Fall Detection Using Ultra-Wideband Positioning

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***Abstract*—Falls are a major health problem in our aging society. Fall detection systems are aimed at automatically sending an alarm in case of falls. Unfortunately most of the systems currently available, which use accelerometric sensors, are characterized by a relatively large number of false alarms. In fact, many activities of daily living may produce fall-like acceleration signals. We propose a method that uses ultra-wideband positioning to track the movements of the user and detect falls. Preliminary results show that the approach is reliable in detecting falls and simple postures.**

***Index Terms*—fall detection; ultra-wideband positioning; wearable sensors.**

I. Introduction

Falls are a major cause for health problems and hospitalization among older people. Some studies report that approximately one third of people at the age of 65 and older fall each year; such fall rate is even higher in the presence of impairments or frailty conditions. Besides physical traumas, falls also have important psychological consequences: senior citizens who fall may be subsequently affected by a post-fall syndrome characterized by depression, reduced self-confidence, and a less independent lifestyle [1]. Some of these problems can be mitigated through the use of devices for automatic detection of falls. A device able to automatically rise an alarm is beneficial from two points of view: i) older adults who wear a fall detection device feel safer; this reduces the chances of incurring in a sedentary lifestyle and, in turn, of incurring in future falls; ii) in some cases, the older adult who falls is unable to press an alarm button, e.g. because of a loss of consciousness, and may remain in lying position for a relatively large amount of time (especially if he/she is living alone); these long lying periods are known to be one of the elements that contribute in the severity of falls, as they are correlated to increased hospitalization and a subsequent decline in performing the activities of daily living [2].

One of the most important factors of a fall detection system is its ability to recognize all falls as falls, without generating false alarms when other activities of daily living (ADLs) are carried out. If a system is unable to detect a real fall (false negative) the subject may remain on the ground for a large amount of time; conversely, if the system generates a false alarm (false positive) the confidence in the system is reduced and it will probably be abandoned by its users [3].

Research about automatic fall detection has been rather intense during the last years, looking for reliable solutions. Nevertheless, despite all the efforts, current methods are still far from perfect and their adoption from general users is yet to come. We present a method for detecting falls using an indoor localization system based on ultra-wideband (UWB). A prototypical implementation of the method is described and discussed. Experimental evaluation shows promising results.

II. Related Work and Motivation

The problem of detecting falls has been faced according to two major approaches: i) instrumenting the environment with sensors and/or cameras; ii) using wearable sensors.

The method described in [4] relies on wall-mounted cameras and it is based on the fact that motion of users is particularly relevant in case of falls. Moreover, if a fall occurs, the shape of the subject changes (from vertical to horizontal). Both these events are detected through a computer vision algorithm. Experimental results show sensitivity [1] and specificity [2] values approximately equal to 88%. Other studies based on computer vision include [5] (using multiple cameras) and [6] (using Hidden Markov Model). One of the problems associated with camera-based approaches is related to their invasiveness in terms of users' privacy. In particular, these systems are not very well accepted by users as they feel "spied".

Systems based on wearable devices mostly use an accelerometer to monitor users' movements. Simple methods just compare collected values against a threshold: if the acceleration value is greater than the threshold an alarm is raised. Unfortunately, threshold-based methods are generally characterized by a large number of false alarms: several ADLs generate acceleration values with magnitude similar to the one generated during real falls. To reduce the problem of false alarms subsequent studies introduced the use of posture information in the fall detection process. Notable examples of accelerometer-based methods include [7] and [8]. Some systems also make use of a gyroscope (e.g. [9]).

Several fall detection systems are based on smartphones. The system presented in [10] monitors the movements of the subject using the embedded accelerometer, extracts a set of features from the acceleration signal, and uses a classifier to recognize real falls or other ADLs (such as sitting, lying, and walking). In case of fall, the system automatically sends an alarm to the caregivers. An external sensing unit can be used to free the user from the burden of wearing the smartphone (the sensing unit is much smaller than a common smartphone). A list of other relevant examples of smartphone-based systems can be found in [11].

[1] Sensitivity: true positives / (true positives + false negatives).
[2] Specificity: true negatives / (true negatives + false positives).

Another problem of acceleration-based systems is related to the detection of falls characterized by reduced acceleration values. Such “slow” falls may occur when the subject faints or when the impact is softened using hands. These falls are usually ignored in acceleration-based systems, since using low acceleration thresholds would lead to a high false alarm rate during normal activities (acceleration-based systems typically require an acceleration magnitude peak near 3 g).

We propose the use of UWB positioning as a way to solve these problems. Differently from acceleration-based techniques, our method aims to detect whether the user's posture is abnormal, and it does not rely on violent impacts to detect a fall (thus reducing the number of false alarms caused by high-energy ADLs). For the same reason, the proposed approach is able to properly detect even slow falls.

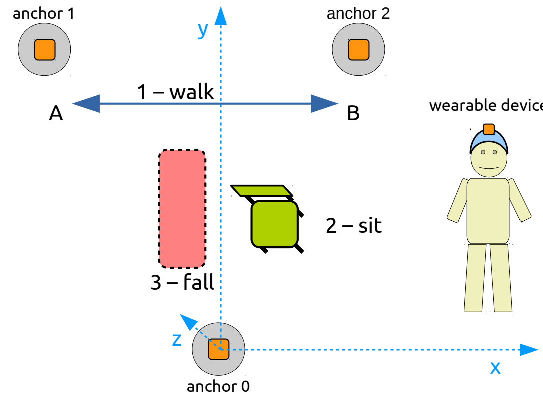

Fig. 1. Experimental setup.

III. Method

A positioning system based on UWB is able to determine the position of a node with an accuracy in the order of 10 cm. In particular, the distance between the node to be located and a number of anchors (nodes whose position is known) is determined by computing the time-of-flight of a signal. Then multilateration is used to compute the position of the node.

We placed the wearable device (the tracked node) in near-head position for the following reasons: i) the head experiences the largest vertical displacement during a fall, and this should thus facilitate the detection process; ii) we envisage that the tracked node could actually be incorporated in glasses, ear-worn devices or in a necklace, thus providing different solutions to achieve high usability and foster user acceptance [12].

A. Fall and Posture Detection Technique

The fall detection technique relies on the assumption that, after a fall, the user's head is near to ground level. Hence, the proposed technique uses the location estimates on the vertical axis for tracking the user's head in real time. A fall is detected when the user's head is below a predefined height for a given time interval. To reduce the effect of noise, location estimates were low-pass filtered at 1 Hz. In addition, we used a moving average computed on 5 seconds of samples.

The method actually detects three different postures: *standing*, *sitting* on a chair, and *lying* on the ground. To this end, three thresholds are used: *sit_th*, *lie_th*, and *transition_interval*. The sitting threshold (*sit_th*) indicates a possible transition between the standing and sitting postures. The lying threshold (*lie_th*) indicates a transition to/from the lying posture. A transition between different postures is confirmed as a posture change only when it lasts for more than *transition_interval* seconds. For example, let us suppose that the following thresholds have been set: *sit_th* = 1.2 m, *lie_th* = 0.5 m, *transition_interval* = 5 s. If the user is currently standing, a transition is detected when the measured height drops below 1.2 m. If the height remains between 1.2 m and 0.5 m for at least 5 s, then the user's posture is changed to *sitting*. Otherwise, the possible transition is discarded.

Lying posture detection can be used to detect falls – a fall alarm is raised when the user remains on the ground for a specified time (*fall_alarm_interval*).

To improve the detection of the transitions between standing and sitting, an initial calibration is required. The aim of calibration is to measure the height estimated by the localization system when the user is in standing position (*standing_ref*). Then, *sit_th* can be set as a proportion of *standing_ref*. This calibration can be either manual (the user presses a button while in standing position, right after wearing the device) or based on automatic detection of walking activity (if the user is walking, he/she is also standing). Walking activity can be detected by analyzing the location of the user or with an accelerometer [13], [14].

IV. Implementation and Results

We implemented a prototype of the proposed method using four UWB-enabled boards. Each board includes an ARM Cortex M3 processor (STMF32105) and a DecaWave DW1000 IEEE802.15.4-2011 UWB compliant wireless transceiver. Three boards were used as anchors. The three anchors were placed at the same height ($\sim$ 2.7m) in a large room. The room contained common furniture and equipment (some desks, chairs and PCs). One board was attached to an helmet so as to track the user's head. UWB transceivers were set up to communicate using a 6.8 Mbps datarate at 3.993 GHz. UWB transceivers operated in two-way ranging mode: each anchor exchanged ranging messages with the tracked node and calculated the time-of-flight, which was then used to estimate the distance. Distances from the anchors were used to find the position of the tracked node via trilateration. The trilateration algorithm was executed on a laptop connected to one of the anchors via USB. Tri-dimensional location estimates were generated with 10 Hz frequency. Collected data was logged to persistent storage in order to enable repeatable evaluation.

Six volunteers were involved in a supervised experiment. Figure 1 describes the experimental setup and the experimental protocol followed by the volunteers. The protocol consisted of simple activities such as walking, sitting down/standing up, and lying down on the floor (falling down). More precisely, the

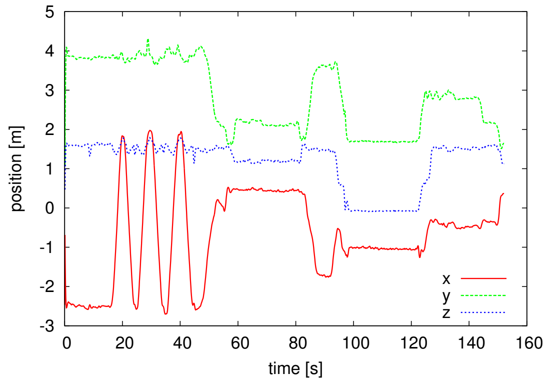

Fig. 2. Estimated location of the tracked node.

volunteers performed the following actions: i) walk back and forth from A to B (three repetitions); ii) sit down on a chair for at least ten seconds; iii) stand up and slowly fall/lie down on the floor, then rest on the floor for at least ten seconds; iv) recover from the fall and stand still for a few seconds.

Figure 2 shows the estimated position of the tracked node during the execution of the above mentioned activities. User's position on the horizontal plane (x, y) uses anchor 0 as the origin, whereas z is the elevation above the ground. Walking takes place in the interval $[15s, 45s]$, sitting corresponds to the interval $[60s, 80s]$, and the user is lying in the interval $[100s, 120s]$ (approximately). All activities are clearly visible.

For each user, the height measured in standing posture (*standing_ref*) was calibrated using 10 seconds of walking activity. The *sit_th* was set to 80% of *standing_ref*, while *lie_th* was set to 0.5 m for all the users. Transitions were confirmed after 5 seconds (*transition_interval* = 5 s). Using these thresholds, the system correctly detected all the posture transitions for all the volunteers.

An additional experiment was carried out collecting one hour of unsupervised data from a volunteer. During the experiment, the volunteer performed simple activities, such as using a laptop and doing short walks. An accelerometer in the volunteer's trouser pocket was also used to gather the "ground truth" about posture transitions (standing vs sitting). The volunteer did not fall or lie down on the floor during the experiment. The aim of this one-hour experiment was twofold: first, to evaluate whether false detections of lying posture occur during normal activities; second, to verify the accuracy of posture detection (standing vs sitting). This preliminary evaluation confirmed that all postures are correctly detected by the system.

Collected traces are available at the following address: `http://vecchio.iet.unipi.it/falldetection`

V. Conclusions and Future Work

Fine-grained localization obtained through ultra-wideband technology can be an important element of future fall detection systems. We believe that, by tracking the movements of the user with improved accuracy with respect to previous methods, it is possible to increase both sensitivity and specificity. For instance it will be possible to detect "slow" falls, which cannot be easily recognized using accelerometers. At the same time, ADLs characterized by high acceleration values, such as sitting on a chair, or lying on a sofa, could be correctly classified as non-falls through accurate positioning.

It is worthwhile to highlight that we do not propose the use of UWB-based positioning as an alternative to acceleration-based methods. In our view, the two approaches should operate side-by-side to combine positive aspects of both. Results obtained through the prototype of the proposed method, although preliminarily, confirm that the approach is effective.

Future work will concern a deeper and wider experimental evaluation, increasing both the number of users and the monitoring period. Other possible placements of UWB transceivers will also be considered (e.g. wrist, waist, and neck).

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