easy modification to help adjust values to the user's personal characteristics such as weight and height, increasing the accuracy of fall pattern recognition. Other fall detection devices are developed but may not be accessible to customers because of affordability. They also require multiple devices that are not comfortable for the customer. The fall detecting is accomplished by analyzing the patterns of various movements while a person is wearing the watch. Embedded in the watch is an algorithm that is designed to detect when the event of a fall is happening. After detecting the pattern, the watch will send a signal, through Bluetooth wireless, to a smart phone that will contact medical assistance. The results of the watch will be the automated communication to receive help instantaneously when a person experiences a fall.

2. Related Work

Others recognize the importance of fall detection and create ways of detection with various devices. Each algorithm designed is according to the specified device used during the experimentation. One device introduced by Bourke and Lyons in "A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor" is the common cell phone.[4] While having positive results in their experiment, flaws maybe seen in the device itself. The problem with using a cellphone as the main device is that people may not always keep the cell phone in their pocket. People usually, when are in their home, set the cell phone on a counter and plug it in to charge. If they were to keep the device in their pocket, they run the risk of running out of battery and having to plug it in to charge. The extra activity of maintenance would be reduced by using a watch. The user will not have to expend any extra energy to maintain the security of a fall detection device. Other devices have the user wearing a device or multiple devices around the torso.[5, 6] This could cause the user to be reluctant to wear the device and may require assistance putting it on and removing it. The positives to these systems using multiple gyroscopes are that the fall can be determined before impact and they result in high positive alarm rates and low false alarms.

3. Methodology

3.1. Data Retrieval

The first step in detecting a fall is to retrieve data from the TI EZ430 Chronos to analyze and determine how a pattern of a normal activity differs from a fall pattern. These data are collected by activating the accelerometer on the watch and retrieving the x, y, and z values. The TI watch used in this simulation uses a USB-based C1111device that communicates with the watch using radio frequency and captures the values live on the computer. To record the values, so they can be analyzed, a program is used to store the values in a text document. The program is developed with a series of methods that are used to read the USB device and the data being sent from the watch. When the USB device is connected to the computer, that device is assigned a COM Port that allows communication to the application. In the application, the COM port of the USB device is detected to interpret the bytes from the watch's embedded processor and converts them into values at the current acceleration from the three-axis accelerometer.

3.2. Graphing Patterns

After developing a method to retrieve the three axes values, they need to be graphed to analyze and determine how a fall pattern can be differentiated from regular activities. The processing of the watch, such as the speed, needs to be understood to accurately chart the values. The data values collected from the watch are opened into a program that allows the creation of a graph for easy interpretation. Below is a sample (Figure 1) of the data retrieve from a simple drop.

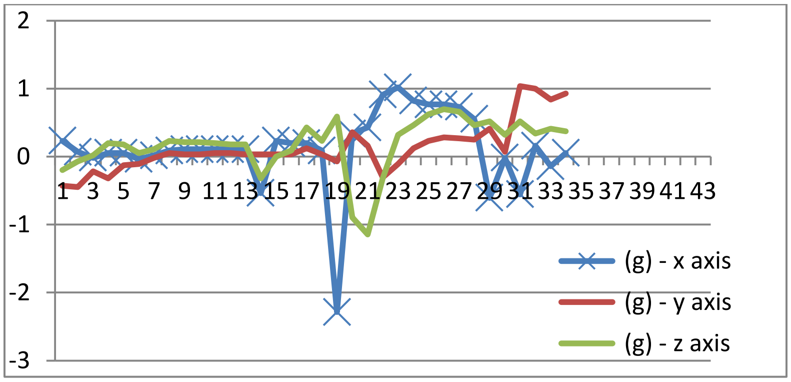

Figure 1. data retrieved after a simple drop of the watch

This graph shows us that there is a reduction on force while the watch is dropping. All the values of the three axes converge towards zero. The initial impact is the result of the watch not having full contact when hitting the ground. The point that stands out is the force exerted on the x-axis. The wristband had a light impact before the main body of the watch hit the ground. After analyzing the chart created above, it is obvious there is a possibility to detect points that represent a fall pattern. Another factor that appears is that there can be interference affecting the main impact point. To detect an actual fall there will be more factors that play a role in affecting the points of impact in which the algorithm needs to incorporate. Such resistance factors can be hitting an object during the fall, the natural resistance of contracting muscles, the attempts to prevent hard impact, falling at different directions and angles, or the height and weight of the person.

3.3. Patterns

Gaining more knowledge of how other normal activities data compares to a fall pattern can help modify the system to know a real fall from a false fall. Situations that may confuse the algorithm in thinking the person is falling could be sitting down, walking, bending over, or lying down. Below are two unique patterns of normal activities (Figure 2). In order to assure that a fall is occurring, restrictions and rules are applied to the algorithm discussed in the next section.

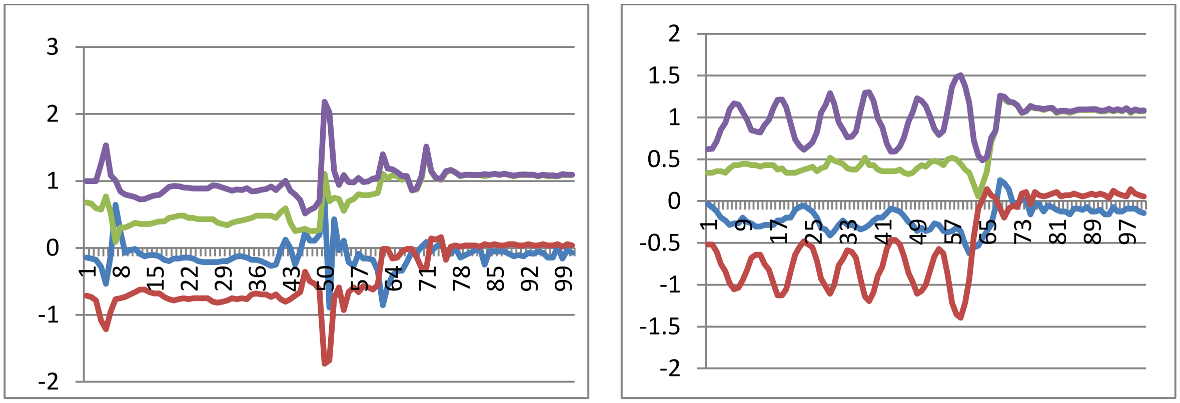

Figure 2. left is a pattern from a person sitting and the right is a pattern of a person walking

3.3.1. pattern interpretation

Some of these patterns may look very similar to the fall pattern if we were only to characterize the shapes of each pattern. This will be eliminated by not only measuring the three axes, but also by calculate the magnitude (1). The magnitude is calculated by the following formula.

$$d= \sqrt{x^2 + y^2 + z^2} \tag{1}$$

This magnitude, computed using the Euclidean norm, is to add more restrictions to the detection of a fall. Instead of only checking, they all are accounted for in the total force (Figure 3) exerted on the watch. This value will be compared to the maximum threshold while also testing the second most force exerted on an individual axis to a lesser minimum threshold.

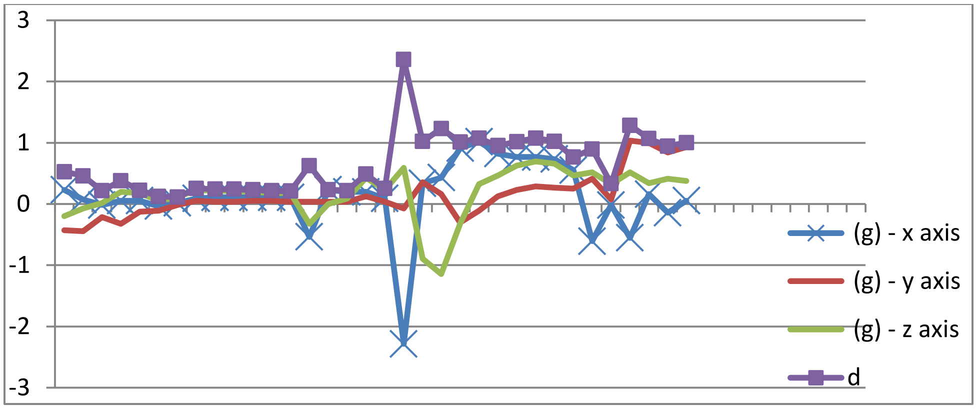

Figure 3. the new simple drop graph appears as the following when including the total acceleration

This enhanced version allows a more accurate test to determine a true fall from a false fall. The diamond pattern created is observed in future interpretations of actual falls we will see later in this paper. An algorithm can be formulated with the interpretation of the simple drop simulation. The points that are tested are the sequence of points before impact, the values during the impact and some points after the impact. Objects fall at a rate of 9.81 m/s. This information will be included to determine the time from when the watch begins to fall, the start, and when the impact happens, the end. If the walking pattern is joined to the drop simulation, we see an oscillating pattern followed by a verge of the axes leading to the impact. The first stage of the fall is the pro-fall stage. This stage passes when the values of *d* can be recorded constantly and the values are consistently close to zero *g*. This will not be activated while walking since the values have a more rapid change and the values will be around one g due to gravity. When the pro-fall stage begins, a timer will start and update a value declared for time, since we know that the rate at which an object falls. We have another test called the pre-fall stage. This stage will only pass when the time of the fall fits the conditions set to the user. When the previous two stages are occurring, another test will be running to determine when the value *d* breaks the threshold. Immediately after *d* breaks the threshold the timer will stop and the post-fall stage will begin. During this stage, the time of the fall is to be compared to the calculations of the person's characteristics. Some values after the impact are tested to see if they both are close to one g. If the post-fall stage does pass, further final steps are taken to contact medical assistance.

3.4. Algorithm

Distinguishing a normal activity pattern from a fall pattern requires an algorithm. The algorithm embedded in the watch records the points live when activated. The values of *p* are points recorded after calculating the magnitude of the three axes. Nine points are recorded, but *p6* and *p7* are currently ignored. The time for *t1* is determined from the start of the fall to the impact. The points within *t1* consist of *p0*, *p1*, *p2*, *p3*. Since when an object is falling and the points converge on zero *g* they should result in *p0 <p2* or *p1<p2*. The time for *t1* ends when *p3* breaks the set threshold and pass when *t1* is within the calculated time for the particular individual. The time *t2* is used to calculate the time from when the threshold is reached and returns to one g. The *t2* also consist of *g1*, which occurs when *p3* breaks the threshold. The points in *g1* are tested by *p3>threshold*, *p2<p3*, *p4<p3*, *p5<p3*, *p2<p0* or *p2<p1*, and *p8-p9< 0.3g*.The points of *g2* are to determine if there is a significant magnitude on one of the three axes. If the threshold is broken, *q1<threshold2*, the other points are tested by *q1<q0*, *q1<q2*, *q1<q3*. A diagram representing this simulation is below (Figure 4). After all the points acquired pass the response time begins which consists of the stages contacting medical assistance.

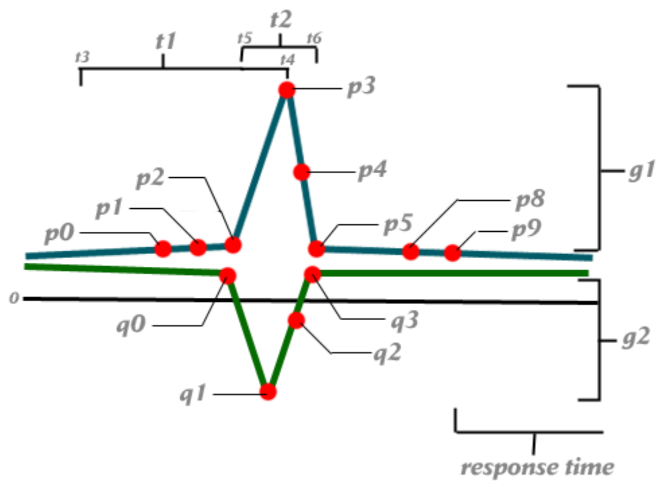

Figure 4. diagram of values recorded against algorithm

3.4.1. fall patterns

Now that there is a method to determine how to test a fall it will be apply to real falls. Since a person usually does not fall straight down at zero g, even though it can still be a possibility such as on a step stool or ladder, there needs to be a maximum threshold a person may experience. From there, if any resistance factors are playing a role, the threshold may have a minimum. Thirty-three sample falls are used to test this information. In this research, the watch is .84 meters from the ground with a forward fall motion. If a person is falling at a short distance, there is a chance they will have resistance by hitting their knees first, or by trying to grab onto a near object resulting in a lower threshold and more interference. In this particular fall (Figure 5), the values of *p3* and *p4* are switch. This is corrected by adding rules in the watch to allow for either event. This is because the values for *p0* through *p2* and *p5* through *p9* need to be in the correct positions, at each side of the diamond shape.

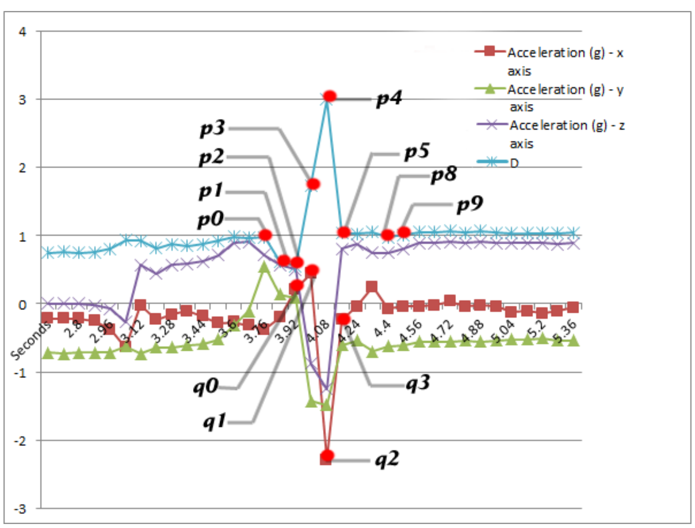

Figure 5. actual fall pattern with diagram of values recorded

3.5. Signaling Communication

After a fall occurs and passes through all the stages, we are ready to send a signal to the phone through Bluetooth wireless. The customer is able to install the software on their personal smart phone free of charge. This application runs in the background and never interferes with the customer's device. The user can also adjust the personal characteristics, such as height, weight, and emergency contacts. The application enables the user to enter a phone number for whom they will want to contact.

4. Results

These data collected from thirty-three samples are analyzed to assure the method discussed will accurately detect a fall pattern from other normal activities or false falls. In order to accomplish this the values of each category, time to impact(t1), time of peak impact(t2), magnitude calculated from Euclidean norm(g1), and the lowest force on any individual axis(g2), are tested with one-sample t-test at 96% confidence to retrieve a minimum of g1 and g2 and maximum for t1 and t2 . After comparing each sample to these values displayed below, ~85% of the samples pass.

Table 1. restrictions set to the variables used in the algorithm

Variable	Restriction
g1	>1.9773
g2	>1.6378
t1	<0.8092
t2	<0.3072

5. Applications

This research proposes that the monitoring of elderly may enhance potential independents for the individual by an intelligent system that can contact medical assistants during an event of a fall. Many other uses of this technology can assist other fields in data collection and detection. This may help people in many ways for the medical field or recreationally. For example, those who participate in sports that involve movement, such as a swinging motion, can use the data recorder to analyze their motion. If they are not getting the full potential out of their swing they would be able to reference it to professionals and analyze where their movement went wrong. Then adjustments are made to potentially achieve better results in future swings. This technology can also be used in the medical labs that are testing or analyzing the effects of drugs on animals. The movements from multiple sensors can be recorded and compared to the normal activity when not monitoring the subject visually. Any unusual activity will throw a red flag and the data can be analyzed. This technology is useful and not limited to fall detection.

6. Conclusion

There is a need for a fall detection device to assist in the contacting of medical assistance since falls can result in serious injuries. Calculating the magnitude of an activity improves these possibilities. The system in this paper can detect a fall pattern to contact medical assistance. The contacting of medical assistance is complete when the values, recording at real-time, from the three-axis accelerometer and magnitude fit the pattern of a fall. After the pattern is confirmed, the activation of a call is completed by a Bluetooth wireless signal being sent from the watch to the smart phone. A possible way to increase the accuracy of the pass rate in this method could be to use much more samples from a variety of sources. Another drawback is that the device used to collect movement data from the watch to the computer uses radio frequency. This can result in missing figures when a simulated fall is attempted due to the lack of distance capabilities of the RF technology. Different methods of data collection can be experimented with to retrieve the most accurate values. The end means of this research is to make it possible to decrease the time of retrieving medical assistance that will create the best care for the individual.

7. References

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