iFall: An Android Application for Fall Monitoring and Response

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***Abstract*— Injuries due to falls are among the leading causes of hospitalization in elderly persons, often resulting in a rapid decline in functionality and death. Rapid response can improve the patients outcome, but this is often lacking when the injured person lives alone and the nature of the injury complicates calling for help. This paper presents an alert system for fall detection using common commercially available electronic devices to both detect the fall and alert authorities. We use a common Android-based smart phone with an integrated tri-axial accelerometer. Data from the accelerometer is evaluated with several threshold based algorithms and position data to determine a fall. The threshold is adaptive based on user provided parameters such as: height, weight, and level of activity. These variables also adapt to the unique movements that a cellphone experiences as opposed to similar system which require users to mount accelerometers to their chest or trunk. If a fall is suspected a notification is raised requiring the user's response. If the user does not respond, the system alerts prespecified, social contacts with an informational message via SMS. When a contact responds with an incoming call the system commits an audible notification, automatically answers the call, and enables speakerphone. If a social contact confirms a fall, an appropriate emergency service is alerted. Our system provides a realizable, cost effective solution to fall detection using a simple graphical interface while not overwhelming the user with uncomfortable sensors.**

I. INTRODUCTION

As age related changes in reaction time and balance reduce the capabilities of people, the likelyhood of a fall leading to significant injury increases. Not only are fall related injuries the number one reason for emergency room visits, it is also the leading cause of injury-related deaths among adults 65 years old and older [19]. Every year, more than 11 million people fall [4]. In 2005, unintentional falls accounted for an estimated 56,423 hospitalizations and 7,946 related deaths in the United States [24]. Many of these deaths are a result of a "long-lie," an extended period of time where the victim remains immobile on the ground [3]. Just the simple fear of a long-lie or falling can lead to one's lower mental health, isolation, and general degradation of quality of living [21], [7].

Current systems are available that attempt to reduce the long-lie period by alerting emergency services when a fall has been detected. These systems commonly use one of three methods for classifying a fall:

1) Acoustic/vibration recognition: This is acheived 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 [1], [22].
2) 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 middle of a common path [13], [15], [23], [16].
3) 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 would then alerts emergency contacts [7], [26], [8].

The majority of fall detection systems require some application specific hardware and software design. This increases 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. Despite implementation differences, all designs have the same requirements: reliability, ease of installation/use, and restriction of false positives [7]. Falls are often sparse with months between occurrences, thus the system must always be ready and accurate. If installation costs or training time is high, users will reject the system. However, the major reason for failure is rejection by monitoring services due to a high number of false alarms [17], [20].

We propose a low priced system that is well suited to all the requirements by using existing mainstream technologies that are reliable and ubiquitous. Our approach is to use a worn device that billions of people already possess, a programmable cellular phone [25]. Using existing cell phone technology not only reduces the cost to the patient, it also exploits a greater range of communication capabilities and integrated hardware and software features. Touch screen response and voice recognition, common to smart phones, provide a reliable interface with the user. By using similar interfaces to applications the user frequently uses, the rare interaction with the fall detection software should be familiar. Cell phones are also more discrete than a dedicated monitor device, this hopes to reduce rejection due to the device's poor aesthetic value and intrusiveness [7]. To limit false positives we implement several fall detection algorithms and two stages of communication. When a fall is detected, we first communicate with the user. If the user does not respond, we then attempt to contact members in his or her social network. If both fail or the social contact confirms a fall, the system alerts an emergency service.

II. Materials and Methods

A. Hardware

The prototyped application is designed for the HTC G1. The G1 has a Qualcomm®MSM7201A™running at 528 MHz. Its dimensions are 117.7 mm × 55.7 mm × 17.1 mm and weighs 158 grams. The touch screen has a 320 x 480 resolution. It has 192 MB of RAM and a 3.2 megapixel camera. It supports a 3G, Wideband Code Division Multiple network running at 2100 MHz, however our prototype is using the T-Mobile 2G network. The phone also supports sending and receiving SMS and MMS messages. A GPS receiver is also embedded and it is both 802.11g and Bluetooth®2.0 capable. [6]

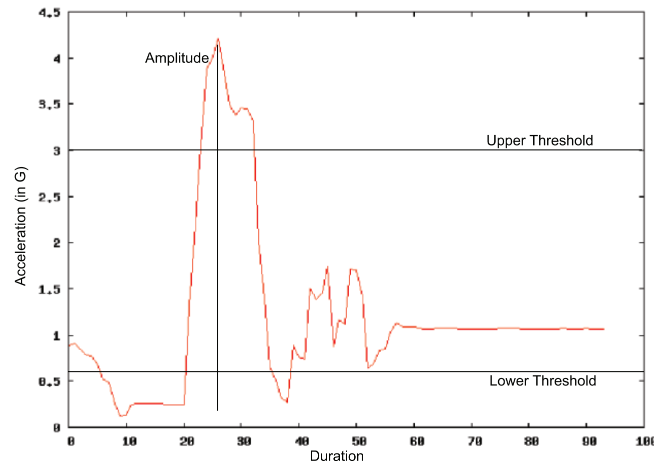
B. Software

We chose to use the Android software stack produced by Google. Android is an open source framework designed for mobile devices. It packages an operating system, middleware, and key applications [10]. The Android SDK provides libraries needed to interface with the hardware and make/deploy an Android application [11]. Applications are written in Java and run on the Dalvik virtual machine. Android uses a SQLite database to store persistent data.

Unlike dedicated systems, our software is intended to integrate with the phone's existing applications. Our application, *iFall*, must share resources with the other apps. To make for a pleasant integration, iFall runs as inconspicuously as possible while using limited resources. We launch a background service that constantly listens to the accelerometer. Only when the algorithm described in the following section suspects a fall will the service wake up and interrupt the user. If the user responds, the previous activity is restored and iFall will sleep again. By only waking up the activity when a fall is suspected or requested by the user, we allow applications to run on top of iFall while we minimize our memory consumption.

C. Fall Detection

Activities of Daily Living (ADL) are normal activities such as walking and standing. The forces exerted during ADL are usually different than the forces during a fall. By taking the root-sum-of-squares of the accelerometer's three axials, we are able to determine the acceleration [3]. A fall must start with a short free fall period. This causes the acceleration's amplitude to drop significantly below the 1G threshold [3]. This represents the period of time when the actual fall is taking place. The fall must stop and it causes a spike in the graph. The amplitude then crossing an upper threshold suggests a fall. Typically the minimum value for the upper threshold is around 3G [5]. If a person is seriously injuried in a fall they usaully remain on the ground for a period of time. This is characterized by the 1G flat line at the end of the graph. All of these events occur within a short duration. The following is a graph of a typical fall.



If the amplitude crosses the lower and upper thresholds in the set duration period a fall is suspected. However, relying strictly on this method would produce an intolerable number of false positives since certain ADL and the upper threshold can overlap [2]. We refine the algorithm by taking position into consideration. The assumption is a fall can only start from an upright position and end in a horizontal position [14]. Thus the difference in position before and after the fall is close to $90°$ [26]. A fall is only suspected if both thresholds are crossed within a duration and the position is changed. Dropping the phone is a frequent motion that resemables a suspected fall. Also a fall may occur but, be minor leaving the user unharmed. To prevent these false alarms we add one more stage to the process, recovery.

If a fall is suspected, we start a short timer. This timer allows a fallen user to regain an upright position or a dropped phone to be picked up. If the original position is resorted within the time limit the algorithm is reset. If the timer expires and position is not restored, we assume the phone/user is lying on the ground [9]. It then emits a prompt that requires the user to respond within a short time window. A fall is confirmed if the user does not respond. This allows users to reduce the number of false positives. An alert only sends when a fall is confirmed.

D. Application Features

The iFall application is designed to be simple to use. To achieve this, we severely limit the number of buttons and options available to the user. The main screen consists of one button and a label. The button starts and stops the fall monitor while the label displays the state. The fall monitor is implemented as a low-powered, Android service. A service allows the fall monitor to constantly run the background. When the monitor suspects a fall, an intent is sent to iFall. This wakes up the application and attempts to get the user's attention by repeatedly vibrating, flashing LEDs, and playing an audio message. The app prompts the user with a simple pop-up window telling them to press an on-screen button if they are okay. Pressing the button cancels the alert, and the interrupted activity is restored. This gives users the opportunity to eliminate false positives [20], [8].

The iFall application has additional methods to reduce the number of false positives. We allow the amplitude's upper threshold described in the 'Fall Detection' section to be variable. The application displays a small list of configuration options when the phone's *menu* key is pressed. One option is to adjust the sensitivity, the capacity to detect a fall [17]. So the less sensitive, the higher the upper threshold is. Given information such as age, weight, height, and level of activity are also factored into the equation [15], [26].

The other option under the application's menu is *Add a contact*. This allows the user to add social contacts to their iFall, emergency contact list. Using social contacts to confirm a fall before alerting an emergency service is another method for filtering false positives. When a fall is confirmed, every contact in the iFall emergency list is sent a SMS message [18]. This message states that a fall was detected at the given time and includes the GPS coordinates of the fall. It also asks the contact to call the fallee. When called, a message is played on the fallee's phone and the call is automatically answered and placed on speaker. Enabling bidirectional voice communication between the fallee and social contact reduces the number of false positives [20]. The dedicated emergency services are only notified when a social contact also confirms the fall, or in the case if no social contacts call the fallee.

III. Challenges

Using smart phone technology for fall detection has numerous advantages in cost and capability of the system. However, leveraging an existing system does pose challenges that single use detectors can avoid. One advantage of using a smart phone, is that the user is more likely to carry the phone throughout the day since it seen as indispensable in daily living, whereas users may forget to wear special micro sensors [27]. Unfortunately, it may be difficult to convince users to mount the phone to various body parts inorder to improve fall detection rate [12]. Instead, the software must dynamically adjust to different methods of carrying the phone (e.g., in the purse, pants or shirt pocket, or on a belt or neck clip). This requires the software to classify acceleration parameters of general use to identify the correct parameters for the fall detection logic.

To adapt for different carrying methods, we dynamically adjust the upper threshold and staring position. If the phone is carried on more accelerated body parts, such as the arms, the level of activity is automatically be risen. This causes the upper threshold to be greater [12]. Likewise, more stationary spots like the trunk will lower the threshold [3]. To account for the different orientations that phone may be held, like vertically or horizontally, we dynamically adjust the starting position. If the phone is resting for an extended period of time with 1G acceleration, we designate that to be the starting position. This allows the position to be dynamically set as the user interacts with the phone throughout the day.

Figure 1 graphs the walking/running activity. Running's amplitude can break the lower and upper threshold. If the user suddenly stops, it can cause an extended period of 1G acceleration. These events together suggest a fall. However,

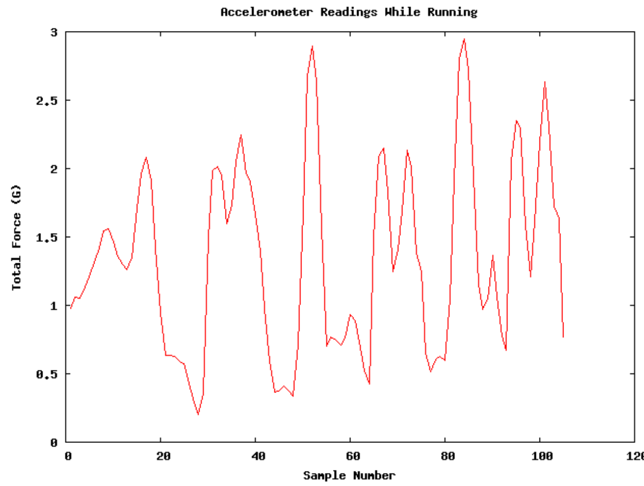


Fig. 1.

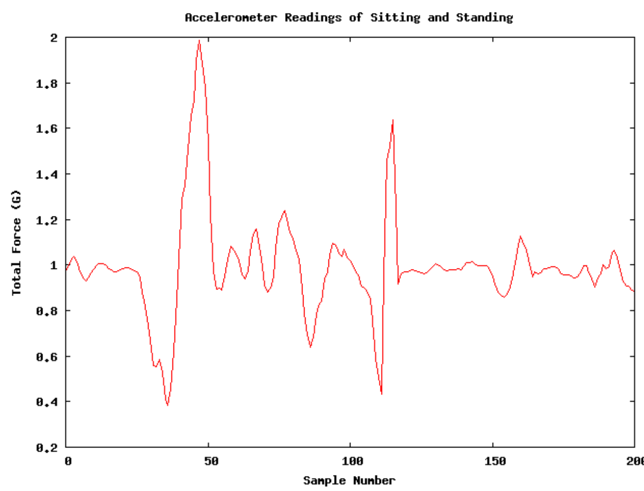


Fig. 2.

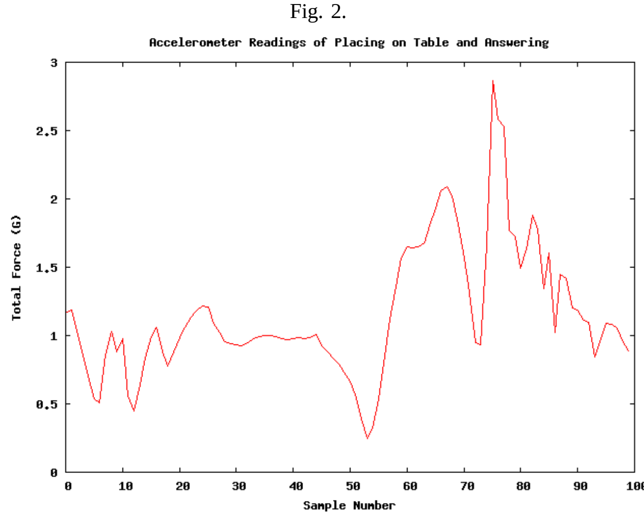


Fig. 3.

a prompt will not be given because the phone's starting and ending position are the same. Figure 2 graphs the sitting and standing activity. This activity changes the phone's position. However, sitting and standing's acceleration will not usually break the upper threshold. Both experiments were performed while the phone was in the user's front pant's pocket.

Some interactions with the phone, such as answering then ending a call, can break the thresholds and change position (see figure 3). Additional refinements to our algorithm must be made to prevent this. We do not allow the starting position to be dynamically changed if a call is in session. This will filter out the false positives in actions such as raising the phone to the user's ear to start a call and lowering the phone from the user's ear to end a call.

IV. CONCLUSION

Our system provides a viable solution to fall detection in the elderly. Using existing, mass marketed technologies will limit cost making it available to the majority of the public. Implementing proven fall detection algorithms makes the system highly reliable. Reliability and reduced number of false positives means greater adoption by emergency services. The importance of the cell phone in everyday life decreases the chances of being forgotten. Everyday interaction with the phone makes the interface more familiar to the user. A cell phone is also less intrusive than dedicated devices. The familiar interface, non-intrusiveness, and affordability leads to less rejection from users. By combining cheap hardware and open source software, we hope to provide a realistic solution to the elderly fall problem.

A. Future Work

The flexibility of the Android platform along with the phone's hardware capability allows this system to be extended in numerous ways. Bluetooth support could allow iFall to gather additional data readings from micro-sensors embedded in articles of clothing [18]. Ideally, a sensor would be embedded in head or eye wear due to the fact that the head is the most reasonable location for fall detection using threshold based algorithms [12]. The system could also use image support from mounted, bluetooth cameras as described in [15], [23], and [16].

The system could also use the Wi-Fi connection to log the data readings on a server. More sophisticated pattern matching algorithms can be then be ran [27]. Efforts are being made to build a database of common ADL readings [20]. This information can be exploited in attempts to classify what type of action the user is performing based on pattern matching techniques.

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