Physical Activity Classification using Accelerometers

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Abstract

There are situations where a person needs to be monitored continuously for their own safety. For example, elderly people tend to not be very physically active and may need to be monitored in cases of an emergency. Designing a product to monitor the physical activity of an individual could be very beneficial to their health. We have developed algorithms that can detect when an individual is walking, running, and falling. With these algorithms, creation of a system that can monitor, store filtered data of activities, and respond to emergencies was successful. This system can easily extended for general physical activity recognition and potentially used in nursing homes, hospitals, gyms, and other areas where physical monitoring is useful.

Introduction

The type of accelerometer used in this project was a tri-axial accelerometer. The use of this accelerometer provides a very beneficial aspect in order to develop a system for physical activity recognition. Accelerometers measure proper acceleration. This is the acceleration of an object with respect to gravity. For example, the acceleration of an object sitting on the surface of the Earth is about 9.8 meters per second or 1 g-force (gravitational force). With the object at rest the z vector would be equal to 1 g-force, and the x and y vectors would equal zero because of the coordinate vectors of the objects geometric center. Since the acceleration values change based on the objects vectors, this provides an intricate way of gathering data about an object's acceleration. Therefore by using accelerometers one will be able to see the effect on the data from different physical activities and development of algorithms to analyze data can begin.

The ability to develop a physical activity recognition system that responds to emergencies holds significant value and using accelerometers can help to achieve this system [6, 7]. There have been numerous research projects constructed around analyzing accelerometer data to monitor specific physical events. These projects are usually designed to either detect or monitor specific events or activities such as falls, walking, running, etc. By incorporating various concepts from each of these projects, the ability to create such a system becomes increasingly more obtainable.

In the area of fall detection many of these projects have achieved great success in accurately detecting a fall. The projects are also very diverse in an attempt to detect falls accurately. There have been projects that use image processing and machine learning techniques in order to achieve this ability [3, 4, 5]. These projects are beneficial to developing algorithms for physical activity recognition using accelerometers because they provide concepts and conditions that accelerometer driven systems need to account for [7]. Concepts such as orientation changes of subjects and what they imply about the activity being performed.

This project is an Android application designed to be a pedometer and fall detector. The application was designed and created using Eclipse as a software environment since Eclipse is extremely compatible with Android software. After development of the algorithms for the pedometer and fall detector, installation of the application was applied to smart phones which ran on an Android operating system of at least 2.3.3. Development of the algorithms began with ideas and similar approaches to that of previous works [2]. As well as reviewing the data on a plotting program called Gnuplot. Once the algorithms were implemented into the application, they were tested continuously to help ensure accuracy of the results.

Analysis and Development

Figure 1: This shows the axes of the phone in respect with the accelerometer embedded onto the smart phone.

When using accelerometers there are some common techniques used to filter and analyze data. One filter is to calculate the magnitude of the axes. This involves finding the root sum of squares of the axes [1]. This method allows one to see the effect on the axes simultaneously as opposed to analyzing each axis individually. Filtering data in this way can lower the complexity of algorithms designed to analyze accelerometer data and provides a more generalized indication of the phone's movement. The graphs of figure 2 and figure 3 show how calculating the magnitude can simplify the data. Within these graphs the subject was required to place a smart phone that contained an accelerometer into their pocket and proceed to limp.

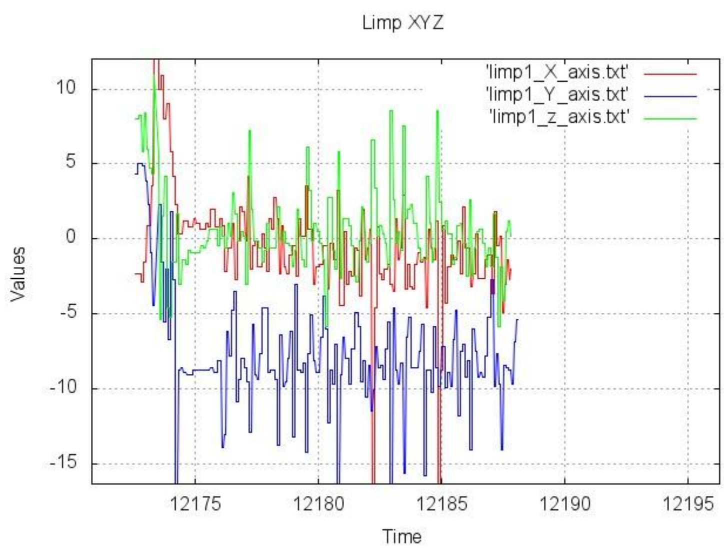

Figure 2: This graph displays the data of the x, y, and z axes of an accelerometer that was embedded onto a smart phone.

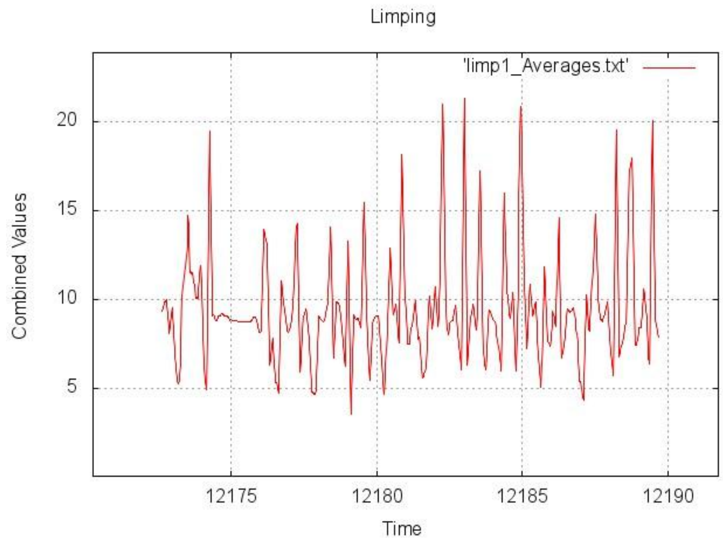

Figure 3: This graph displays the magnitude of the data presented in Figure 1.

Another technique is to incorporate some kind of threshold based system that the data must breach in order to trigger a specified response. These types of systems usually develop some kind calculation to determine the threshold or simply specify a point in which the data should not breach unless a specific activity was performed [3]. For example if one was falling the filtered data usually begins to dip at a gradual pace and then a massive spike in the data arises, refer to figure 4 and 5. The spike represents an impact with either the ground or another object. With two thresholds, one low threshold and one high, if the data were to become lower than the lower threshold and higher than the high one, then one could imply that a fall has occurred. This technique provides many benefits in differentiating activities but also has many faults. With a pure threshold based system, various activities could trigger different thresholds creating inaccurate results. These types of results are known as “false positives” and can greatly impact any type of accurate analysis of the data [3]. Due to the effects of this technique and calculating the magnitude of the data, these features were used to help develop algorithms for a pedometer and fall detector.

Before further development, the Android application was altered to write the data to a file for analysis and quickly recognized patterns within the data for different activities. Activities such as walking and running have a very cyclical pattern. The data follows a similar pattern to that of a sound wave by repeating a cycle of a high peak followed by a low peak. When reviewing the data of falls the pattern is usually a gradual decline in the data followed by a spike as mentioned before. Figure 4 depicts the patterns of walking, running, and falling that each data set fairly consistently follows.

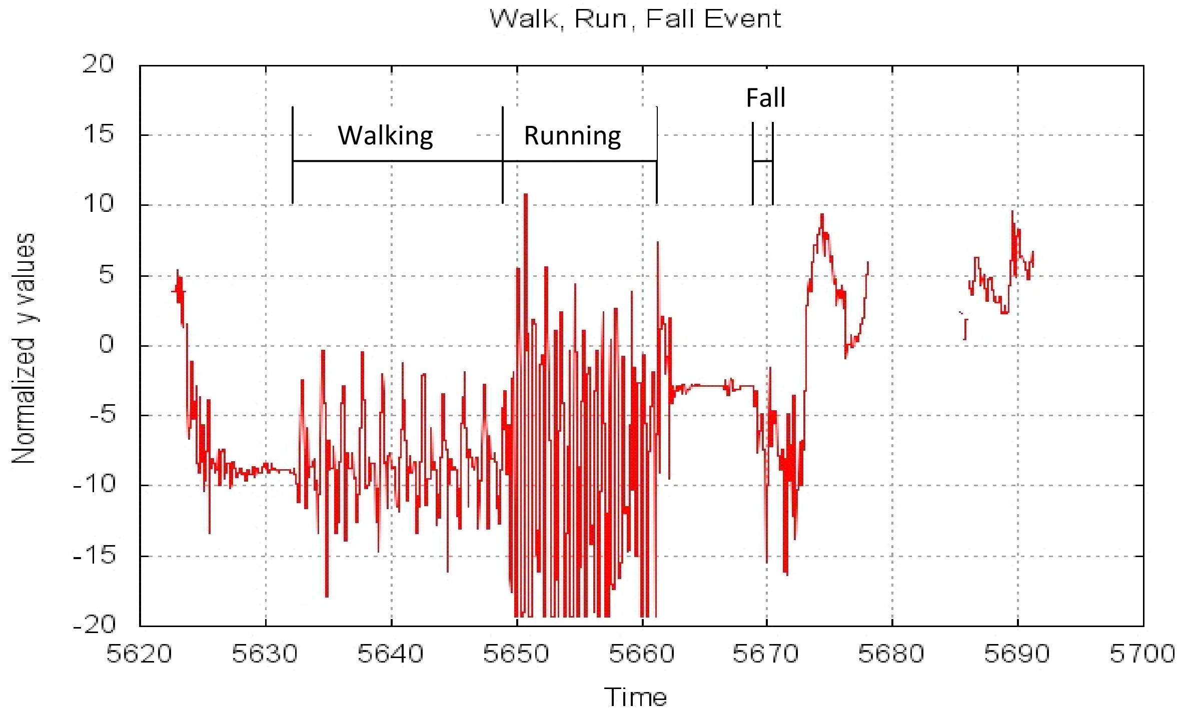

Figure 4: Data from a subject who performed three activities sequentially. Those being walking, running, and falling.

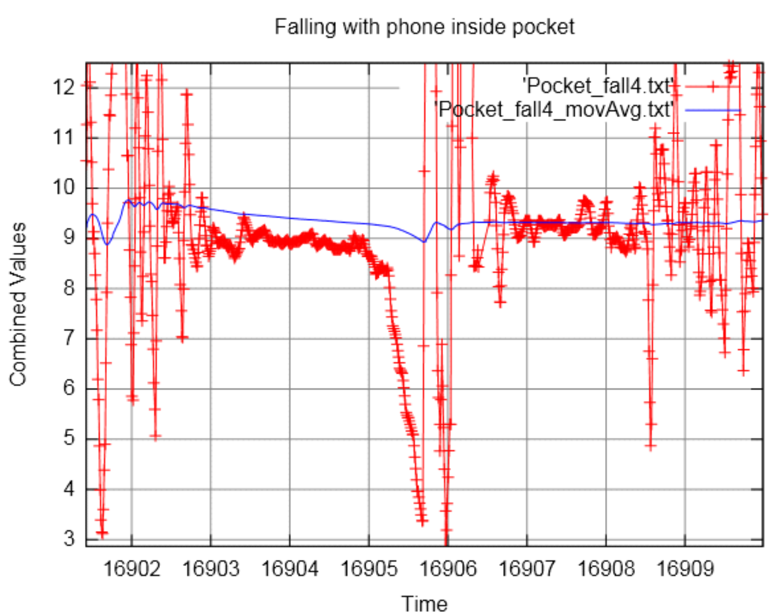

Figure 5: Data from a subject who stood still then proceeded to fall onto seat cushions

From review of figures 4 and 5 there are clear distinctions between walking, running, and falling from accelerometer data. Walking follows a similar pattern as running but the period of running is much faster than that of walking. Also the difference between peaks is drastically different in both events. During a falling event the data tends to gradually decreases then the data spikes and flattens out. As well as further tests that were conducted show that falls tend to last slightly longer than .7 seconds.

Based upon these patterns, the algorithms use thresholds, filters, and statistical analysis. The first filter used calculates the average of every ten magnitude data points to generalize the data since the average frequency of data gathered is around two hundredths of a second. This eases data analysis for the algorithm. While filtering, the average of all the data up to the current run time of the event in progress is tracked. This variable resets every thirty seconds to analyze the overall depiction of the data. These pieces of data are collected and sent to the different algorithms for analysis.

The pedometer follows a simplistic algorithm and requires the user to have the phone in their pocket. It calculates the difference between high and low peaks to see if that difference is greater than twenty three. This number calculated from an average of differences of peaks from prior tests and is used to help account for steps when an individual is running. The other condition is that a peak in the data was greater than 162% of the overall average and the time interval between peaks was greater than .35 seconds. These thresholds help to alleviate misleading data that help contribute to inaccurate results.

The fall detector follows a more complex algorithm since it does not require the user to have the phone within their pocket. Since the phone can be in or out of one's pocket an adjustment is made to the thresholds because the drastic changes to the data when a phone is not inside one's pocket. To determine when the phone is inside a pocket or not, a proximity sensor built within the phone is used. If the proximity sensor reports with 0.0 then the phone is considered inside a pocket, otherwise outside. While the phone is considered inside the pocket the adjustment is set to 55% otherwise it is 65%.

$$LT = pit - (pit \times adjustment) \qquad \text{Eq. 1}$$

In order for a fall to be detected a series of switches must be triggered. With the filtered data, it determines a pit point by storing the last point in the data that is between 95-97% of the overall average. This point is used as a reference of when the data begins to gradually decrease. With this point set, the difference between the current data element and the pit is checked to determine if that difference exceeds LT, see equation 1, and then a switch is triggered on. If the data continues to decrease for at least .7 seconds another switch is triggered. To account for variability of different types of falls implementation for finding the standard deviation of a data segment during the fall to the mean of the overall falling event is analyzed. This data segment is collected from all the data points that are below LT. If the deviation is greater than 22% then that switch is triggered. If all of these switches are triggered and the z axes is around 1 g-force then a fall is detected. If any switch is triggered then the data is checked to see if there was is a spike of at least 15 after some gradual decrease and that the data proceeds to flatten out. To determine if the data is flattening out, a comparison to the most current data value to the overall average is made and if that value is within 2.5% of the overall average for at least 2 seconds a fall is detected.

Since there are situations when a person falls and recovers and the algorithm needs to account for this scenario. So after a fall is detected for the next five seconds the total number of data points is counted as well as points that are within 15% of the overall average. If the percentage of data outside this range is greater than 35% then a recovery is recorded and the fall detection algorithm is started back up. If a recovery was not detected an emergency response is triggered to try and help the individual who fell. This response system currently sends a text message to emergency contacts to help the individual. The system is currently being implemented to send emails, text messages, and notifications to medical response systems.

Results

After the implementation of the algorithms and some small scale tests were conducted to ensure the functionality of the algorithms, large scale tests were conducted. To test the pedometer, a series tests involving walking at various paces and walking a predetermined amount of steps at a specific pace. The results of the pedometer were fairly successful. When the pedometer was tested with the subject walking 120 beats per minute (bpm), the success rate of detecting a step was in a range of 93-96% accuracy. This accuracy holds for the highest bpm test conducted which was 130 bpms. When tested at lower bpms, those below 80 bpms, the accuracy diminishes to about 82-85%. Upon reviewing data from at these time intervals, the data tends to become more scattered and not a cyclical as a higher bpm.

The fall detector was tested using a similar testing procedure discussed in the work of "Fall detection – Principles and Methods" [3]. The following table displays the results of the fall detector.

Category	Name	Results
Backward fall	Ending sitting	positive
	Ending lying	positive
	Ending in lateral position	positive
	With recovery	negative
Forward fall	On the knees	positive
	With forward arm protection	positive
	Ending lying flat	positive
	With rotation, ending in the lateral right position	positive
	With rotation, ending in the lateral to the left position	positive
	With recovery	negative
Lateral fall to the right	Ending lying flat	positive
	With recovery	negative
Lateral fall to the left	Ending lying flat	positive
	With recovery	negative
Syncope	Vertical slipping against a wall finishing in sitting position	negative
Neutral	To sit down on a chair then stand up (consider the height of the chair)	negative
	To lie down on the bed then to rise up	negative
	Walk a few meters	negative
	To bend down, catch something on the floor, then rise up	negative
	To cough or sneeze	negative

Figure 6: A set of results from the fall detector developed in this project.

A positive result correlates to the detector reading a fall has occurred and an emergency response was activated. A negative response is either no fall was detected or the emergency response was not activated. Although these results show great potential, continuous testing of the detector was performed and did not achieve 100% fall detection accuracy with zero false positives which is practically necessary for this type of detector [8].

This project has provided different approaches to analyzing data coming from accelerometers than that from other projects and research. These filters simplify the data to provide a generalized depiction of how different physical activity events are represented. This simplifies an algorithm and boosts its efficiency and effectiveness. Many current projects do not filter the data as thoroughly which can cause their algorithm to become more complex and hinder the results.

With the current project's success in building a pedometer and fall detector, extension of these algorithm's concepts can be used to develop a physical recognition system to respond to emergency events. More data from various daily activities has been gathered to develop other algorithms that can accurately depict different physical activities. After these have been developed and incorporated into one algorithm, a physical activity recognition system will have been developed.

Future tests will include an extended time frame of the algorithms to ensure that the application reports accurate deductions of different activities. As well as small scale tests for individual parts how the algorithm is performing. An attempt to conduct these tests with as many subjects that volunteer to participate in the study will be pursued. This will help to see the performance of the application on a larger population size. From this data, the accuracy of the physical recognition software can be improved. To analyze this data, graphs will be created to represent the data in different formats to find patterns or signals that can aid in improving the application. The emergency system's performance will also be tested for response time to get the individual medical attention.

Relevance to Engineering Education

This project has had a tremendous impact on furthering the understanding of concepts within the degree of computer science. The ability to design algorithms that work both effectively and efficiently is an essential part of computer science where simplicity is needed. This requires knowledge of statistical probabilities, physics, and advanced mathematic principles to be able to attempt to accurately depict the activities that an accelerometer is recording. During the course of this project the ability to convey various algorithm processes, data analysis, and programming ability was enhanced tremendously. In order to participate in this project one needs to understand computer science concepts. There is a high level of attention to detail when creating programs that are required to manage larger amounts of data and be able to function for extended periods of time. This type of project is extremely valuable because it provides opportunities for new ideas for the medical field as well as the opportunity to improve on a variety of skills within an academic setting.

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