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Wearable Sensors for Reliable Fall Detection

Jay Chen*, Karric Kwong†, Dennis Chang‡, Jerry Luk§, Ruzena Bajcsy¶
Department of Electrical Engineering
and Computer Sciences
University of California, Berkeley
Berkeley, CA 94720
{¶bajcsy, ‡dhchang}@eecs.berkeley.edu, {*jayzchen, †karrickk}@berkeley.edu, §jerryluk@cal.berkeley.edu

***Abstract*— Unintentional falls are a common cause of severe injury in the elderly population. By introducing small, non-invasive sensor motes in conjunction with a wireless network, the Ivy Project aims to provide a path towards more independent living for the elderly. Using a small device worn on the waist and a network of fixed motes in the home environment, we can detect the occurrence of a fall and the location of the victim. Low-cost and low-power MEMS accelerometers are used to detect the fall while RF signal strength is used to locate the person.**

I. INTRODUCTION

A. Background

Falling can be a frequent and dangerous event for the elderly population. It is estimated that over a third of adults ages 65 years and older fall each year [1], making it the leading cause of nonfatal injury for that age group.

Among older persons, 55 percent of fall injuries occur inside the home. An additional 23 percent occur outside, but near the home [2]. Traditionally, placing seniors in nursing homes or other care centers has mitigated the dangers of the elderly falling. However, with the advent of wireless ad-hoc networks and low-power mote technology, we can now approach the problem from a different perspective.

B. Motivation

The goal of the Ivy Project [3] is to provide an infrastructure of networked sensors that supports multiple applications simultaneously. The sensor network, like ivy, would spread throughout the environment, whether it is an office space or home, linking leaves (motes) to the root (base station). In general, the motes can be divided into two types: 1) Fixed/infrastructure motes, for example attached alongside the walls and corridors, and 2) mobile motes, whose geographical position can change over time.

In our application, this networked infrastructure is used to detect when a person has sustained a fall and relay this information across some medium such that immediate and appropriate action can be taken. This is currently the focus of the Ivy Project and motivates the experiments discussed in this paper.

In addition, localization technology can be used to complement the fall detection. Seniors who are living by themselves have problems getting help when they fall and may not be able to describe where they are. Combined with the fall detection technology, localization can detect where the incident occurred and request the relevant services.

II. FALL DETECTION AND LOCALIZATION

A. Previous Work on Fall Detection

Accelerometry has been used in various studies and applications to objectively monitor a range of human movement, for example to measure metabolic energy expenditure, physical activity levels, balance and postural sway, gait, and to detect falls [4]. With respect to fall detection, there has been relatively little work published. According to [4], the basic approach of using accelerometry to detect the fall was first published by [5], [6]. In this approach, a change in body orientation from upright to lying that occurs immediately after a large negative acceleration indicates a fall. These two conditions have been incorporated into fall detection algorithms using accelerometers [7], [8].

Reference [9] presents a fall detector worn on the wrist that incorporates a multi-stage fall detection algorithm. The first condition is the detection of a high velocity towards the ground. Next an impact needs to be detected within 3 seconds. After impact, the activity is observed for 60 seconds, and if at least 40 seconds of inactivity are recorded, an alarm is activated. The results were positive in the sense that no false alarms were given, but also disappointing since a large percentage of backwards and sideways falls were not detected.

Reference [6] documents the design of the commercially available Tunstall fall detector that uses a patented two-stage detection algorithm. The detector wakes up from the sleep state when a strong impact is detected. Then a second sensor estimates the wearer's orientation and if he/she is in a lying state for a set time period, an alarm is raised. Various locations for the device were considered and it was determined that the waist was the optimum location that suited the wearer and allowed reliable measurement of impacts.

III. SYSTEM DESIGN

Our application utilizes TinyOS and Mica2Dot motes developed at UC Berkeley as a research platform for low-power wireless sensor networks [10], [11]. The Mica2Dot mote is equipped with the Atmel ATmega 128L microcontroller, 4 KB of RAM and a 433 MHz radio capable of data transfer

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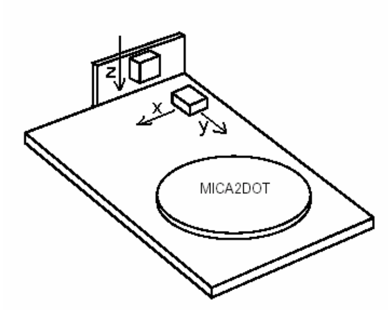

Fig. 1. Fall detection sensor board

at 38.4 kbps with a radio range of 1000 ft, and is powered by two AA batteries.

A. Fall Detection Sensor Board

The goal was to design an accelerometer mote that is small and lightweight that can be worn comfortably without obstructing normal activities. The fall detector board has two dual-axis MEMS accelerometers (Analog Devices ADXL210E) mounted at right angles to each other, such that three orthogonal axes of acceleration can be measured. The ADC in the microcontroller converts the analog output of the accelerometers to an integer in the range $[0, 1023]$, corresponding to a measured voltage of $[0, V_{DD}]$. Two AA batteries power the accelerometer mote, chosen for their widespread availability and relatively low cost. The mote fits inside a plastic box measuring 1 1/8" x 3/8" x 1 5/8", while the batteries are enclosed in a separate small battery pack slightly bigger than the size of the batteries themselves.

Originally, the accelerometer mote was intended to be worn on the arm or wrist, similar to a watch, but previous experiments [6], [9] have shown that the frequent and severe movements of the arm in everyday activities make it difficult to use the acceleration forces observed in that part of the body to determine the activity performed. Other studies on fall detectors have placed them on the waist for more success [6]. Clearly, the placement of the device on the body is of primary concern. Some of the criteria are that it should be comfortable and that the device itself should not pose a threat to the wearer in the event of a fall. For our experiments, we attached the mote to a belt worn around the waist.

IV. Methodology for Fall Detection

In order to detect a fall, the sampled acceleration data can be processed locally at the mobile mote or forwarded back to the base station, where a powerful computer can do it. Having a computer do the processing allows for faster and more sophisticated analysis such as pattern matching, but places a great burden on the network. The data would need to be continually transferred over the network when the device is on. Since the aim is to detect a simple fall event, it is more efficient and plausible to process the data locally at the mote, even with its limited processing and storage capabilities. When a fall has been detected, the mobile mote can then send an alert back to the base station, and the computer can then take the necessary measures, such as notify an emergency center.

A. Detecting Impact

For reliable operation of the fall detection system, fall events should not be missed while false positives should be minimized. In experiments of common, safe activity such as walking and sitting, and dangerous activity as in falling, the resulting analysis sought to identify how to reliably distinguish the fall from normal activity. As expected, the magnitudes of acceleration in falling are generally greater than those in normal activity. Setting thresholds for each of the three axes of measurement does not work well, because it does not cover all the possible directions of impact in a uniform way.

To consider the acceleration uniformly, the norm of the three axes can be taken, which is the magnitude of acceleration in three-dimensional space when the three acceleration values are for the same point in time. The mote's processor samples the three accelerometers sequentially, but when sampled fast enough this is acceptable for estimating the norm. The norm is calculated at the rate that the accelerometers are sampled and when it exceeds a threshold then it is possible that a fall has occurred.

The threshold can be set based on empirical data. The smallest acceleration measured from a fall was about 3 G, but usually ranged up to several G's higher. Normal activity usually does not exceed 3 G, but occasionally may during some rigorous movements, for instance in jumping, running or sitting down abruptly. Since there is some overlap in the ranges of the acceleration norm between safe activities and falling, we need another way to distinguish falling from normal activity for a more robust algorithm.

B. Observing Orientation

From the experimental data, it is evident that a limited measure of the orientation of the mote could be easily determined when it is stationary or moving very slowly. In the absence of actual acceleration with respect to the ground, the accelerometers detect the normal force of gravity, 1 G, directed upward from the ground. This force is always present and is a static component in the acceleration data. When the mote is stationary, the norm reflects the normal force, and so it is possible to infer the orientation of the mote with respect to an imaginary vertical line.

Over a finite time interval, assuming the orientation is unchanged, if the initial and final velocities are the same, then for a given axis, the average accelerometer reading is that due to the normal force of gravity. It was observed that averaging over a 1-second window of data worked well for estimating orientation, even when the mote was moving as it would in normal activities such as sitting, bending over, etc.

When a person falls, he or she undergoes a large change in position from before the fall to after. The simplest example would be from standing upright to lying flat, an orientation change in the mote of 90 degrees. The actual change in orientation may be more or less than that, depending on the initial and final position of the person, but in any case, there is usually such a change, except for special cases like when a person rolls off the bed. From the orientation information, such an angle of change can be estimated using the dot product of the acceleration vectors before a fall and after, where the vectors are from averaging over 1-second windows.

Letting t_0 be the time of impact, we estimate the orientation one second before falling, at $t_0 - 1$, by averaging over $[t_0 - 1.5, t_0 - 0.5]$, and 2 seconds after falling, at $t_0 + 2$, by averaging over $[t_0 + 1.5, t_0 + 2.5]$. Those numbers are reasonable considering the short amount of time it takes from one losing balance to hitting the ground, and the possibility of some movement after the first impact is detected. The algorithm also considers the case when multiple impacts are detected, as may be the case when falling down stairs, and estimates the orientation after falling, at $t_n + 2$, where t_n is the time at which the last impact is observed. That is, no more impacts are observed in $(t_n, t_n + 2]$. The angle change that constitutes a change in orientation can be set arbitrarily based on empirical data.

Once the two fall conditions are met, an alert is forwarded back to the base station via the fixed mote network, and appropriate action can be taken, such as calling for medical assistance and determining the location of the individual. While we can accurately determine the location of the individual by measuring the radio signal strength between the mobile node and the fixed nodes, this process will not be discussed here. The flowchart in Fig. 2 summarizes the fall detection algorithm.

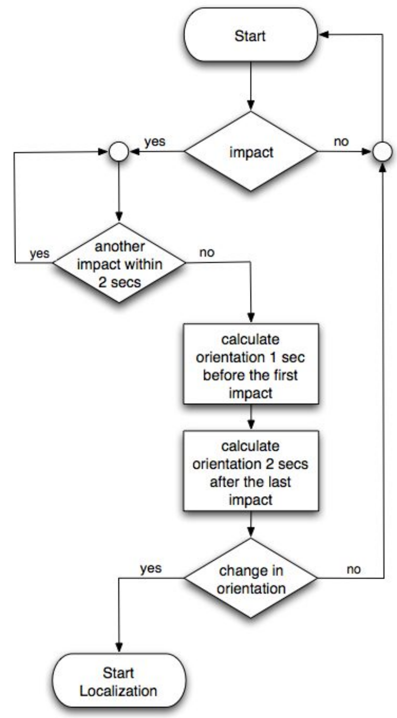

Fig. 2. Fall detection algorithm

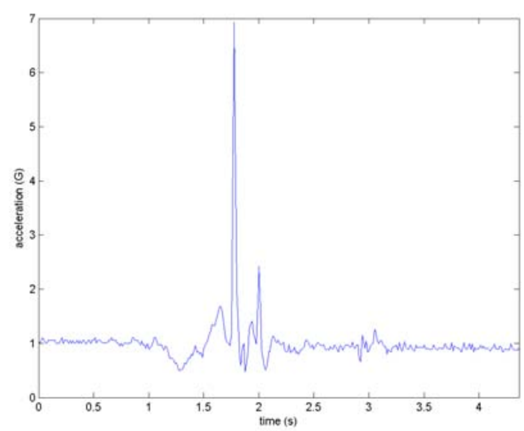

Fig. 3. Acceleration observed while falling backwards

V. Experiments and Evaluation

A. Accelerometer Experiments

Several experiments were performed using a test board built for the purpose of accelerometer data collection, which includes two orthogonally positioned dual-axis MEMS accelerometers with ± 10 G range, as described previously. Two martial arts students were recruited to demonstrate some common fall motions while wearing the sensor boards. Over 10 trials (5 for each person), we found that the average peak acceleration measured was about 6.9 G for falling backwards and 12.7 G for falling sideways. Fig. 3 shows the norm of the acceleration observed during a fall backwards. There are several important points to notice: 1) Between time $t = 1$s and $t = 1.5$s, there is a small dip, indicating a short period of freefall; 2) At time $t = 1.75$s, there is a large peak, indicating impact; 3) After peak of impact, there is a dampening effect, as the force of landing is absorbed by the body and the ground; 4) The initial and final accelerometer reading remains constant at approximately 1 G, as expected. Similar results were observed for falling sideways.

To ensure a robust methodology for fall detection, it is important to verify that normal activities do not produce false positives. It was originally proposed that due to the large impact from falling, normal activities would not create nearly large enough accelerations to trigger any alarm. To verify this claim, the test subjects were also asked to perform some normal activities such as walking and sitting. Over 4 trials (2 for each person), we found that the average peak acceleration for walking reached only 1.9 G. In 10 trials, the average peak acceleration for sitting down was 2.5 G. It is interesting to note that the action of sitting down is somewhat similar to that of falling. Namely, it is basically a short period of controlled downward acceleration followed by a small impact. The ability to distinguish between these similar events is critical to the success of our system. Luckily, the measured peak acceleration for sitting is much less than the average of 6.9 G observed from falling backwards. In addition, there is usually little of no orientation change

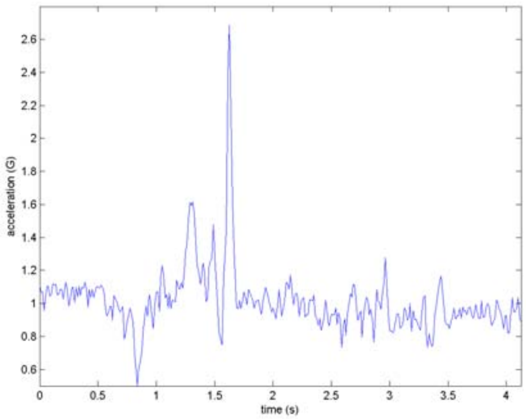

Fig. 4. Acceleration observed while sitting

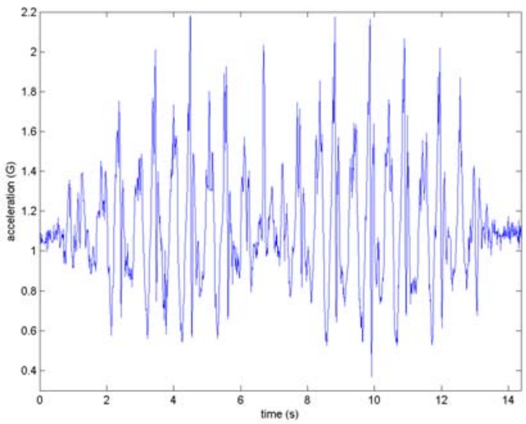

Fig. 5. Acceleration observed while walking

involved when sitting down, even if a large magnitude is detected. As shown in Fig. 4, the acceleration profile of sitting looks very similar to that of falling, with the notable difference that the magnitude is much smaller.

Compared to other designs for a wearable fall detector, the methodology as described benefits largely in two ways. Other devices rely mainly on threshold detection while paying little attention to orientation change. Although the commercially available Tunstall fall detector considers the final orientation of the wearer, it only raises alarm if the user is in a lying state. Many times, a fall may occur near walls or furniture, which may result in the user being in a reclined position. Using a differential measurement of orientation, this change from standing upright to reclining can be detected.

Since only the change in orientation is considered, the algorithm is much less prone to user error. With an absolute orientation detection method, it is imperative that the device be worn properly so the correct orientation can be detected. However, by using the change in orientation, this requirement is mitigated, thus avoiding many of the problems caused by improper use of the device.

VI. Current and Future Development

In this paper, we have demonstrated the feasibility of using a wireless sensor network to detect fall events. Interestingly, we observed that different activities have unique acceleration profiles. Also, amplitudes and frequencies of movement vary with the size and weight of the wearer, which suggest that the design can be improved by customization, whether for individuals or groups with similar activity levels. For example, Fig. 5 clearly shows the periodic nature of walking, which suggests that frequency analysis may be a possible tool to better distinguish between events. The threshold algorithm can also be tuned in software to more reliably distinguished falls from safe activity.

While the system discussed in this paper works well for an indoor environment, it relies heavily on a fixed network to relay events. Current development involves building a sensor mote which can operate outside of such a network. For example, a GPS chip has been integrated with the current design to provide localization outside the home. We also hope to combine the sensor board with a cellular device so that wireless communication is possible outside a fixed network.

Acknowledgment

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