ABSTRACT

KULKARNI, CHAITANYA DEEPAK. Design and Development of a Smartphone-based Fall Detection and Alerts Generation System. (Under the direction of Dr. Douglas Reeves.)

Falls in people happen due to reasons like old age, dementia, Parkinson's disease, learning disabilities and poor motor control. Falls result in broken or fractured bones, cuts, abrasions, soft tissue damage, and even death. They have psychological consequences, fear of falling leads to isolation, worsening of mental health, and general degradation of quality of living.

If falls cannot be prevented, the next best option is detecting them accurately, and summoning the required help immediately. An automatic fall detection system can do this; however, to be usable, the system should not be prohibitively expensive, should be convenient to carry on one's person, and should be capable of generating alerts even if the user is rendered unconscious due to fall. Smartphones are thus uniquely positioned; they can gather information about their surroundings using built-in sensors, process it in real-time, and generate alerts in various forms.

In this thesis, we design and develop an Android application that monitors device sensors to calculate device acceleration and orientation, and detects occurrence of fall using these inputs and real-time pattern recognition techniques. We also describe sensor data collection, including fall signature patterns, and alternative approaches tried for fall detection. On detecting a fall, the application generates alerts like emails, text messages, and voice calls.

The specifics of alerts to be generated and persons to be contacted are configured by user. We use speech recognition to reduce false positives and improve fall detection accuracy. We also test this application against a number of daily activities and falls, and present the results.

Design and Development of a Smartphone-based
Fall Detection and Alerts Generation System

by
Chaitanya Deepak Kulkarni

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Computer Science

Raleigh, North Carolina

2011

APPROVED BY:

Dr. Laurie Williams

Dr. Robert St. Amant

Dr. Douglas Reeves
Committee Chair

DEDICATION

To Aai, Baba, Aditya

BIOGRAPHY

Chaitanya Kulkarni was born on March 17, 1984 in Maharashtra, India. He holds a Bachelor's degree in Computer Science and Engineering, awarded in 2005, by National Institute of Technology, Calicut, India. He has been a Master's student at North Carolina State University, in Department of Computer Science, since August 2009. He has worked at Cisco Systems as a summer intern, and will be joining them as a Software Engineer on successful completion of his Master's.

ACKNOWLEDGMENTS

I thank my parents and my brother for their unwavering support and rock-steady faith in me. I would not have made it without their constant encouragement and motivation.

I am deeply grateful to my adviser Dr. Douglas Reeves for knowing where my interests lay and for orienting me in those directions. In addition to his many useful suggestions and constant guidance, I cherish the trust he placed in me, and the freedom I was allowed during the course of this work. I would like to thank Dr. Laurie Williams and Dr. St. Amant for making their courses both fun and valuable, and for graciously agreeing to be in the thesis committee. Special thanks are due to Dr. Thuente as well, for the support he extended in difficult times.

I would like to thank my cousin Mr. Mohit Padalkar for his persistence in pushing me to do more. He wants to see me succeed, and it is good to know that someone cares as much. I would like to thank my cousin Mr. Prashant Joshi for being there for me when I needed him the most. I will never forget his driving down to Raleigh to meet me in my initial days in USA.

I would like to thank my friends for life - Arundhati, Pushkaraj, Abhishek, Neha, and Pradeep. Thanks for being with me through all the ups and downs and twists and turns.

Thanks are due to my roommates for two years, Vinay, Prasanna and Bharath Bhushan. Thanks for making KP the place it is for us.

Thanks Deepshikha, Misha, Bharath Kaushik, Gopal, and Mario, for your support and for all the help you have extended from time to time.

Thanks Vinay, Srikantha, and Sriprabha for everything - for your genuine interest in my work, for being my test subjects, for helping me with the presentation, and for doing everything possible to make my life easier, for such a long time. Thanks a lot. Thanks Sriprabha, for your patient answers to my even most mundane questions throughout the course of this work.

Lastly, thanks Smitha! My stint with Android began with you, and I will always remember that project. Thanks for being the awesome friend you are; thanks for being there in my times of need. Thanks for all your support, help, encouragement, and for caring so much.

I realize that this work would not have completed without all your contributions, and I am glad to have received this chance of expressing my gratitude. Thanks a lot!

TABLE OF CONTENTS

LIST OF TABLES....viii

LIST OF FIGURES....ix

Chapter 1 Introduction 1

1.1 Falls – Reasons and Impact 1

1.2 Current Methods for Automatic Fall Detection 3

1.3 Our Solution 5

1.4 Thesis Structure 6

Chapter 2 Related Work 7

2.1 Fall Detection Using Sensors 7

2.2 Activity Recognition Using Sensors 8

Chapter 3 Fall Detection Algorithm 11

3.1 Sensors 11

3.2 Sensor Data Collection 15

3.3 Weka Data Mining Suite 21

3.4 Multilayer Perceptron Neural Networks 21

3.4.1 Use of two classifiers: 23

3.5 Algorithm and Implementation 23

3.6 Other Approaches 25

3.6.1 Threshold-based Fall Detection 25

3.6.2 Dynamic Programming based Approach 26

3.7 Challenges 28

3.7.1 Noise in Sensor Data 28

Chapter 4 Implementation and Alerts Generation 30
4.1 Why Android 30
4.2 Application Design Considerations 32
4.2.1 Background Monitoring 32
4.2.2 Designing for Responsiveness 33
4.3 Alerts 35
4.3.1 Settings for Alerts 35
4.3.2 User Feedback during Alerts Generation 39
4.3.3 Alerts Generation 40
Chapter 5 Experiments and Observations 44
5.1 Experiment Methodology and Results 44
5.2 Evaluation and Observations: 47
5.3 Battery Consumption 49
Chapter 6 Summary and Future Work 51
6.1 Future Work 52
References 54
Appendix 60
Appendix A Application for Data Collection 61
A.1 Why This Application 61
A.2 Design and Implementation 61

LIST OF TABLES

Table 1 - Parameters for MLP Classifier 22
Table 2 - Results for ADL: Walking........ 45
Table 3 - Results for ADL: Strolling 45
Table 4 - Results for ADL: Sitting........ 46
Table 5 - Results for ADL: Sleeping 46
Table 6 - Results for fall 47
Table 7 - Comparison of approaches 47
Table 8 - Battery power consumption of applications - 1........ 49
Table 9 - Battery power consumption of applications - 2........ 50

LIST OF FIGURES

Figure 1 - SensorEvent API coordinate system 12
Figure 2 - Reference coordinate system for device orientation 14
Figure 3 - Acceleration signal - fall pattern 17
Figure 4 - Pitch signal - fall pattern 17
Figure 5 - Acceleration pattern during walking 18
Figure 6 - Acceleration Pattern during strolling 18
Figure 7 - Acceleration pattern during sitting 19
Figure 8 - Acceleration pattern during sleeping 19
Figure 9 - Pitch pattern during walking 19
Figure 10 - Pitch pattern during strolling 20
Figure 11 - Pitch pattern during sitting 20
Figure 12 - Pitch pattern during sleeping 20
Figure 13 - Dynamic Time Warping [20] 27
Figure 14 - Raw acceleration and orientation data during an ADL 29
Figure 15 - Android Application Not Responding (ANR) dialog 34
Figure 16 - Settings 36
Figure 17 - Waiting duration 36
Figure 18 - Audio alert settings 37
Figure 19 - Text and email alerts 38
Figure 20 - Calls settings 38
Figure 21 - Alerts generation countdown 40
Figure 22 - A received email alert 43
Figure 23 - Screenshots of application for data collection 63

Chapter 1

Introduction

In this thesis, we address the problem of falls in people. Our approach relies on smartphones to detect falls and summon the appropriate assistance. We develop an Android application that monitors the phone's built-in sensors, detects falls using pattern recognition, and generates pre-configured alerts on fall detection. We test the application against a number of Activities of Daily Life (ADLs) and fall events, and present the results.

1.1 Falls – Reasons and Impact

Falls are defined as 'an unexpected event in which the participant comes to rest on the ground, floor, or lower level.' [1] A slip (sliding of the support leg) and a trip (impact of the swinging leg with an external object or a body part) both represent loss of bodily balance, and both can cause a fall [2].

A variety of reasons like old age, dementia, Parkinson's disease, learning disabilities and poor motor control contribute to falls in people. Falls represent a serious problem among the elderly. One out of three adults age 65 and older falls each year. Falls are the leading cause of injury-related death among this population. Falls are also the cause of nonfatal injuries like broken or fractured bones, cuts and abrasions, and soft tissue damage, and hospital admissions. [3] [4] Falls can also result in ‘long-lie’, which is defined as remaining on the ground for an hour or more following a fall. This occurs in more than 20% of the elderly people who are admitted to hospital due to fall. Even if no direct fall-related injury has occurred, half of the elderly people who experience a long-lie die within 6 months of the fall [4]. Additionally, falls in elderly also have psychological consequences. The fear of falling or long-lie can lead to the worsening of one’s mental health, isolation, and the general degradation of quality of living [5]. Fall researchers also describe a ‘fear of falling’ cycle in which, after a fall, seniors may limit their daily activities due to fear of falling again, leading to decrease in fitness, mobility and balance, decreased social interactions, reduced satisfaction and increased depression. This fear may increase the risk of another fall [6].

Falls also occur because of dementia. Studies show an annual fall incidence as high as 60% among people with dementia, and as many as 400 falls per 100 persons with dementia. In a misguided attempt to prevent injury, physical restraints are used for such patients [7].

Most patients suffering from Parkinson’s disease (PD) sustain recurrent falls. Researchers have observed that almost 70% of patients fell during a 1-year follow-up. Recurrent falls occurred in approximately 50% of patients during 1 year. Compared to healthy subjects, the relative risk of sustaining recurrent falls during a 6-month period was 9.0 (95% confidence interval, 2.0 – 41.7) for PD patients [8].

For people with learning disabilities, falling is a common cause of physical injury and impaired quality of life. Studies have shown that over a 33-month period, more than half of people with a learning disability who live in residential facilities will have a fall, with a third of these falls resulting in injury. A recent Scottish study found that 41% of community-based adults with a learning disability had experienced a fall in the previous 12 months. For the people involved, falls result in institutionalization, increased incidence of injury, higher healthcare costs, heightened fear of falls and reduced physical activity [9].

Falls are thus a clinically frequent case, can be caused by a variety of reasons, and adversely affect a sizable population.

1.2 Current Methods for Automatic Fall Detection

Falls can be prevented from happening through personal care and constant monitoring. A person who has sustained a fall can be helped by others in the vicinity. However, for falls that occur in isolation, quick and accurate detection of fall and summoning the much-needed help becomes important. Automated fall detection systems or Personal Emergency Response Systems (PERS) are used for this purpose. Such systems attempt to reduce the period between the fall and arrival of medical attention by generating alerts on detecting a fall. However, most common form of PERS, a push-button pendant for alerts generation, is not always a useful method, as the pendant will not be activated if the fall renders the person unconscious [10].

Automated fall detecting systems commonly use one of following three methods for classifying a fall: [5]

- **Acoustic/vibration recognition:** This is achieved by having a device, usually implanted in the floor, monitor sound and other vibrations. It listens for the vibratory signature of a human fall, which is vastly different from the signatures of walking, small objects falling, and other common activities.

- **Image recognition:** By using overhead cameras in a fixed location, one can track objects and learn movement patterns. The system adapts to the locations in which a single human enters/exits the room and remains inactive (lying/sitting on bed/chair). Common paths from entry points to inactive areas are then traced and remembered. It suspects a fall if a person becomes inactive in the middle of a common path.

- **Worn Devices:** These systems require the user to wear external sensors. The devices track the vector forces exerted on the user. Usually these devices are a tri-axial accelerometer or gyroscope. If a specific pattern or threshold is broken, the device alerts a wireless receiver, which then alerts emergency contacts.

Majority of fall detection systems require some application specific hardware and software design. This increases their cost and limits the commercial viability to the wealthiest, or most impaired, users. Many also have significant installation and/or training times, also limiting greater adoption [5]. Systems employing overhead cameras are hardly effective once the person is outside the monitored area. Systems that use worn sensors would be rejected by users if they are inconvenient and affect mobility/activities of daily life.

1.3 Our Solution

We thus propose using smartphones as fall detection and warning system. Today’s smartphones include sensors like Accelerometer, Gyroscope, Magnetic Field sensor, Light/Proximity Sensor to collect information from their environment. They have processing power required for real-time analysis of collected data to detect a fall, and they can also generate various forms of alerts like a loud ring, text, email etc., on detecting a fall [11] [12]. They provide access to this functionality via developer API. Moreover, as a phone is carried on one’s person, there is no need for dedicated sensor hardware, and the fall monitoring is not dependent on presence of external overhead cameras.

In this thesis, we develop an application on Android platform that runs in the background and monitors for fall. On detecting a fall, it generates alerts. The specifics of alerts generated are configured by the user, as are the persons to be contacted. For detecting the fall, the app uses Weka implementation of Multilayer Perceptron Classifier.

1.4 Thesis Structure

Remainder of this thesis is organized as follows. Chapter 2 presents an overview of the related work, discussing existing fall-detection algorithms, use of worn sensors, and an existing Android application. Chapter 3 presents the design and implementation of our fall detection algorithm, including a discussion of different approaches explored and challenges faced. Chapter 4 presents the details about implementation and alerts generation. Chapter 5 discusses the experiments performed for validating the app and presents the results. Finally, chapter 6 provides a summary, and gives pointers for future work.

Chapter 2

Related Work

2.1 Fall Detection Using Sensors

Fall detection using sensors is a well-researched area. The algorithms generally use inputs from one or more sensors, and are threshold-based – a fall is concluded to have happened if the thresholds are crossed. The actual thresholds differ based on the specific sensors used, and the experimental results obtained.

Bourke et al. [4] use a tri-axial accelerometer housed in a plastic case, mounted on thigh and trunk using harnesses, and conduct experiments using young subjects for performing falls and elder subjects for Activities of Daily Life (ADLs). Using the experimental data, they determine upper and lower thresholds for accelerometer data for detecting fall. They also recommend trunk as the ideal position for the sensor. Hwang et al. [13] develop a chest-attached fall detection system. They use accelerometer for determining kinetic force, gyroscope for determining posture transition and a tilt sensor to determine whether people are standing or are supine. They use buffered windows of sensor data, with readings in each window averaged out. Due to the use of multiple signals, they increase the accuracy of detection (96.7%). A warning system is described by Hansen et al. [14], which involves the sensor communicating with a camera-phone over Bluetooth. The phone tries to ascertain whether the user has indeed fallen, and generates alerts if that is the case. In [6], changes in acceleration magnitude, followed by orientation and position change; are used as fall indicators. In [15], Li et al. distinguish between intentional transitions (such as sitting or lying down) and unintentional transitions (such as falling) – unintentional transitions involve sudden changes in the sensor readings. Finally, Sposaro and Tyson [5] develop an Android application that uses a threshold-based algorithm for fall detection, using accelerometer data and orientation change. They provide a 'sensitivity setting' to reduce number of false positives. Their alerts generation system consists of two-way communication between the person who has sustained the fall, and his/her social contact. This method also reduces the impact of false positives.

2.2 Activity Recognition Using Sensors

Sensor inputs are also used for activity recognition. Various machine-learning methods are usually employed for this purpose.

Yang [16] describes use of Clustering mechanisms from Weka data mining suite for physical motion recognition using accelerometer sensors in mobile phones. Kwapisz et al. [17] use decision trees (J48), logistic regression and multilayer neural networks from Weka data mining suite for inducing models for predicting user activities. Sun et al. [18] develop a SVM based classifier using Weka implementation to recognize common physical activities, specifying six pocket positions for the phone. Brezmes et al. [19] use K-nearest neighbors for pattern recognition.

Finally, dynamic programming based methods are also used for pattern recognition. Liu et. al. [20] describe use of Dynamic Time Warping (DTW) for gesture recognition. Dynamic Time Warping is a method for calculating matching cost for temporally differing patterns using dynamic programming. [20] uses Euclidean distance as the distance calculation function for DTW.

Threshold-based algorithms cannot generalize to varied use cases of sensors in mobile phones, neither can they learn from or adapt to user behavior. Dynamic programming based algorithms cannot effectively distinguish between patterns involving extended periods of no activity – a fall that renders the person unconscious versus sleeping, for example.

In this thesis, we develop smartphone-based fall detection and warning system that uses a supervised learning method for pattern recognition. By re-training the classifier using user-identified true and false positives, recognition accuracy of our method improves over time, for the specific user. Moreover, utilizing the capabilities of the smartphone, we can perform effective alert generation – asking user whether he/she is okay, ringing a bell, and sending emails/text messages to pre-selected contacts. Our method does not need special-purpose hardware because the phone is carried on one's person, and thus is likely to be less intrusive for the user. However, as our method is phone-based, it does not detect falls suffered by users while not having the phone on them – for example, while sleeping or bathing.

Chapter 3

Fall Detection Algorithm

In this chapter, we describe our fall detection algorithm, preceded by a discussion of sensors inputs utilized, sensor data collected, and the classifier used. We also discuss the challenges in algorithm design and alternative approaches tried.

For detecting a fall event, the application monitors the Accelerometer and Magnetic field sensors in background. A Multilayer Perceptron Classifier is trained on a sample dataset consisting of both fall and non-fall events, and then used for real-time classification of sensor data. Multiple, overlapping, sliding windows over the stream of sensor data are utilized to provide instances for this real-time classification. A fall event is characterized by detection of changes similar to fall patterns in both acceleration and orientation occurring within a short interval.

3.1 Sensors

Android API exposes the device sensors through a class called SensorManager. As we need to track acceleration and orientation changes, we register with SensorManager to listen for accelerometer and magnetic field sensors. Upon change in sensor values, an object of class SensorEvent is passed to the sensor event listener method. The SensorEvent class holds the information like sensor type, sensor's data, event timestamp, and accuracy. Following diagram depicts the coordinate system used by the SensorEvent API [32].

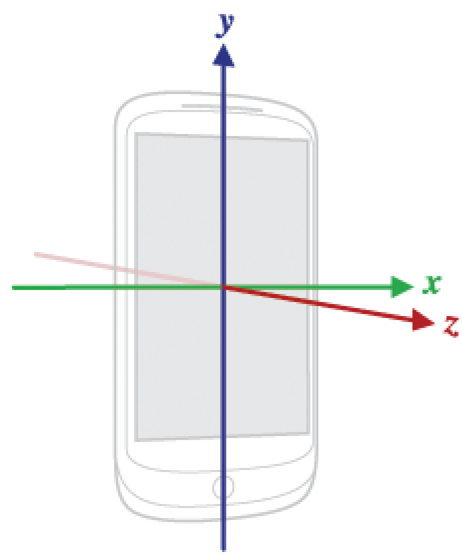


Figure 1 - SensorEvent API coordinate system

The coordinate system is defined relative to the screen of the phone in its default orientation. The axes are not swapped when the device's screen orientation changes. As shown in the diagram above, X axis is horizontal and points to the right, the Y axis is vertical and points up and the Z axis points towards the outside of the front face of the screen.

An application subscribing to sensor events is also supposed to unregister the listeners when it no more requires the sensor monitoring. This is required to prevent the unnecessary battery drain. Likewise, in our application, we stop listening to sensor events when the user stops the fall monitoring.

Acceleration:

The SensorEvent object received in the sensor listener contains an array of sensor values. The length and the contents of this array depend on the type of sensor. For accelerometer, following values are returned (unit: m/s^2): [32]

- [0]: acceleration minus G_x on x-axis
- [1]: acceleration minus G_y on y-axis
- [2]: acceleration minus G_z on z-axis

Accelerometer sensor measures the acceleration applied to the device. The force of gravity is always influencing the measured acceleration. Thus, for instance, for a device stationary on a table, accelerometer reads a magnitude of $g = 9.81\ m/s^2$. Similarly, when the device is in free-fall and therefore dangerously accelerating towards to ground at $9.81\ m/s^2$, its accelerometer reads a magnitude of $0\ m/s^2$.

In our application, we first record the accelerometer sensor values for subsequent use in the calculation of device orientation. We then find out the acceleration applied to the device by squaring and adding the acceleration along the three axes, and taking the square root of the result. We then quantize the result using a non-linear quantization scheme described by Liu et.al. [20]. The resulting value is used in forming the instances for real-time classification.

Orientation:

Device orientation is calculated using the values obtained by accelerometer as well as magnetic field sensor. Just as we record the values obtained by accelerometer, we record the values obtained by magnetic sensor as well, in the sensor event listener. Using these two sets of the values and the methods provided by the Android API, we first calculate a rotation matrix transforming a vector in device coordinate system into world coordinate system. We then calculate the device orientation from this rotation matrix. The reference coordinate system used for device orientation is depicted below: [33]

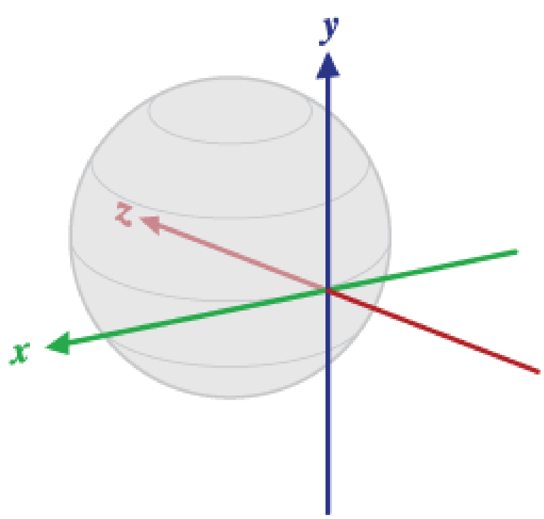


Figure 2 - Reference coordinate system for device orientation

In the reference coordinate system

- X is defined as the vector product Y.Z (It is tangential to the ground at the device's current location and roughly points in the West direction).

- Y is tangential to the ground at the device's current location and points towards the magnetic North Pole.
- Z points towards the center of the Earth and is perpendicular to the ground.
- All three angles above are in radians and positive in the counter-clockwise direction.

These are the values obtained for device orientation: [33]

- [0]: azimuth, rotation around the Z axis
- [1]: pitch, rotation around the X axis
- [2]: roll, rotation around the Y axis

During a fall, user position changes from standing to supine, in a sudden manner. This change produces a variation in pitch. In our application, the pitch values form the dataset that is used for real-time classification.

3.2 Sensor Data Collection

We created an application for sensor data collection. This application monitors the sensors in background using a service, and writes the sensor data to files on phone’s external storage. This data can then be uploaded to a server from the application. We used Comma-Separated Values (CSV) format for files. Microsoft Excel was used for analyzing the data by generating graphs. More details about this application are given in Appendix A.

We conducted a number of experiments involving falls. A fall involves transition from a standing position to a supine one. We empirically observed the time taken and the number of sensor data values generated for the stationary->fall->stationary transitions. We also considered the fact that both acceleration and pitch variations need to be tracked. Using these observations, we arrived at a length of 40 values for a data instance used for both training the classifiers and for real-time classification. These values are typically collected over a period of 6 seconds. The data instance length 'spans over' a fall transition. During our experiments, we observed that longer instance lengths contain additional sensor data, and adversely affect recognition accuracy.

Fall events produce similar patterns in the sensor data. Acceleration exhibits a sudden change on fall - it has the pattern of a downward spike followed by an upward one. Pitch also exhibits a large and sudden change.

Following figure shows the acceleration signal pattern during fall:

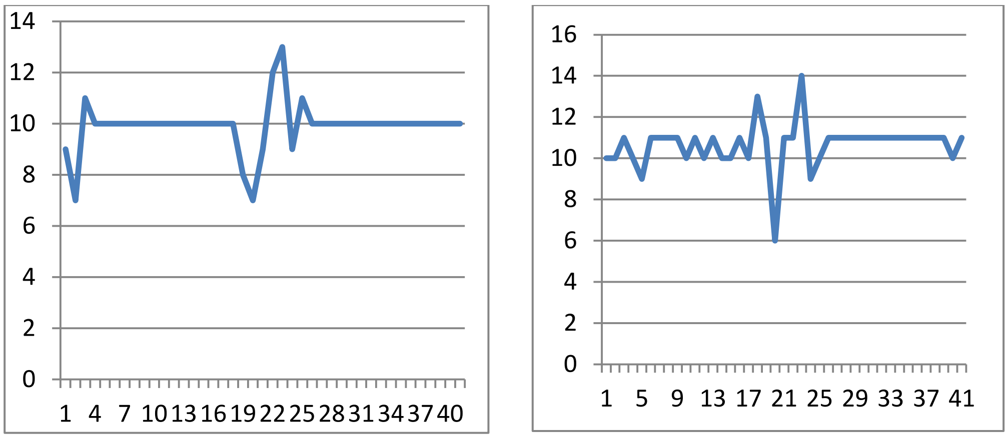


Figure 3 - Acceleration signal - fall pattern

Following figure shows the pitch signal pattern during fall:

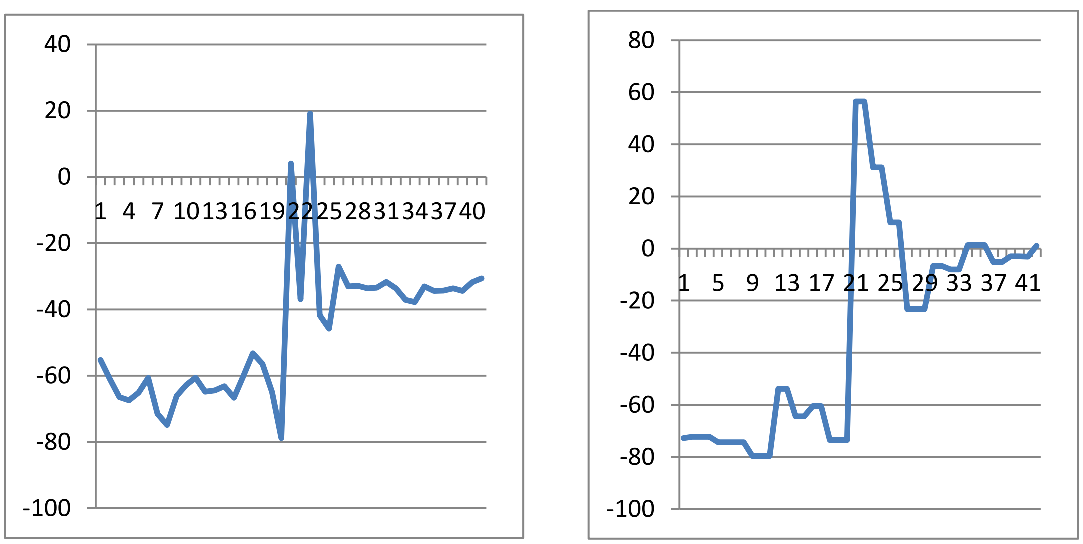


Figure 4 - Pitch signal - fall pattern

We also collected the sensor data for a number of Activities of Daily Life (ADLs), like walking, sitting, sleeping, and being stationary or strolling. The ADLs are performed from a starting point of the person standing, with the phone in the front pocket of the trousers. We selected this particular position, as it is a common one. [18]

Following figures show patterns in acceleration during these ADLs:

Walking:

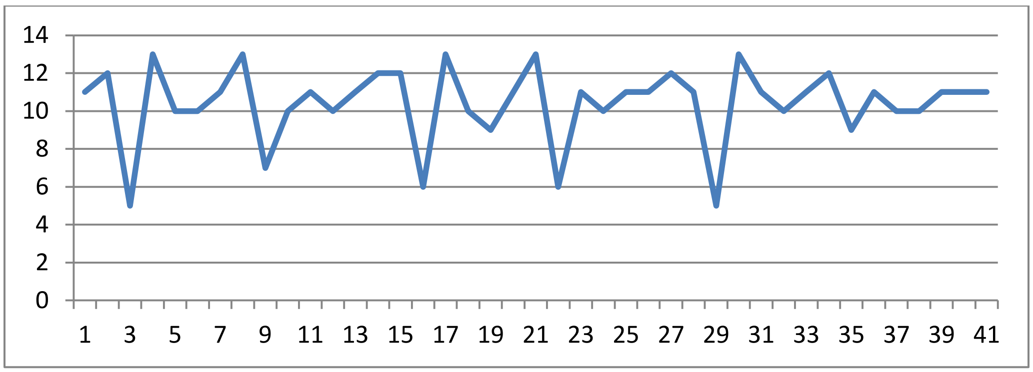


Figure 5 - Acceleration pattern during walking

Stationary to Strolling:

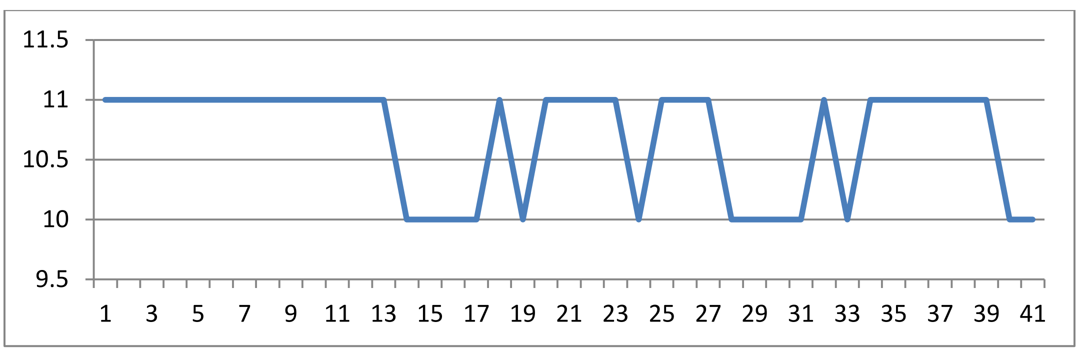


Figure 6 - Acceleration Pattern during strolling

Sitting:

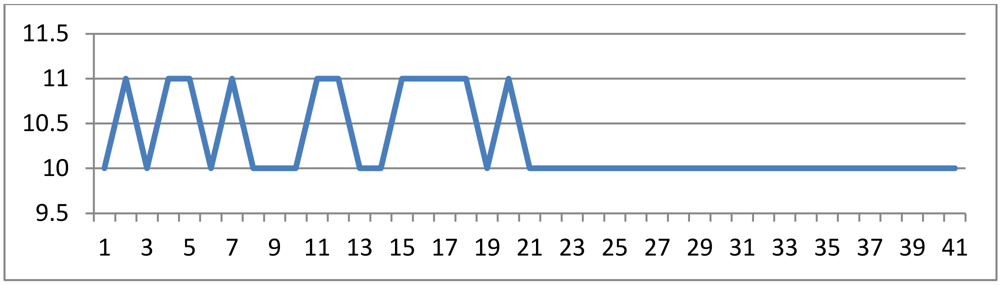


Figure 7 - Acceleration pattern during sitting

Sleeping:

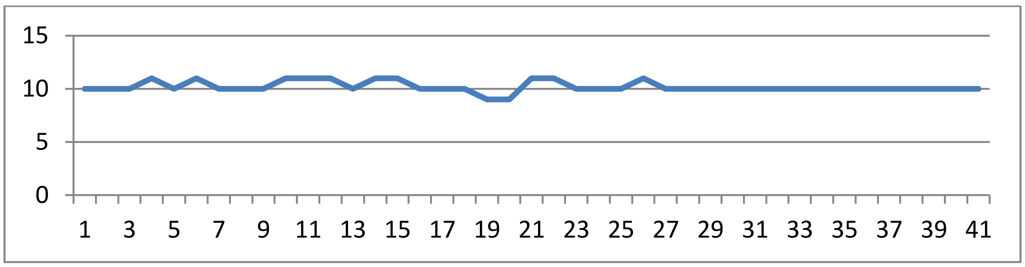


Figure 8 - Acceleration pattern during sleeping

Following figures show patterns in pitch during the ADLs:

Walking:

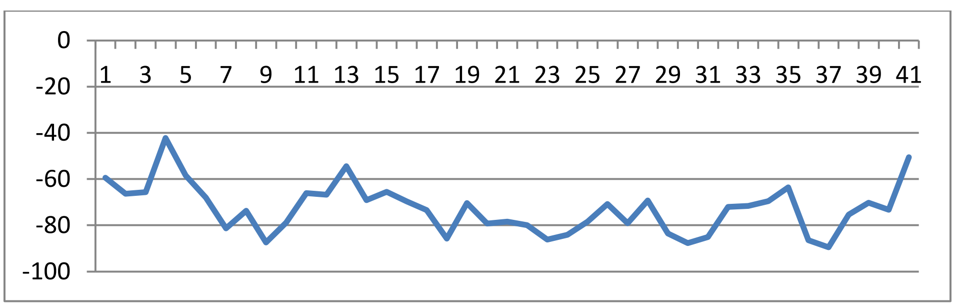


Figure 9 - Pitch pattern during walking

Stationary to Strolling:

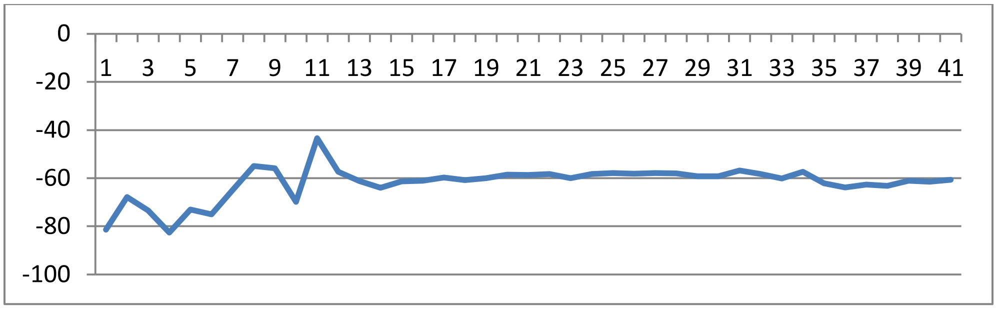


Figure 10 - Pitch pattern during strolling

Sitting:

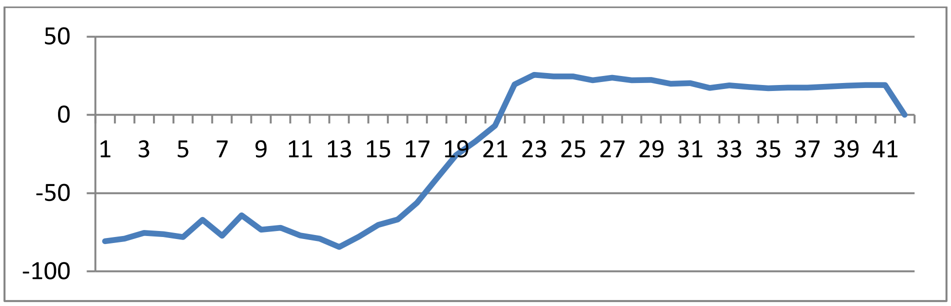


Figure 11 - Pitch pattern during sitting

Sleeping:

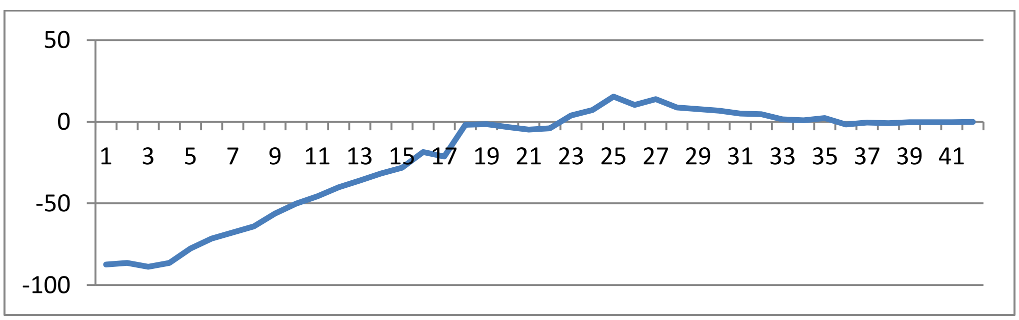


Figure 12 - Pitch pattern during sleeping

3.3 Weka Data Mining Suite

Waikato **E**nvironment for **K**nowledge **A**nalysis (Weka) is a machine learning software suite in Java, developed at the University of Waikato, New Zealand. Weka is open source, and is available under the GNU General Public License. The machine learning algorithms in Weka can either be applied directly to a dataset or called from Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization [34].

In our application, we use Weka Multilayer Perceptron classifier for real-time classification of sensor data. Weka is chosen because of its free availability, java implementation, portability to Android platform, and finally, ability of performing Classification from Java code.

3.4 Multilayer Perceptron Neural Networks

An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems process information. An ANN consists of a large number of highly interconnected simple processing elements (neurons) working in unison to solve specific problems. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Once trained, it can be used to provide projections for given new situations. Adaptive learning, self-organization, and real-time operation are some advantages of ANNs.

A Multilayer Perceptron (MLP) is a feed forward artificial neural network. It has a layered architecture consisting of input, hidden, and output layers. Each layer consists of a number of perceptrons. The output of each layer is transmitted to the input of nodes in next layer through weighted links. Training or weight adaptation is done using supervised backpropagation learning [35].

Weka uses sigmoid activation function for its Multilayer Perceptron classifier [36].

In our application, we use a network with one hidden layer, one input layer, and one output layer. Following table presents the parameters and their default values for Weka MLP classifier configuration. We use the same values in our application.

Table 1 - Parameters for MLP Classifier

Parameter	Explanation	Value
L	Learning rate – factor used for weight adjustment during backpropagation learning phase	0.3
M	Momentum - factor used for weight adjustment during backpropagation, for speeding up convergence and avoiding local minima	0.2
N	Number of passes made over the training data, during learning phase	500
V	Percentage size of the validation set from the training data – setting this to 0 means that the network will train for N number of epochs	0
S	Seed for random number generator, random numbers are used for setting the initial weights of the connections between nodes and for shuffling the training data	0
E	Threshold for consecutive errors allowed during validation testing	20
H	Number of nodes in the hidden layer, value ‘a’ indicates default wildcard values, calculated as a = (attributes + classes) / 2	a

The training set for the classifier consists of both fall and non-fall samples. Fall samples all exhibit similar patterns, while the non-fall samples are selected from sensor data collected during ADLs. They exhibit patterns markedly different from the fall patterns. As there are virtually unlimited ADL patterns and our aim is fall detection, our training set contains more fall patterns than non-fall patterns; it is trained to recognize the presence of a pattern similar to fall pattern in the sensor output.

3.4.1 Use of two classifiers:

Our experiments showed that fall involves change in both acceleration and in pitch. More important, changes similar to fall pattern occur in acceleration when one is walking/running but pitch changes are absent at this time, and changes similar to fall pattern occur in pitch when one sits or lies down but changes in acceleration are absent at this time. This mutual exclusivity of the two indicators and the fact that they both are present in a fall leads to our choice of monitoring them both.

3.5 Algorithm and Implementation

User starts fall monitoring by pressing a button from within the application. On this user trigger, we start a Service for background sensor monitoring and real-time fall detection.

Within the Service, we first build Weka Multilayer Perceptron (MLP) classifiers for acceleration and pitch signals using pre-stored training data. As this is likely to be a blocking operation, it is done in a separate thread, thus keeping the application responsive.

Once the classifiers are built, we start the fall detection thread, and start sensor monitoring.

In the sensor event listener, we calculate acceleration using sensor values, quantize the results, and build data instances, each of length 40. The choice of this window length is explained earlier, in section 3.2. We use four overlapping, sliding windows over the sensor data stream. Multiple overlapping windows are required to capture the sensor data patterns accurately; a fall pattern should not be incorrectly identified because it did not begin at the start of the window. Similarly, we calculate pitch and build data instances, each of length 40, with four overlapping, sliding windows over data stream. For both acceleration and pitch, once an instance is created, we classify it using the corresponding classifier, and signal the fall detection thread if the result of classification is ‘fall’.

In the fall detection thread, we keep track of the timestamps of the acceleration and pitch fall indication messages. If both the classifiers report the occurrence of a fall pattern in 3.5 seconds (value slightly higher than instance duration/2) of each other, we conclude that a fall has occurred, and signal the alerts generation module.

3.6 Other Approaches

In addition to real-time classification of sensor data using a Multilayer Perceptron classifier, we also explored following approaches for the design of fall detection algorithm.

3.6.1 Threshold-based Fall Detection

This approach endeavors to detect the occurrence of fall by monitoring whether the values output by sensors cross certain thresholds.

During our experiments involving falls, we observed that a fall produces a downward spike followed by an upward one in the acceleration pattern. During a fall, acceleration typically falls below 6 m/s^2, and then goes above 12 m/s^2, before stabilizing around 10 m/s^2. Higher-impact falls produce variations that are more pronounced; we observed acceleration going below 2 m/s^2 during some falls. Orientation exhibits high-magnitude change, mirroring the change in position from standing to supine. We observed changes in pitch signal by more than 75 degrees. We decided our thresholds for fall detection based on these observations. A fall was characterized as ‘acceleration falling below 6 m/s^2 and then going above 12 m/s^2, and pitch changing by more than 75 degrees.’ For fall detection, we monitored both acceleration and pitch value streams, starting ‘observation windows’ on crossing the thresholds. For example, we monitored for acceleration crossing the upper threshold of 12 m/s^2 every time it crossed the lower threshold of 6 m/s^2.

However, this approach leads to a large number of false positives due to the noise in sensor output. We observed that acceleration thresholds are routinely crossed during activities like walking, and sitting down or sleeping involves position changes that produce variations of more than 75 degrees in pitch. Additionally, noise leads to out-of-pattern values in the sensor output, which negatively affect conclusions by a threshold-based algorithm.

As a further improvement, we eliminated effect of out-of-pattern values by tolerating a certain number of them in the algorithm. For example, we would conclude that the position has changed only if 'x' consecutive values show the change, allowing for 'y' out-of-pattern values, where $y << x$. We observed occurrence of false positives even with this change.

3.6.2 Dynamic Programming based Approach

Liu et. al. [20] employ Dynamic Time Warping (DTW) for gesture recognition using accelerometer data. Dynamic Time Warping is a classical algorithm based on dynamic programming to match two time series with temporal dynamics, given the function for calculating the distance between two time samples. Euclidean distance is employed in [20].

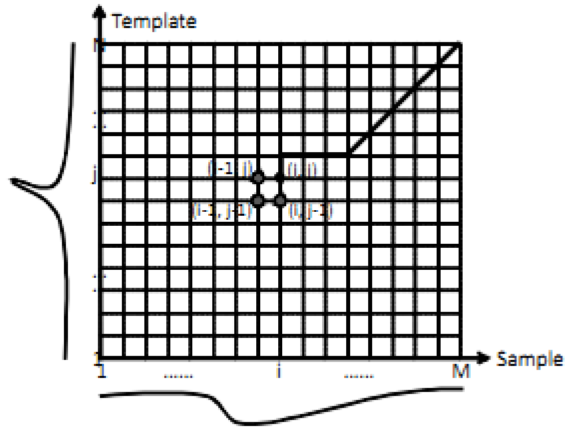


Figure 13 - Dynamic Time Warping [20]

Let S[1…M] and T[1…N] denote the two time series. As shown in the figure above, any matching between S and T with time warping can be represented as a monotonic path from the starting point (1, 1) to the endpoint (M, N) on the M by N grid. A point along the path, say (i, j), indicates that S[i] is matched with T[j]. The matching cost at this point is calculated as the distance between S[i] and T[j]. The path must be monotonic because the matching can only move forward. The similarity between S and T is evaluated by the minimum accumulative distance of all possible paths, or matching cost. DTW employs dynamic programming to calculate the matching cost and find the corresponding optimal path [20].

In our approach, using dynamic programming for fall detection involved finding similarity between a real-time sensor data pattern and existing fall templates using DTW. A fall is identified by matching cost < threshold. The threshold value was chosen by calculating the matching costs of various fall patterns.

For distance calculation in DTW implementation, we tried Euclidean distance and Levenshtein distance. We also tried the Dynamic Programming based algorithm for speech recognition described by Sakoe and Chiba [38].

We observed that this approach produced very good results for distinction between activities like sitting and walking, and for distinction between fall and walking. However, as a fall pattern involves values corresponding to user being stationary after fall, any sensor data pattern containing values corresponding to user being stationary – for example, sitting or sleeping - would have a low matching cost with fall patterns. This led to a number of false positives in fall detection. Additionally, both the approaches made no provisions for using user feedback about fall classification for improving fall detection accuracy.

3.7 Challenges

3.7.1 Noise in Sensor Data

Output from sensors in smartphones is contains considerable amount of noise, with even simple motions producing pronounced variations in the output. Following figure shows an example. The patterns depict changes in raw acceleration and orientation signals for the simple motion of picking the phone from table and placing it in trouser pocket.

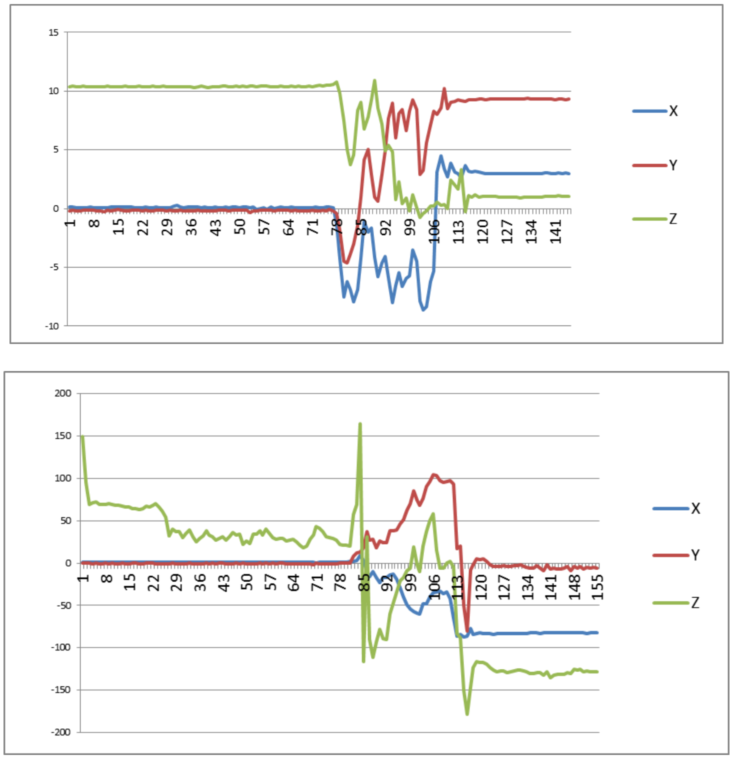


Figure 14 - Raw acceleration and orientation data during an ADL

For an application relying on sensor data, sensor noise forms a source of false positives and similar erroneous conclusions. Following techniques are commonly employed for smoothening out the sensor output:

- filtering techniques like low-pass filters, high-pass filters, and Kalman filters
- buffering the sensor values and averaging them over window size
- using lower and upper thresholds for sensor data based on empirical observations

In our application, both quantization and Multilayer Perceptron based pattern matching help offset the impact of noise in sensor data.

Chapter 4

Implementation and Alerts Generation

The Android application we have developed is comprised of two major parts - fall detection, and alerts generation. This chapter starts with a discussion of our choice of platform, followed by some application and platform-specific design considerations. We then discuss our Alerts mechanism, describing the application settings for alerts generation, various alerts, and their generation.

4.1 Why Android

Android is a software stack for mobile devices that includes an operating system, middleware and key applications [21]. The operating system is based on Linux kernel. Android started as an independent company, which was purchased by Google in 2005 [22]. T-Mobile G1, the first phone powered by Android, was released in 2008 [23]. As of mid-2011, Android powers over 310 devices, in 112 countries. Over 100 million Android devices are activated worldwide, with more than 500, 000 new devices activated every day [24] [25]. In USA, Android is the mobile platform with highest market share (May 2011) [26].

There are over 200,000 Android applications, and 450,000 developers [24]. Android application development is done in Java. Every Android application runs in its own process, with its own instance of the Dalvik virtual machine [27]. The executable application can be deployed using a multitude of ways – via Google's Android Market, via third-party distribution websites, and even via email. Applications put on the Android Market do not need to go through an approval process, and thus avoid the delay in distribution [28].

In summary, Android platform is selected for this work because,

- It has a widespread and ever-widening reach in the consumer market.
- A thriving developer community surrounds the platform. The collective community knowledge provides valuable help throughout the application development.
- The application development API is Java-based, and it provides access to varied functionalities, satisfying the needs of this work. For example, the API allows us to constantly monitor device sensors in the background, track location, obtain user address, send emails and text messages, and place voice calls.

Hardware and Software Used

For primary application development and testing, we used a Google Nexus S device, running Android software version 2.3.4, a.k.a. 'Gingerbread'. We used Eclipse IDE with ADT plugin running on a Microsoft Windows 7 machine for development. We also used a Motorola Droid, running Android software version 2.2.2 a.k.a. 'Froyo', for additional compatibility testing. Both the devices have accelerometer and magnetic sensors; the data collected from these is used for fall-detection.

4.2 Application Design Considerations

4.2.1 Background Monitoring

In our approach, detection of fall requires real-time classification of data from accelerometer and magnetic field sensors. As the occurrence of fall is an unpredictable event, sensor monitoring and classification of data needs to go on continuously - even when the user is not interacting with the app, and even when the phone is locked and its screen is off. We thus use a ‘Service’ for sensor monitoring, real-time classification of data, and identification of a fall event.

Android platform makes a distinction between Activity and Service. An activity is an application component, which is described as a single, focused thing that the user can do, and almost all activities interact with the user [29]. An activity thus has a user-visible part – a screen with witch the user interacts. An activity is considered active if it is in the foreground of the screen. An Activity is paused when it loses focus, and it is stopped when another Activity completely obscures it. When an Activity transitions to the paused or stopped state, the process hosting the Activity can be killed by the system at any time depending on memory requirements. Thus, if the fall detection algorithm is implemented as an activity, it cannot be guaranteed to run when the user is not directly interacting with the application.

A Service, on the other hand, is an application component representing an application's desire to perform a longer-running operation while not interacting with the user [30]. Using this facility, an application tells the system about something it wants to be doing in the background, i.e., even when the user is not directly interacting with the application. As a response to the startService() API call, the system schedules work for the Service, to be run until the Service or someone else explicitly stops it. Moreover, by requesting appropriate permissions from the system, a Service can be made to run even when the phone is locked and the screen is switched off. Thus, it is appropriate to implement the sensor monitoring, real-time classification and fall-detection as a Service.

On detecting a fall, we create an Activity from the Service, giving the user a chance to interact with the application.

4.2.2 Designing for Responsiveness

On the Android platform, the application has to be designed to be *responsive*. An application that is not responsive feels sluggish, hangs or freezes for significant periods, or takes too long to process input [31]. The system guards against such applications by displaying a dialog to the user, called the Application Not Responding (ANR) dialog. An example of this dialog is shown below.

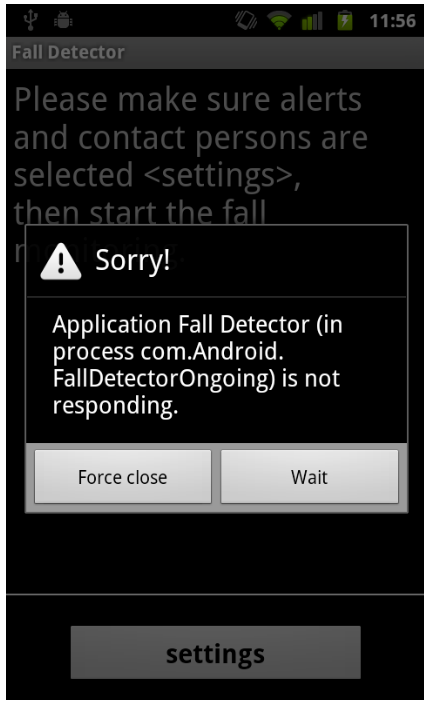


Figure 15 - Android Application Not Responding (ANR) dialog

Though the Service construct can be used to indicate background processing, a Service is neither a separate process nor a separate thread. Like other application objects, it runs in the main thread of the process. Thus, for the application to be responsive, tasks that are CPU intensive (like building the classifier) or blocking (like networking) need to be performed in separate threads. The main thread that runs the user-interface event loop needs to be kept free.

In our application, tasks like building the classifier, real-time classification of data, fall detection, and alerts generation are all performed in separate threads. For uploading of the sensor data to a server in our application for data collection, we use an IntentService, which is an Android standard implementation of a service that has its own thread where it schedules its work to be done, and finishes itself once done [30].

4.3 Alerts

This section describes alerts configuration and generation, including the user feedback mechanism.

4.3.1 Settings for Alerts

We provide following alerts: a ‘bell’ to notify those around about the fall; and text message, email and missed-calls to user-selected contact persons. Multiple contact persons can be selected. User can choose to include location and a list of hospitals nearby in text messages and in email. Number of missed-calls to place is configurable as well.

Following screenshots assist in understanding the various configurations.

The settings screen lists available options.

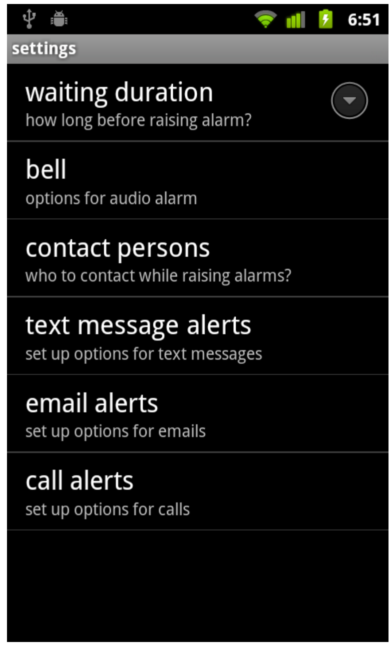


Figure 16 - Settings

Waiting Duration refers to the Alerts Generation countdown duration, explained below.

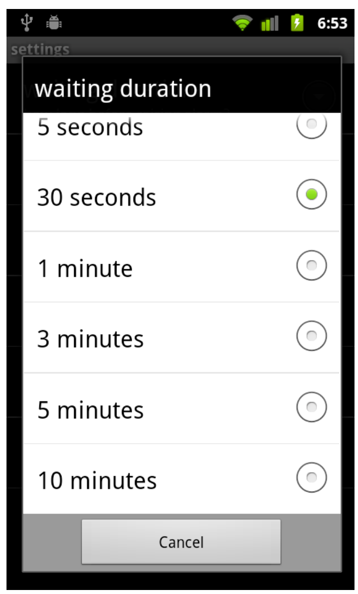


Figure 17 - Waiting duration

User can choose whether the bell sound should be generated, duration of bell and the sound to play from the ringtones available on the phone.

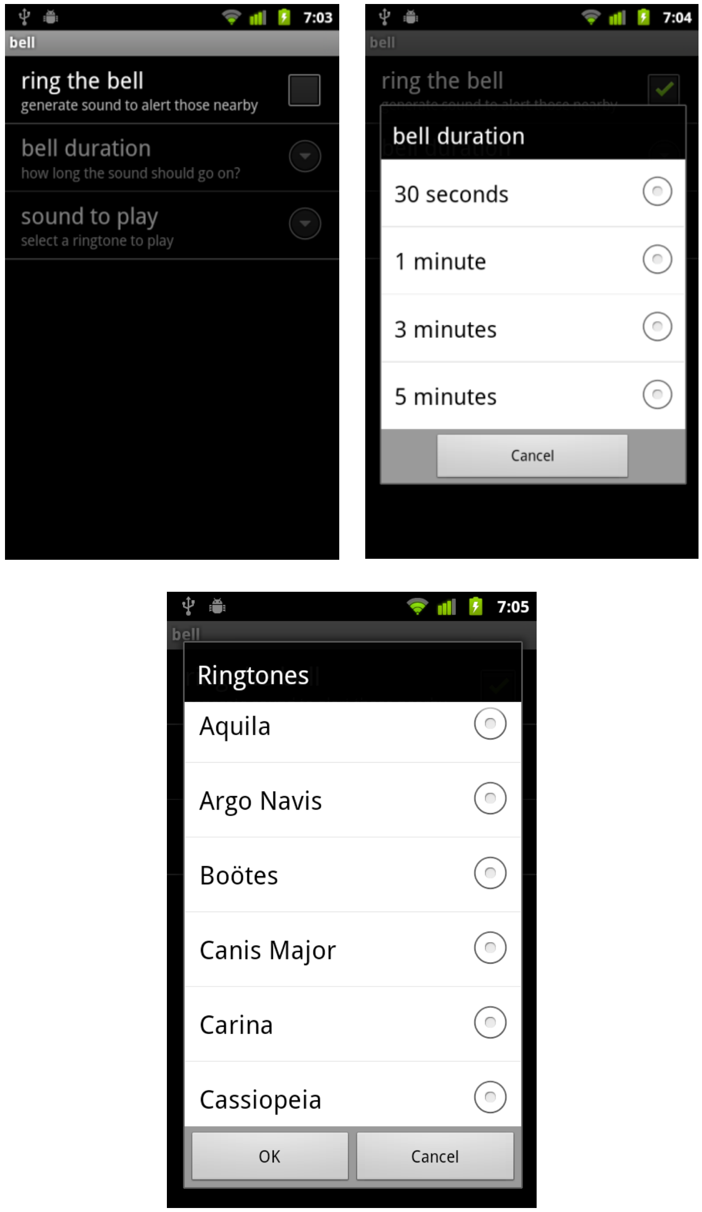


Figure 18 - Audio alert settings

User can choose whether to generate text and email alerts, and whether to include location and list of hospitals nearby.

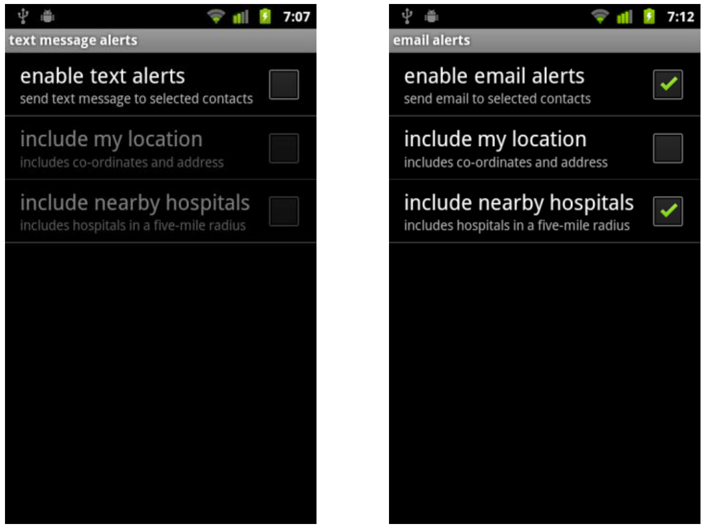


Figure 19 - Text and email alerts

Similarly, user can choose whether to place missed-calls to selected contacts, and the number of calls to place.

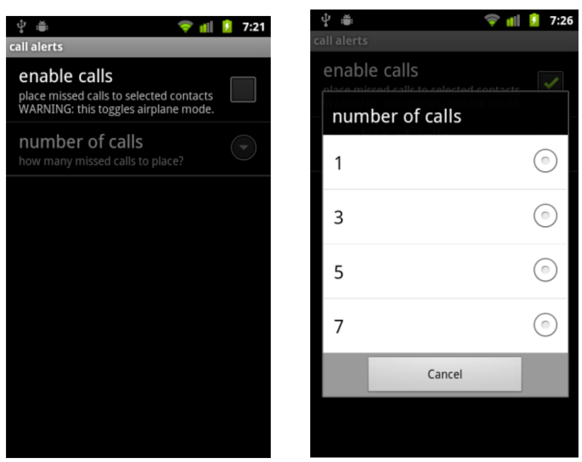


Figure 20 - Calls settings

4.3.2 User Feedback during Alerts Generation

When the monitoring service detects a fall, it starts an Activity to ascertain whether the user has indeed suffered a fall, and to generate alerts as selected by the user.

If the Android device supports speech recognition, an audio message is played to the user, informing him/her about the detection of fall, and asking whether he/she is all right. If the user replies in negative, we generate the alerts as explained below. If the user does not respond within a fixed time interval, we perform the alerts generation countdown, which is explained below.

User's response at this stage also serves the purpose of improving the fall-detection accuracy. The acceleration and orientation data set classified as fall is used to re-train the classifier, with the user providing the classification for the data set. If the user fails to respond, no assumption is made about the accuracy of the classification, and no re-training of the classifier happens.

If the Android device does not support speech recognition, alerts generation countdown is started.

4.3.3 Alerts Generation

Phone's speaker volume is set to maximum during alerts generation countdown. Seconds are counted down to zero from the Waiting Duration selected by user. During this countdown, user can cancel the alerts generation by pressing the 'cancel' button. Following screenshot demonstrates an ongoing countdown.

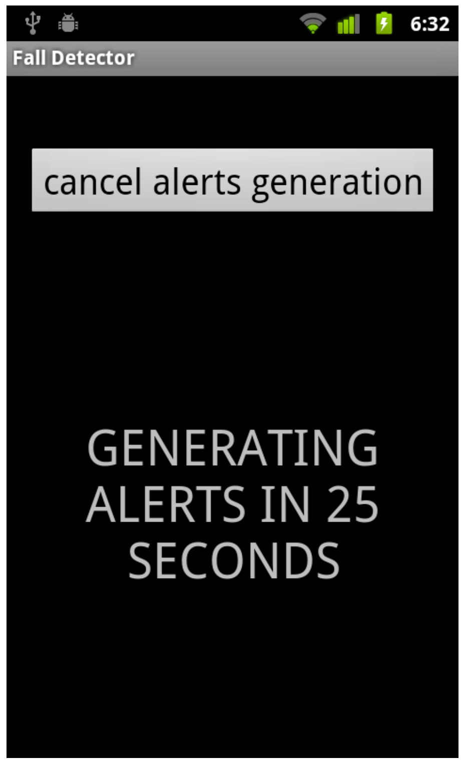


Figure 21 - Alerts generation countdown

Alerts are generated after the end of countdown, and a message informing the user about it is displayed on the screen.

If the audio alert is configured, a thread is started to handle it. This thread plays the selected ringtone for the selected duration. Before playing the ringtone, the phone speaker volume is set to maximum, and the ‘ring mode’ is set to normal. Ring mode setting enables the sound, whether the phone vibrates depends on user choice. These changes are reverted at the end of bell duration.

Several constraints guide the design of text, email and call alerts generation. These alerts can all be selected individually, and within text and email, location and hospital can be individually selected. Finding the user location is an expensive operation, so is getting the details of contact persons. Moreover, sending text and email has to wait on finding user address and fetching list of hospitals, which in turn have to wait on fetching user location. Additionally, trying to fetch user location has to (eventually) timeout.

A thread is started if any of text, email, and call alerts are selected. Phone numbers of selected contacts are fetched if call or txt alerts are selected, and email addresses are fetched if email alerts are selected. Then, if the user address or ‘list of hospitals’ is selected in either text or email alerts, a thread is started to fetch user location. Once these common operations are done, individual threads are started to handle generation of each of the selected alerts.

Now, user’s location can be obtained using GPS or using nearby wireless network access points and cellphone towers [37]. Accordingly, Android lists two providers for location – GPS and Network. These can be individually selected in ‘Phone Settings -> Location &

Security'. A ‘fix’ obtained using GPS is typically more accurate, but GPS requires a clear view of sky. We depend on the Network provider if the user is, for example, inside a building; but a fix using Network provider requires connectivity to cellular or wireless network.

In the location fetching thread, if GPS provider is enabled, we attempt to obtain a fix using GPS. On timeout, an attempt is made using the Network provider, if enabled. Connectivity to the network is verified for obtaining fix using network. On obtaining a fix, user address is fetched if the option is selected in either text or email alerts. Using Google Places web-service, a list of hospitals is fetched if the option is selected in either text or email alerts.

Text and email alerts generating threads wait for updates from location thread. For example, if the user has selected ‘list of hospitals’ in text alerts, the thread waits till the list of hospitals is fetched, then retrieves it, and appends it to the text message. Once all the required information is gathered, text messages and emails are sent from the phone. Timeouts ensure sending of messages, even in case of failures in fetching details.

Following screenshot shows an email, alerting a contact person about fall.

Gmail
by Google

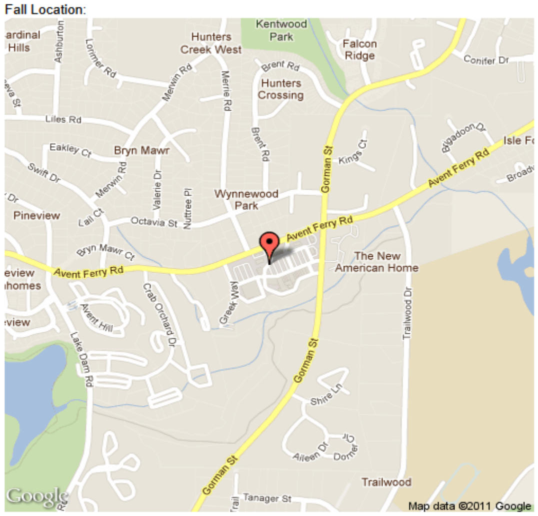
FALL EVENT

1 message

fall.detector.sender@gmail.com <fall.detector.sender@gmail.com>
To: [redacted]

Fall event occured on 6/6/2011, at 06:02 PM
Location Coordinates:35.76695475643962, -78.69634617392181, Accuracy of location: 65.616798 ft

Fall Location:



Address: 3289 Avent Ferry Rd Raleigh, NC 27606

Nearby Hospitals:
Dorothea Dix Park
Address: Umstead Dr, Raleigh, North Carolina 27603, United States
Phone: (919) 733-5540

Rex Hospital
Address: 4420 Lake Boone Trail, Raleigh, NC 27607-6599, United States
Phone: (919) 784-3100

Duke Raleigh Hospital
Address: 3400 Wake Forest Road, Raleigh, NC 27609-7373, United States
Phone: (919) 954-3000

Blue Ridge Surgery Center
Address: 2308 Wesvill Court, Raleigh, NC 27607-2949, United States
Phone: (919) 781-4311

Western Wake Medical Center
Address: 1900 Kildaire Farm Road, Cary, NC 27518-6616, United States
Phone: (919) 350-2300

Central Prison
Address: 1300 Western Boulevard, Raleigh, NC 27606-2196, United States
Phone: (919) 733-0800

Figure 22 - A received email alert

Finally, user-configured number of missed-calls are placed to selected contact persons in a separate thread. The Airplane mode is toggled to terminate a call.

Chapter 5

Experiments and Observations

In this chapter, we discuss the experiments conducted for evaluating our fall detection algorithm. We also document the impact of our applications on phone's battery.

5.1 Experiment Methodology and Results

We evaluate our Multilayer Perceptron based classifier against a number of ADLs and falls. Additionally, we also evaluate a threshold-based approach that mirrors the algorithm in [5] against the same activities. The ADLs performed are walking, strolling, sitting, and sleeping. Each activity, including falls, starts with the user being in an upright position, with the phone in the trouser pocket. Each activity, including falls, is repeated 5 times for each approach. For continuous activities like walking and strolling, the duration of one instance in our algorithm (roughly 6 seconds), is considered as the duration of each repetition as well.

In the following tabulations of our results, the symbols '✓' and '✗' indicate correct and incorrect identification, respectively. For example, a '✓' for 'walking' indicates that the activity was not detected as fall, while a '✓' for 'fall' indicates that the fall was indeed detected as fall.

Results for Walking:

Table 2 - Results for ADL: Walking

Count	Classifier-based	Threshold-based
1	✓	✗
2	✓	✓
3	✓	✓
4	✓	✗
5	✓	✓

Results for Strolling:

Table 3 - Results for ADL: Strolling

Count	Classifier-based	Threshold-based
1	✓	✓
2	✓	✓
3	✓	✓
4	✓	✓
5	✓	✓

Results for Sitting:

Table 4 - Results for ADL: Sitting

Count	Classifier-based	Threshold-based
1	✓	✓
2	✗	✓
3	✓	✓
4	✓	✓
5	✓	✓

Results for Sleeping:

Table 5 - Results for ADL: Sleeping

Count	Classifier-based	Threshold-based
1	✓	✓
2	✓	✓
3	✓	✓
4	✓	✓
5	✓	✓

Results for fall:

Table 6 - Results for fall

Count	Classifier-based	Threshold-based
1	✓	✓
2	✓	✓
3	✓	×
4	✓	✓
5	×	×

5.2 Evaluation and Observations:

Following table provides a comparison of the approaches:

Table 7 - Comparison of approaches

Approach	True Positives	False Positives	True Negatives	False Negatives
Threshold-based fall detection	3	2	18	2
Classifier-based fall detection	4	1	19	1

We can thus see that Classifier-based fall detection fares better in our experiments.

During our experiments, in addition to the results presented above, we observed a large number of false positives for the threshold-based approach; falls were reported while taking the phone out of pocket, keeping it in, taking it off the ear at the end of a call, and while performing high-impact activities like walking, running, and climbing up the stairs. A large number of false positives are hazardous as a detection system that produces too many false alarms can be rejected by the users [5]. We observed that the classifier-based approach too produced false positives during such ADLs, but to a significantly lesser extent; and on classifying such instances as non-falls, they were not falsely identified again, as the classified 'learnt' from them.

Finally, threshold-based approach also reported false-negatives for falls. This was also observed during our work with threshold-based approach. The reason behind such false negatives is – pitch does not change by a value close to 90 degrees in all falls, the change is mostly about 75 degrees.

Limitations

The experiments and results above document only a small sample of tests. Though we have observed that classifier-based approach yields better results than threshold-based approach, it would be beneficial to perform the experiments with a wider variation of test subjects, falls, and activities of daily life. Such data, in addition to sensor data patterns from real falls (as opposed to intentional ones performed for data collection and experiments), could also help in building a better classifier, further improving fall-detection accuracy. We plan to address some of these issues as explained in section ‘Future Work’ in Chapter 6 below.

5.3 Battery Consumption

Following table presents a measure of battery consumption for both the applications developed by us. We calculated the time taken for the battery power level to reduce from 100% to 80%, with and without our applications running. Phone’s usage conditions for these measurements included audio playback, voice calls, and moderate internet access over both WiFi and 3G networks.

Table 8 - Battery power consumption of applications - 1

Application	Time taken for battery power level to reduce by 20%
Neither applications running, phone’s normal usage conditions	117 minutes
Data Collection application running, two successful uploads of sensor data, coupled with phone’s normal usage	99 minutes
Fall Detection application running – fall detection, alerts generation and classifier retraining; coupled with phone’s normal usage	91 minutes

We also evaluated time taken for the battery power level to reduce from 100% to 5%, with the phone being idle for most of the time. Following table presents the findings.

Table 9 - Battery power consumption of applications - 2

Application	Time taken for battery power level to reduce by 95%
Neither applications running	23 hours and 18 minutes
Data Collection application running	13 hours and 40 minutes
Fall Detection application running	13 hours and 10 minutes

Thus, we observed that both Data Collection and Fall Detection applications have an impact on battery life; it took 18 minutes less for the battery to lose same amount of power with Data Collection application running, and it took 26 minutes less with the Fall Detection application running. For a complete discharge, the differences become more pronounced, with constant sensor monitoring and background processing by our applications resulting in considerable battery power consumption.

Chapter 6

Summary and Future Work

In this thesis, we developed an Android application for automatic fall-detection and alerts generation. The application monitors the built-in accelerometer and magnetic field sensors in the background using a Service, to calculate device acceleration and orientation. A Multilayer Perceptron classifier from Weka Data Mining Suite is trained on training data comprised of both fall and non-fall samples, and is used for real-time classification of sensor data. Multiple, overlapping, sliding windows over the sensor data stream are used to provide instances for classification. A fall is characterized by near-simultaneous occurrence of fall-patterns in both acceleration and orientation.

The alerts to be generated and the persons to be contacted on fall detection are configurable by user. We provided following alerts: an audible bell with the phone's volume set to maximum to alert those nearby, and emails, text messages and missed-calls to selected contact persons. Additionally, users can choose to include their location and a list of hospitals in their vicinity, with addresses and phone numbers, in the email and/or text message.

To reduce the false positives, we used following method. On detecting a fall, the application asks the user about his/her condition and seeks a spoken response from the user. The response serves two purposes - it is used to re-train the classifier, and in case of a false positive, it aborts the alert generation. In the absence of response, alerts are generated, preceded by user-configured waiting duration. Users can cancel alerts generation during this waiting duration as well, in case of a false positive.

In addition to an Artificial Neural Network based classifier, we also explored threshold-based and Dynamic Programming based approaches for fall detection.

6.1 Future Work

Classifier accuracy could be improved by using real-world data from application users. We propose the following scheme. Sensor data instances that are classified by users as true or false positives are currently used to improve the classifier locally. These instances could be communicated to a server, where they could serve as training data for the classifier. A better-trained classifier could be delivered to users through periodic updates of the application via Android Market. This would also improve application performance as the blocking task of building the classifier would be transferred to a server.

Collected data could also serve further research requirements in this domain. We have not come across publically available sensor data involving fall patterns during the course of this work, and one of our aims is to create one. Our data collection application is already available in Android Market. Via an update to this application, we are making possible the collection of raw acceleration and orientation data, and uploading it to a public server.

We have used two classifiers, one each for acceleration and pitch signal. Our fall signal considers outputs from both the classifiers. Instead of using multiple separate classifiers and combining their outputs, an approach utilizing a multidimensional classifier could be explored.

Additionally, in the fall detection application, users could be provided a 'sensitivity setting' for fall detection. Provided setting value could be used while interpreting the classifier prediction.

References

[1] S. E. Lamb, E. C. Jostad-Stein, K. Hauer and C. Becker, "Development of a Common Outcome Data Set for Fall Injury Prevention Trials: The Prevention of Falls Network Europe Consensus," *Journal of the American Geriatrics Society*, vol. 53, no. 9, pp. 1618-1622, September 2005.

[2] A. A. Zecevic, A. W. Salmoni, M. Speechley and A. A. Vandervoort, "Defining a Fall and Reasons for Falling: Comparisons Among the Views of Seniors, Health Care Providers, and the Research Literature," *The Gerontologist*, vol. 43, no. 3, pp. 367-376, 2006.

[3] "Falls Among Older Adults: An Overview," Centers for Disease Control and Prevention, National Center for Injury Prevention and Control, Division of Unintentional Injury Prevention, 8 December 2010. [Online]. Available: http://www.cdc.gov/HomeandRecreationalSafety/Falls/adultfalls.html. [Accessed 20 July 2011].

[4] A. K. Bourke, J. V. O' Brian and G. M. Lyons, "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," *Gait and Posture*, vol. 26, no. 2, pp. 194-199, 2007.

[5] F. Sposaro and G. Tyson, "iFall: An Android Application for Fall Monitoring and Response," in *31st Annual International Conference of the IEEE EMBS*, Minneapolis, Minnesota, USA, 2009.

[6] G. Brown, "An accelerometer based fall detector: development, experimentation, and analysis," Summer Undergraduate Program in Engineering Research at Berkeley (SUPERB), Berkeley, 2005.

[7] J. Tilly, DrPH and P. Reed, "Falls, Wandering, and Physical Restraints: Interventions for Residents with Dementia in Assisted Living and Nursing Homes," August 2006. [Online]. Available: http://www.alz.org/national/documents/Fallsrestraints_litereview_II.pdf. [Accessed July 2011].

[8] B. R. Bloem, J. M. Hausdorff, J. E. Visser and N. Giladi, "Falls and Freeing of Gait in Parkinson's Disease: A Review of Two Interconnected, Episodic Phenomena," *Movement Disorders*, vol. 19, no. 8, pp. 871-884, 2004.

[9] W. TG, "Falls in people with learning disabilities: what are the risk factors and prevention strategies?," *Nursing Times,* 2010.

[10] A. K. Bourke and G. M. Lyons, "A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor," *Medical Engineering and Physics,* 2006.

[11] Apple Inc., "iPhone 4 Technical Specifications," [Online]. Available: http://www.apple.com/iphone/specs.html. [Accessed July 2010].

[12] Google Inc., "Nexus S Tech Specs," [Online]. Available: http://www.google.com/nexus/#/tech-specs. [Accessed July 2010].

[13] J. Y. Hwang, J. M. Kang and H. C. Kim, "Development of Novel Algorithm and Real-time Monitoring Ambulatory System Using Bluetooth Module for Fall Detection in the Elderly," in *26th Annual International Conference of the IEEE EMBS*, San Francisco, CA, USA, 2004.

[14] T. R. Hansen, J. M. Eklund and J. Sprinkle, "Using Smart Sensors And a Camera Phone to Detect and Verify the Fall of Elderly Persons," in *European Medicine, Biology and Engineering Conference,* Prague, Czech Republic, 2005.

[15] Q. Li, J. A. Stankovic, M. Hanson, A. Barth and J. Lach, "Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information".

[16] J. Yang, "Toward Physical Activity Diary: Motion Recognition Using Simple Acceleration Features with Mobile Phones," 2009.

[17] J. R. Kwapisz, G. M. Weiss and S. A. Moore, "Activity Recognition Using Cell Phone Accelerometers," in *Fourth International Workshop on Knowledge Discovery from Sensor Data*, 2010.

[18] L. Sun, D. Zhang, B. Li, B. Guo and S. Li, "Activity Recognition on an Accelerometer Embedded Mobile Phone with Varying Positions and Orientations," in *Ubiquitous Intelligence and Computing*, 2010.

[19] T. Brezmes, J.-L. Gorricho and J. Cotrina, "Activity Recognition from Accelerometer Data on a Mobile Phone," in *Proceedings of IWANN*, Salamanca, Spain, 2009.

[20] J. Liu, Z. Wang, L. Zhong, J. Wickramasuriya and V. Vasudevan, "uWave: Accelerometer-based Personalized Gesture Recognition," Rice University and Motorola Labs, June 2008.

[21] "http://www.webcitation.org/5wiw1JXa2," [Online].

[22] K. Cline, "The History of Android," [Online]. Available: http://venturefizz.com/blog/history-android.

[23] "T-Mobile Unveils the T-Mobile G1 — the First Phone Powered by Android," [Online]. Available: http://www.htc.com/www/press.aspx?id=66338&lang=1033.

[24] "Android: Momentum, Mobile and More at Google I/O," [Online]. Available: http://googleblog.blogspot.com/2011/05/android-momentum-mobile-and-more-at.html.

[25] [Online]. Available: https://twitter.com/#!/Arubin/status/85660213478309888.

[26] "comScore Reports May 2011 U.S. Mobile Subscriber Market Share," [Online]. Available: http://www.comscore.com/Press_Events/Press_Releases/2011/7/comScore_Reports_May_2011_U.S._Mobile_Subscriber_Market_Share.

[27] "What Is Android?," [Online]. Available: http://developer.android.com/guide/basics/what-is-android.html.

[28] "Signing Your Applications," [Online]. Available: http://developer.android.com/guide/publishing/app-signing.html.

[29] "Activity | Android Developers," [Online]. Available: http://developer.android.com/reference/android/app/Activity.html. [Accessed July 2011].

[30] "Service | Android Developers," [Online]. Available: http://developer.android.com/reference/android/app/Service.html. [Accessed July 2011].

[31] "Designing for Responsiveness | Android Developers," [Online]. Available: http://developer.android.com/guide/practices/design/responsiveness.html. [Accessed July 2011].

[32] "SensorEvent | Android Developers," [Online]. Available: http://developer.android.com/reference/android/hardware/SensorEvent.html#values. [Accessed August 2011].

[33] "SensorManager | Android Developer," [Online]. Available: http://developer.android.com/reference/android/hardware/SensorManager.html#getOrientation%28float[],%20float[]%29. [Accessed August 2011].

[34] "Weka 3 - Data Mining with Open Source Machine Learning Software in Java," [Online]. Available: http://www.cs.waikato.ac.nz/ml/weka/index.html. [Accessed August 2011].

[35] "Learning and Neural Networks - 1," [Online]. Available: http://goo.gl/ojDwz. [Accessed August 2011].

[36] "MultilayerPerceptron," [Online]. Available: http://weka.sourceforge.net/doc/weka/classifiers/functions/MultilayerPerceptron.html. [Accessed August 2011].

[37] "Obtaining User Location," [Online]. Available: http://developer.android.com/guide/topics/location/obtaining-user-location.html. [Accessed July 2011].

[38] H. Sakoe and S. Chiba, "Dynamic Programming Algorithm Optimization for Spoken Word Recognition," *IEEE Transactions on Acoustics, Speech and Signal Processing,* vol. 26, no. 1, pp. 43-49, 1978.

[39] "IntentService | Android Developers," [Online]. Available: http://developer.android.com/reference/android/app/IntentService.html. [Accessed August 2011].

[40] [Online]. Available: http://www.cs.waikato.ac.nz/ml/weka/. [Accessed July 2011].

[41] L. Sun, D. Zhang, B. Li, B. Guo and S. Li, "Activity Recognition on an Accelerometer Embedded Mobile Phone with Varying Positions and Orientations," in *Ubiquitous Intelligence and Computing, Lecture Notes in Computer Science, Volume 6406*, 2010 , pp. 548-562.

[42] "Object Modeling with OMG UML Tutorial Series - Behavioral Modeling," November 2000. [Online]. Available: http://www.omg.org/news/meetings/workshops/presentations/uml_presentations/Tutorial%202%20-%20UML_Lecture2_R2.pdf. [Accessed August 2011].

APPENDIX

Appendix A

Application for Data Collection

A.1 Why This Application

We created an application for collecting data from sensors and sending it to a server. We needed a dedicated application because,

- A fast and reliable method was required to get the sensor data from the monitored phone to our development system for further analysis.
- Sensors monitored and the nature of data collected changed frequently during design phase. We needed our own application to accommodate these changes.
- We used our own format for the sensor data.
- For collecting data from other people, we needed an application in Android Market as many Android device manufactures/carriers disable downloads of non-Market applications.

A.2 Design and Implementation

We start a Service once the user starts the sensor monitoring from within the application. This Service monitors the sensor output in background, and writes the sensor data into files stored at a predefined location on the phone's external storage. It also periodically reminds the user about uploading the data to our server using the Android system notifications.

Additionally, the user can choose to upload the data at any time from the application. The user can optionally provide date and time of fall event while uploading the sensor data.

When the user chooses to upload the data, we start an IntentService. An IntentService is a Service for on-demand handling of asynchronous requests. Once started, an IntentService handles the request and stops itself when it runs out of work [39].

The stored sensor data files can possibly grow large over time. Thus, we compress the files before sending them over the network, and de-compress them at the server before storing. Additionally, on successful upload, we delete the files from phone's storage.

Sensor monitoring and writing to files is paused during upload, and restarted once upload is done.

Following screenshots show application start page, upload page, and an ongoing upload.

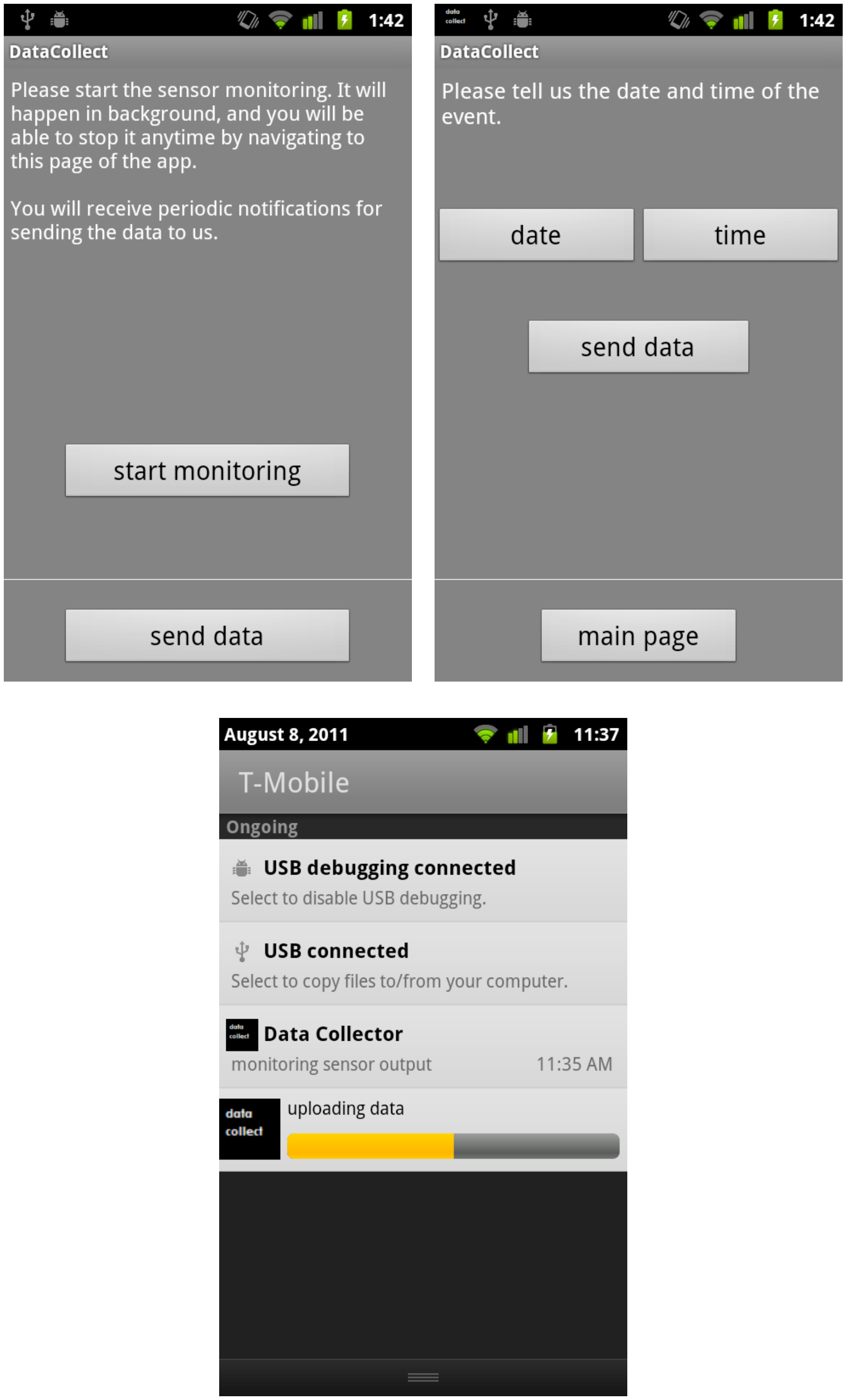


Figure 23 – Screenshots of application for data collection