Towards automatic detection of falls using wireless sensors

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Abstract— **Accurate detection of falls leading to injury is essential for providing timely medical assistance. In this paper, we describe a wireless sensor network system for automatic fall detection. To detect falls, we use a combination of a body-worn triaxial accelerometer with motion detectors placed in the monitored area. While accelerometer provides information about the body motion during a fall, motion detectors monitor general presence or absence of motion. From all sensors, the data is transmitted wirelessly using the IEEE 802.15.4 protocol to a central node for processing. We use an implementation of Carrier Sense Multiple Access - Collision Avoidance scheme for channel reuse. A simple forwarding scheme is used to provide an extended coverage for a home environment. Fall detection is accomplished by a two-stage algorithm that utilizes the triaxial acceleration and the motion data sequentially. In the first stage, the algorithm detects plausible falls using a measure of normalized energy expenditure computed from the dynamic acceleration values. In the second stage, falls are confirmed based on the absence of motion. Systematic evaluation on simulated falls using 15 adult subjects shows that the proposed system provides a highly promising solution for real-time fall detection.**

I. INTRODUCTION

According to several studies, falls account for about two thirds of all causes of injuries by mechanism in older adults [1]. About one in three adults aged 65 or more fall each year and the rate of falls incidence has risen significantly in the past decade [2]. Incurred direct medical costs for non-fatal injuries that include hospitalization, emergency department visits and outpatient costs are substantial and totaled $19 billion only in 2000. Even though these costs are already high, the main concern are lifetime medical costs associated with long-term treatment and recovery from a fall injury, mental health costs, as well as socio-economic implications. In many cases, the elderly never fully recover from the injury suffered due to a fall which has profound implications on their independence, health and overall quality of living, and imposes additional burden on their caregivers. The fear of repeated falls may cause elderly to limit their activities, leading to sedentary lifestyle and reduced physical fitness, which may increase their risk of falling and adversely affect management of chronic conditions [3].

To reduce these costs and improve the outcome for the patients who suffer an injury, health care professionals implement measures to identify high risk fallers and provide fall prevention strategies. It is important to provide reliable fall risk assessment tools first and then provide tools for monitoring of those in the high risk group. In other words, two applications are of interest from the monitoring point of view: 1) detection of fallers, and 2) detection of falls once they occur. In this paper, we are focusing on the latter application.

An important measure in fall prevention is education of not only how to avoid a fall but also what to do in the case of a fall. Among other things, fallers are instructed not to move after a fall. It is therefore important that caregivers and staff are notified about the fall in a timely manner to provide necessary assistance. There are three phases associated with a fall event that provide important cues for reliable detection of falls: 1) dynamic changes in gait preceding a fall, 2) free fall phase, 3) impact of the body against the ground. The principle of operation of a fall detector relies on detecting one or more of these three phases together with the orientation of the detection device. Most approaches utilize acceleration spikes generated by the fall impact together with changes in orientation [4], [5]. Inclination has been independently used as the determining factor in detection of falls (see, for example, [6]), which simplifies computational requirements but suffers from false alarms caused by normal daily activities. On the other hand, gait and postural measurements have been primarily used to assess risk of falls rather than to alert about an impending fall [7], [8].

Detection of various types of falls is valuable in clinical studies to determine fall incidence and costs associated with the treatment of fall injuries. Falls that do not require medical treatment often go underreported but are still very important in order to implement appropriate fall prevention guidelines. However, fall detection is mostly used in personal safety applications, where the main purpose is to detect and alert about a fall that results in an injury. For these applications, a fall detection system must satisfy several properties: 1) continuous monitoring should not be obtrusive to the user; 2) all fall events resulting in injury must be detected; 3) alerts should not be triggered during normal daily activities; 4) system should not require frequent maintenance or special operating procedures.

We investigate a wireless system consisting of body-worn accelerometers and motion detectors embedded in the environment that monitor motion of the user and communicates information to the central data processing station to reliably detect different types of falls. Wireless communication is used to provide continuous monitoring and coarse localization of users. We present an initial prototype of the system, show preliminary results, and discuss design decisions we consider for the next generation of the fall detector.

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II. System Description

We designed a wireless network consisting of a base-station, a mobile unit attached to the subject, and statically placed motion detectors to monitor a defined living area for falls. A simplified architecture of the system for the case of one subject and a motion detector is shown in Figure 1. Measurements from each sensor node are transmitted wirelessly to the base station which is connected to a PC via a serial interface. The mobile sensor node contains a triaxial accelerometer, an MSP microcontroller, and a wireless transceiver. The static nodes are attached to passive infrared (PIR) motion detectors strategically placed to cover the monitored space. The mobile sensor node is used to perform motion measurement and analysis for detection of fall events. The device is worn by the subject around the waist level close to the center of gravity to record motion signals generated by the person's movements. The signals are transmitted in real time to the PC for analysis. Additional longitudinal information about the motion is provided from the static PIR detectors. The PIR detector contains an infrared sensor and a Fresnel mirror that collects infrared radiation from a fan shaped zone in front of the detector up to the nominal range of about $16m$ (See Figure 1). All PIR detectors are mounted on a wall at a height of $2.2m$. They have adjustable sensitivity levels and Fresnel mirror orientation to tune them to the specific room geometry and movement traffic patterns. In the case motion is detected, PIR sends out a high level signal for $2s$. The signal will remain high for as long as motion is detected. Under the assumption the faller remains motionless for a period of time, this information is used to confirm or reject the event detection from the mobile node to improve detection performance. The sensitivity of the PIR can be adjusted so that minor movements of limbs and body after the fall are ignored.

The wireless nodes employ physical layer modulation and spreading compliant with the IEEE 802.15.4 protocol. A CSMA-based MAC layer is designed to cover the experiment region, similar in size with a typical home for independent living elderly, using multiple nodes. A simple multi-hop network protocol is set up at Bosch Research Center to provide communication links with the base-station in the entire office region. The network paths are statically configured. The communication protocol design, while sub-optimal in energy consumption, is designed for rapid deployment to provide support to the fall detection application.

In the case of the presence of multiple persons in the monitored space, data association has to be established between the body-worn device and the motion detector in the close proximity of the subject. We use a coarse localization mechanism based on RF proximity sensing using Received Signal Strength Indicator (RSSI). This method allows us to: 1) relay signals of the body-worn device using nearby local motion detection nodes, and 2) associate the motion detector signal to the motion of the nearest device wearer. Using only this simple approach may lead to situations where a signal strength of a motion detector node in adjacent room is strong enough to result in erroneous data association. In the case of multiple persons but only one wearer, it is possible to alleviate this problem by associating data with the nearest active motion detector node. However, for multiple wearers, this method needs to be improved by more advanced techniques to localize mobile nodes such as [9], [10] and is under current investigation.

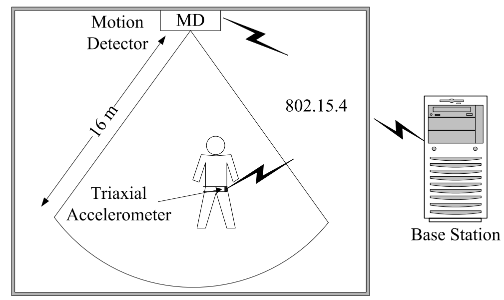

Fig. 1. Wireless system of body-worn and static sensors

In the current solution, all data association, storage and processing is done on the PC side for rapid evaluation of different networking schemes and detection algorithms. A future solution will feature embedded processing on the mobile node and transmission of only relevant event information to minimize power consumption.

III. A Two-Stage Fall Detection Algorithm

The system implements a two-stage fall detection algorithm that sequentially processes the acceleration and the motion data. In this paper, we only consider falls that result in an impact against the ground. We first detect fall candidates by thresholding the magnitude of the triaxial acceleration data. Additionally, we check for a change in the orientation of the worn device. The detected falls are then confirmed by the absence of motion from the motion sensors.

In the first stage, the triaxial acceleration data is denoised using a 13^{th} order median filter [11]. Note that low-pass filtering using the median filter reduces the sensitivity to high-frequency noise [12]. We then use a high-pass, finite impulse response filter of order 50 and a stop frequency of 0.5 Hz to remove the static component and compute the dynamic acceleration [13]. Fig. 2 shows the magnitude spectrum of horizontal acceleration for three different human actions as a solid line. For comparison, the magnitude response of the high-pass filter is overlaid onto the same figure as a dashed line. The top plot displays the data corresponding to standing still, the middle plot walking and the bottom the plot falling. Notice that the pass-band of the high-pass filter allows for all significant frequency components corresponding to dynamic activities of walking and falling.

The magnitude of the 3-dimensional, dynamic acceleration vector is related to the energy expended in performing a

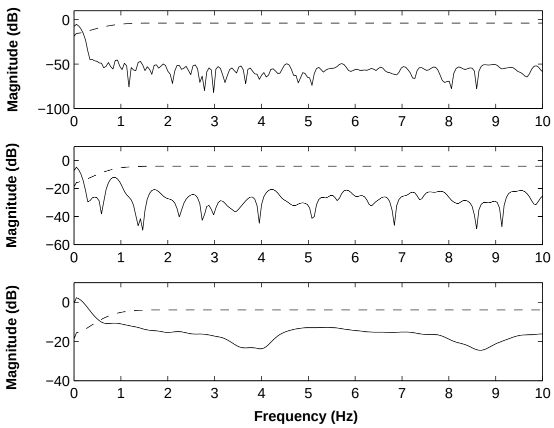

Fig. 2. Magnitude spectrum of acceleration data corresponding to various activities. The solid line represents the magnitude spectrum of acceleration in the horizontal direction and the dashed line represents the magnitude spectrum of the high-pass filter used to obtain the dynamic acceleration. The top plot corresponds to standing, the middle plot walking and the bottom plot falling.

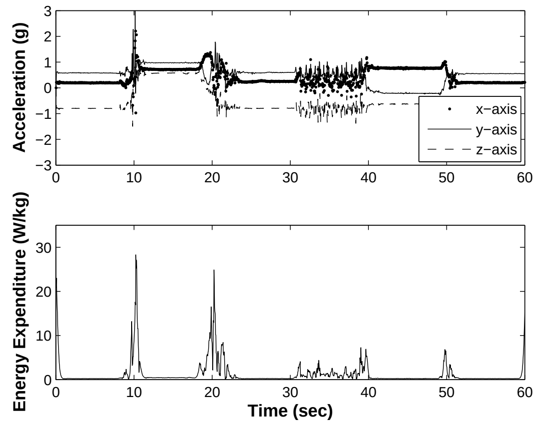

Fig. 3. Using triaxial acceleration data to estimate energy expended in performing various activities . The top plot shows the acceleration data corresponding to the following sequence of activities: standing, falling, standing, walking, sitting and standing. The bottom-plot shows the estimated energy expended in performing these activities.

particular physical activity such as walking or falling [4]. The top plot in Fig. 3 shows the observed acceleration for the sequence of activities: standing, falling sideways, getting up, standing still, walking, sitting and finally standing up. The bottom plot shows the corresponding magnitude of the acceleration vector. Notice that each dynamic activity has a distinctive magnitude, and therefore energy expenditure. We can also see that transitions between activities, including falls, exhibit the highest values.

Based on the previous observations, we design the fall detection algorithm as follows. First, if the 3-dimensional vector magnitude exceeds a threshold or the magnitude in xy plane exceeds another threshold, we consider the data sample to correspond to a plausible fall. Thresholding the magnitude in the xy plane helps avoid false alarms due to sitting or climbing down (see Section IV). In the second stage, a plausible fall is confirmed four seconds later if none of the motion detectors sense any movement and there is a change in the orientation of the person. In particular, we check whether the inequality in (1) is satisfied to confirm the change in orientation.

$$\alpha \cdot \int_{t1}^{t2} a_z(t) \leq \int_{t3}^{t4} a_z(t), \tag{1}$$

where $a_z(t)$ is the denoised acceleration value in the z direction at time t seconds that corresponds to a plausible fall. $t1$, $t2$, $t3$ and $t4$ are set to be $t-3$, $t-2$, $t+2$ and $t+3$ seconds respectively. α acts as a threshold on the change of orientation and is set to a value of 0.75 for all our experiments reported in Section IV. Subsequently, to confirm the absence of motion, we check the outputs from all motion sensors in a one second window beginning at $t+3$ seconds.

TABLE I

FALL DETECTION AND FALSE ALARM RATES.

Performance Measure	Without Motion	With Motion
Detection rate	91/96	91/96
False alarm rate	11/1288	0/1288

IV. EXPERIMENTAL RESULTS

The proposed system is tested on 2 female and 13 male subjects, whose ages ranged from 24 to 37. Each subject performed a varied sequence of following actions: sitting, standing, walking, walking fast, hopping, climbing up, climbing down, rotating in a chair and simulated fall. The following categories of falls are considered: falls in the sagittal plane (left and right) and falls in the coronal plane (frontal and backward falls). With our subjects, we observe that for most falls, the hip is the point of initial impact against the ground. However, especially with front and backward falls, subjects tend to protect themselves by use of their hands.

Table I shows the results in terms of number of trials where each action performed once constitutes one trial. There is a total of 96 simulated falls and 1288 non-fall trials. The results are shown in terms of standard binary hypothesis testing terminology where the null hypothesis is that the observed data corresponds to a fall. Notice that the use of acceleration data alone leads to a small number of false alarms. However, with the use of motion data, false alarms are eliminated.

Table II further categorizes the fall detection performance of the system in terms of the fall type. While our simulated falls can not be strictly classified as coronal and sagittal, their labels are chosen depending on the predominant direction during the act of falling.

V. CONCLUSION

The wireless sensor system presented in this paper captures, transmits, and processes data from mobile and static

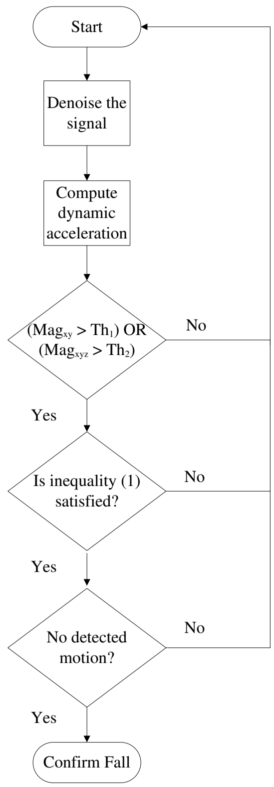

Fig. 4. Detection algorithm flowchart

TABLE II
FALL DETECTION RATE BY FALL TYPE.

Fall Type	Detection Rate
Coronal falls	6/6
Sagittal falls	85/90

sensors to determine if a person has fallen. Motion monitoring to catch fall events is provided by a body-worn triaxial accelerometer while static PIR motion detectors add the dimension of longitudinal monitoring. The combined processing provides for improved reliability of detection.

Preliminary results show that the detection of falls is highly reliable in our simulated environment. However, we point out that the following have to be taken into consideration when interpreting the presented evaluation: 1) The sample size in our experiments is relatively small and includes only young healthy subjects; 2) All falls during experimentation are acted by the subjects to the best of their abilities and includes a limited set of cases; 3) False alarm rate is calculated by simulating daily activities that could be construed as falls (e.g., jumping or transition from standing to sitting) in a defined amount of time. More extensive trials are necessary to confirm the performance accuracy in free living environments.

In the next phase, the system will provide more accurate localization and data association techniques in the case of a large number of monitored subjects in common living spaces such as assisted living homes. This will provide a spatio-temporal context to improve detection accuracy and track individuals who are at the highest risk of falls. Local processing of measured data for detection of fall events will reduce the required communication bandwidth and power requirements.

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