Non-wearable Based Fall Detection System for the Elderly

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Abstract—**Throughout the semester, I have learned of new statistics that greater illuminate the issue of elderly falls. Falls are the leading cause of fatal and nonfatal injuries to elders in the modern society. According to the CDC, one out of three adults aged 65 and over falls each year. Falls bring both a serious threat to the health of seniors and account for a large part of medical costs as well. In 2010, elderly falls cost the US $30 billion dollars, which is an increase from $19 billion recorded in 2000. Most elderly people are unable to get up by themselves after a fall; that fact is why LifeAlert's slogan "I've fallen, and I can't get up!" resonates so well. Several studies have shown that the medical outcome of a fall is largely dependent on the response and rescue time. The delay of medical treatment after a fall can increase the mortality risk in some clinical conditions; half of those who experienced an lying on the floor for over an hour died within six months after the incident. For this purpose, Symbiont Health's mission is to accelerate rescue and save lives. In addition to physical injuries and high medical costs, falls also cause psychological damage to elders. This imminent fear refers to the fact that after a fall, even without injury, elders become so afraid of falling again that they reduce physical activities. This reduced activity then decreases their fitness, mobility and balance, leading to an increased risk of another fall.**

I. Overview

For elders, over 40% of falls are due to syncope, which is a sudden loss of consciousness. This statistics proves that products like LifeAlert are not helpful, as almost half of seniors will not be conscious to press the emergency button on their pendant device. Therefore, various techniques ranging from wearable sensor-based, ambient device-based, to computer vision based solutions have been proposed. These methods were mentioned in the proposal for ENEE499L. However, the wearable-based method was pivoted upon for a new system. I will speak on the issues regarding this method. Wearable sensor-based approaches were among the first techniques developed for fall detection. The most common approach is an accelerometer-based approach. Numerous kinds of sensors have been explored for fall detection in the past decade such as gyroscopes, barometric pressure sensors, RFID, and smart phones. These systems can only work when sensors are worn by the senior. However, the always-on-body requirement makes the wearable difficult to comply with, especially for the elderly. Ambient device-based approaches try to make use of ambient information caused by falls. The ambient information being used includes audio noise, floor vibration, and infrared sensing data. In these systems, dedicated devices need to be implanted in the environment. However, the other sources of pressure or sound around the subject in the environment account for a large proportion of false alarms. Computer vision-based approaches use cameras installed in the monitoring environment to either capture images or video sequences for scene recognition. The privacy intrusion, inherent requirement for line of sight, and intensive computation for real-time processing are still open issues that have not been addressed. Due to the limitations of these newly mentioned fall detection solutions, none have caught on. That is why products like LifeAlert, initially build in 1987 and minimally innovated upon, is still the leading solution. In fact, the latest and greatest product is offered by electronics manufacturer Philips Lifeline. It is the same pendant alert system, and with just a 1% market penetration rate, it generates $2 billion in revenue. In recent years, the rapid development in wireless techniques has stimulated the research in studying the relationship between the wireless signal and human activities. Symbiont Health recently recognized the power of the physical layer on WiFi devices. By exploiting this technology on WiFi devices, significant progress has been made in applications in motion detection and activity recognition. The rationale behind all these research efforts is that different human activities can cause different signal change patterns, and activities can be recognized in real-time by mapping the observed signal change patterns to different human activities. This methodology is similar to how a bat navigates a dark cave through echolocation, but instead of using sound waves, we use electromagnetic waves. Professor Ray Liu of the Electrical and Computer Engineering Department built out an application of this technology is 2013 here at the University of Maryland. He created a "Time Reversal" machine with which he demos a fall detection capability. Throughout the semester, Symbiont Health sought to re-create his work within this ENEE499L course as the potential for impact was obvious. With the motivation of my grandmother's fall and almost $50,000 of grants and awards from the University of Maryland, I aimed to investigate if real-time and automatic fall detection can be achieved using cheap and widely deployed WiFi devices at home, without requiring the seniors to wear or carry any objects.

II. Methodology

In order to automatically detect falls in real-time with WiFi signals in real life settings, there are several challenges that must be addressed. Symbiont Health accrued data on the Activities of Daily Living (ADLs) of the elderly. The first challenge was how the fall and other human activities affect the amplitude and phase information of WiFi signals. I questioned if there are there any specific features in theWiFi signal streams that can characterize the fall and other human activities. The second challenge is as activities are performed continuously, the boundary of the WiFi signal of subsequent activities is not given. I wanted to know how to automatically and accurately segment the corresponding fall and other activities in the continu-ously captured WiFi wireless signal streams. Finally, as there are numerous daily activities, from the perspective of activity recognition, the problem space is large. I noticed that even if the activities are segmented out, differentiating the fall from all the other daily activities will be challenging.

In this rest of this section, Symbiont Health introduces the concept of signal exploitation in WiFi devices. I also specify the fall activity types targeted in my ENEE499L lab research.

The signal exploitation is derived by the typical IEEE 802.11 definitions. The experiments were held in a typical indoor environment where signals propagate through physical space via multiple paths such as the ceiling, floor, wall, and furniture. As the physical space constrains the propagation of wireless signals, the received signals in turn contain information that characterizes the environment they pass through. If a person is present in the environment, additional signal paths are introduced by the scattering of the human body. This realization is similar to the work of Professor Ray Liu is his research. Next, the received signals also convey information that characterizes the effects of human presence in the environment. Symbiont Health tested this functionality at the Maplewood Retirement Community to prove that the same technology is recognized among the elderly. If we consider the physical space, which includes all object and people, as a wireless interference, then the output will depict the effects when the wireless signals pass through these wireless interferences. From Professor Liu's work, it is apparent that in the frequency domain, the channel can be modeled with the received and the transmitted signal vectors respectively. The signal noise is taken into consideration in his work as well as a derived signal matrix. The signal matrix is presented in the format of state information. I should mention that current WiFi standards, which is the common IEEE 802.11 framework, use orthogonal frequency division modulation (OFDM) in their "physical layer." Professor Liu exploits OFDM because it splits its spectrum band, which is 20 MHz, into multiple frequency sub-bands and sends the digital bits through these sub-bands in parallel. His research reveals a set of channel measurements depicting the amplitude and phase of every OFDM sub-band.

I set a steady-state for the case if there is no one or no motion in the environment. In this case, the signals are relative stable. However, along with the motion of a person, the scattered signals are changing, which results in apparent channel distortion. This distortion involves both amplitude attenuation and phase shift, which is a realization my lab came to that is also related to Professor Liu's work. I was excited to find that human activity can be recognized by mapping different channel distortion patterns to corresponding human activities.

A stated previously, I extensively studies much date on the Activities of Daily Living (ADLs) among the elderly. This study helped me to define the fall activity types that I would target in my lab work. There are many ways in which an elderly individual can fall. In my ENEE499L lab, I sought to detect falls that occurred in situations with respect to two activities:

1) A standing-fall refers to the situation that the fall occurs when a senior transfers out of a bed or chair, meaning the senior stands up from the chair and falls down

2) A walking-fall refers to situation that the fall occurs while a senior is walking.

According to a study by the NCOA (National Council on Aging) on falls for the elderly, 24 percent of falls occurred in this first case and 39 percent occurred in the second case. This study was independent of the elderly falls due to syncope which was previously discussed. Therefore, I aimed for 63 percent of the fall situations in this lab.

III. Errors

This section discusses the major reasons that caused fall detection errors. I recognized that the sensitivity and specificity are not 100 percent. Therefore, Symbiont Health analyzed what caused the classification errors in fall detection. After careful analysis about the classification algorithms and results, I found two major reasons that prevent completely correct fall detection. The first reason is that the features extracted for fall-like activities are very close to those of falls under a certain context, which lead to wrong classification results in terms of both sensitivity and specificity. This error was caused by over-examination of the Activities of Daily Living (ADLs) previously described in this ENEE499L report. For example, when a test subject was to quickly sits down onto the chair and make other swift movements while sitting, the event is sometimes classified as a fall. For this type of incorrect classification, I plan to introduce more salient features as the input to help distinguish the fall and fall-like activities. However, after licensing Professors Liu's strongly accurate technology, development on top of the false positives will not be necessary. The second reason is that the extracted features for fall and fall-like activities are context-dependent. This error means the same type of activities may show different features for different places. Therefore, a promising research direction is to introduce context such as location information in the fall detection algorithm to improve the system performance. This idea could work by roughly locating the senior in the room first. Then, I could select a location-based classification model for accurate fall detection.

IV. Conclusion

In my ENEE499L, I pivoted from a wearable concept and sought to design and implement a real-time, non-wearable, accurate indoor fall detection system, using WiFi devices. I modeled my work and was inspired by the innovative technology invented by UMD's own Dr. Ray Liu. To the best of my knowledge, he created the first work to reverse engineer radio waves and electromagnetic waves for fall detection. My lab work further discovers the sharp decline pattern of the fall in the time-frequency domain and leverages the insight for accurate fall segmentation and detection. Experimental results conducted in actual retirement homes demonstrate that this proposed solution has great potential to become a practical and non-intrusive fall detection product. Fall detection has long been a research challenge, especially in the IEEE sphere. Similar to the many papers of fall detection research, there are still many interesting problems that deserve further testing in both Dr. Liu's work and my ENEE499L lab. I want to develop a personalized fall detector for each individual senior so that caregivers can respond more effectively. I also want to create a fall detector that can adapt according to the environment change with Support Vector Machine (SVM) learning algorithms. Dr. Liu believes that this technology could be an effective enabler for activity recognition in general, and I seek to commercialize it quickly for the sake of accelerating rescue and saving lives.

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