Real-Time Fall Detection System by Using Mobile Robots in Smart Homes

L. Ciabattoni, F. Ferracuti, G. Foresi, A. Freddi, A. Monteriù, D. Proietti Pagnotta

Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona, Italy
Email: {l.ciabattoni, f.ferracuti, a.freddi, a.monteriu}@univpm.it , {g.foresi, d.proietti}@pm.univpm.it

***Abstract*—An unobtrusive method to realize human fall detection by using bluetooth beacons, a smartphone and a low cost mobile robot is presented. The method is composed by five steps. The first consists in extracting features from the smartphone acceleration data, which are then analysed online by the fall detection algorithm. Once the fall event is detected, then the location is determined by using the bluetooth signal received from beacons. Then, the mobile robot moves towards the user's location, and finally verifies if the detected fall event is a true positive or not, through a procedure based on voice interaction with the potentially fallen user. The method has been tested in laboratory, proving to be a viable solution to perform fall detection in smart homes via consumer devices.**

I. Introduction

Since the number of older adults is increasing, more attention is being paid these years to develop systems and technologies which allow monitoring falls directly at home [1]. The World Health Organization evaluates that, each year, approximately 28–35% of adults aged 65 and older fall, and this percentage increase to 32-42% after 70 [2]. The most important objective of fall detection systems is to rapidly alert when a fall happens, in order to decrease the time spent on the ground. Therefore, fall detection systems may help people (especially elderly) to improve the quality of their lives and to receive rapid assistance after a fall [3].

Fall detection systems recently proposed in the literature can be divided into two main categories: environment or context-aware systems, and wearable systems [4]. In the former case, sensors are placed in the environment such as cameras, microphones, vibration sensors or infrared sensors in order to detect falls. These systems have the advantage that they do not require sensors to be worn, but their range of action is restricted to where they are deployed [5], [6]. In the wearable systems case, the most common sensors are accelerometers, gyroscopes and inertial sensors which are now available on almost every commercial device [7], [8].

However, at the best of the authors knowledge, most of the available fall detection systems, both context-aware and wearable, are not able to reach the detection accuracy of 100%, except for some particular scenarios [9], [10]. This paper presents a smartphone-based fall detection system which uses the accelerometer to detect body movements and falls. Furthermore, a low cost mobile robot is used to check whether a detected fall is a true positive or a false positive through a procedure based on voice interaction with the user.

II. System Implementation

The architecture of the proposed application is shown in Figure 1. The system is composed by a smartphone where the acceleration data are acquired and processed, a low cost mobile robot and its computer to fulfill the fall detection and fall check processes, and a number of Bluetooth Low Energy (BLE) beacons to localize the room where the fall took place. The smartphone application performs the acquisition and the processing of the acceleration data, and provides, through a socket, the features values to the Fall Detection algorithm, described in Section III-B.

The fall detection algorithm and the fall check steps, are developed as Robot Operating System (ROS) nodes, which, respectively, carry out the detection of a fall, and the process that checks if the detected fall is a true or a false positive making use of a low cost mobile robot. The room where the fall has happened is localized through the use of BLE beacons, which send bluetooth signals containing distance information to the smartphone. The detailed ROS nodes scheme is shown in Figure 2.

III. Methods

A. Data Processing

The fall detection process is based on acceleration data, sampled at a frequency of $50\,\mathrm{Hz}$. Mean Acceleration Magnitude (MAM) and Reference Velocity (RV) [11] features are computed using a sliding window of $1\,\mathrm{s}$ with a step of $0.4\,\mathrm{s}$. MAM and RV are defined as

$$\begin{aligned} MAM &= \frac{\sum_{i=1}^{N} \|a(i)\|}{N} \\ RV &= \int_{t\in W} \|a(t)\| \, dt \end{aligned} \tag{1}$$

where $\|a(i)\| = \sqrt{a_x^2(i) + a_y^2(i) + a_z^2(i)}$ is the acceleration magnitude and N is the number of samples in a time window W. These features are sent as input to the fall detection algorithm.

B. Fall Detection Algorithm

The proposed fall detection algorithm consists of two main steps:

Thresholding phase where an adaptive threshold, calculated through a smoothed z-score thresholding algorithm, is

978-1-5090-4014-8/17/$31.00 ©2017 IEEE

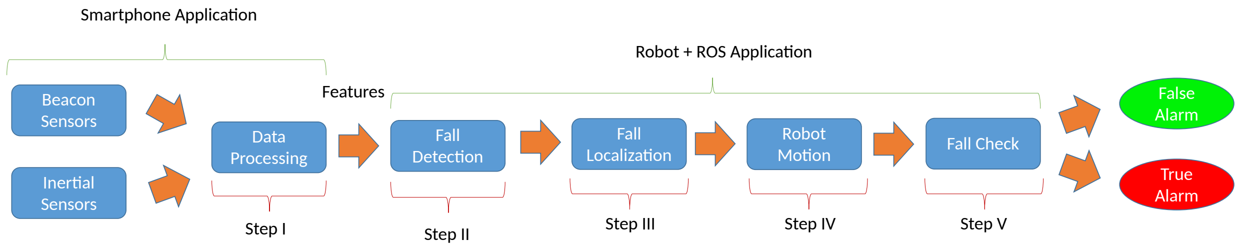

Figure 1: System implementation.

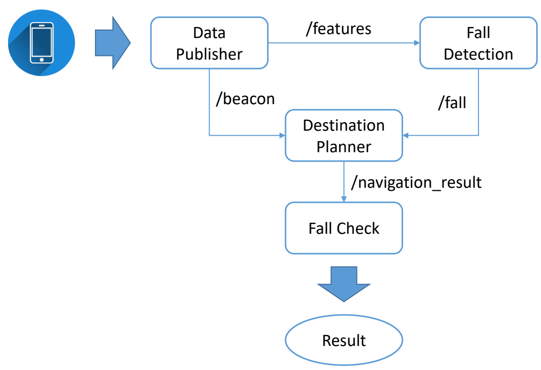

Figure 2: Application ROS nodes structure.

applied to new MAM and RV values in order to detect peaks.

Fall Detection phase where the output of the thresholding step is used to decide if a fall has happened.

The fall detection method checks whether a peak is detected on both features at the same time.

C. *Fall Localization, Robot Motion and Fall Check*

In order to check whether a detected fall is a true positive or a false positive, a low cost mobile robot is used. A number of BLE beacons is used to localize the room where the fall has been occurred.

The *Destination Planner* node receives information about falls from the *Fall Detection* node, and those about the beacon of the room where the fall has happened from the *Data Publisher* node, as it is shown in Figure 2. The Destination Planner manages the robot to reach the room, and communicates to the *Fall Check* node when the navigation is complete.

The fall check procedure is actually based on the voice interaction between the mobile robot and the user. The Python Speech Recognition APIs are used to decode what the user is saying and to decide if the detected fall is a true or a false positive, recognizing some keywords.

IV. Experimental Results

The system is tested with a heterogeneous set of Activities of Daily Living (ADL) (i.e., walking, sitting, standing, lying). The system performances are evaluated in terms of sensitivity, specificity and accuracy. Table I shows performances of both fall detection only and of fall detection plus fall check.

Table I: Performance results.

Metric	FD	FD + FC
Sensitivity	99 %	99 %
Specificity	74 %	98 %
Accuracy	77 %	98 %

If only fall detection is applied, the sensitivity is about 99% due to the small number of false negatives, but the specificity is quite low (74%), comparable with similar smartphone-based techniques [10]. On the other hand, if also fall check procedure is fulfilled, most of false positives become true negatives and the specificity does increase to 98% (in few cases, the voice message of the user can not be heard due to the environmental noise), although the sensitivity does not change.

References

[1] Z. Pang, L. Zheng, J. Tian, S. Kao-Walter, E. Dubrova, and Q. Chen, "Design of a terminal solution for integration of in-home health care devices and services towards the internet-of-things," *Enterprise Information Systems*, vol. 9, no. 1, pp. 86–116, 2015.

[2] W. H. O. Ageing and L. C. Unit, *WHO global report on falls prevention in older age*. World Health Organization, 2008.

[3] L. Z. Rubenstein and K. R. Josephson, "The epidemiology of falls and syncope," *Clinics in Geriatric Medicine*, vol. 18, no. 2, pp. 141–158, 2002.

[4] R. Igual, C. Medrano, and I. Plaza, "Challenges, issues and trends in fall detection systems," *BioMedical Engineering OnLine*, vol. 12, no. 1, p. 66, 2013.

[5] Y. Li, K. Ho, and M. Popescu, "A microphone array system for automatic fall detection," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 5, pp. 1291–1301, 2012.

[6] F. Erden, S. Velipasalar, A. Z. Alkar, and A. E. Cetin, "Sensors in assisted living: a survey of signal and image processing methods," *IEEE Signal Processing Magazine*, vol. 33, no. 2, pp. 36–44, 2016.

[7] I. H. López-Nava and A. Muñoz-Meléndez, "Wearable inertial sensors for human motion analysis: A review," *IEEE Sensors Journal*, vol. 16, no. 22, pp. 7821–7834, 2016.

[8] T. Shany, S. J. Redmond, M. R. Narayanan, and N. H. Lovell, "Sensors-based wearable systems for monitoring of human movement and falls," *IEEE Sensors Journal*, vol. 12, no. 3, pp. 658–670, 2012.

[9] M. Cheffena, "Fall detection using smartphone audio features," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1073–1080, 2016.

[10] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, and A. Vecchio, "A smartphone-based fall detection system," *Pervasive and Mobile Computing*, vol. 8, no. 6, pp. 883–899, 2012.

[11] C.-N. Huang and C.-T. Chan, "A zigbee-based location-aware fall detection system for improving elderly telecare," *International Journal of Environmental Research and Public Health*, vol. 11, no. 4, pp. 4233–4248, 2014.