Automatic Fall Detector based on Sliding Window Principle

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Abstract

Fall incidents and the sustained injuries represent the main causes of accidents for elderly people, and also the third cause of chronic disability. The rapid detection of a fall event can reduce the mortality risk, avoiding also the aggravation of injuries. In this paper an automatic fall detector based on microwave radar measurements is presented. A Continuous Wave (CW) Doppler radar is used to detect the changes in speed of different persons experienced during four activities, namely falling, walking, sitting, and no movement. The measurements, performed with the radar fixed on the wall, are introduced in a machine learning process to estimate an activity classification model. A sliding window principle is then used to detect fall incidents in signals consisting of multiple activities. Experimental results, conducted on real human volunteers in a real room setting, have shown a success rate of 95% in detecting fall events. Moreover, no false positives have been reported.

Keywords: classification, fall detection, signal detection, LS-SVM, signal estimation, sliding window, radar remote sensing.

1 Introduction

The elderly population has been steadily increasing worldwide. This situation, together with the shortage of nursing homes and the natural desire to stay at home, has resulted in a growing need for healthcare approaches that emphasize routine long-term monitoring in the home environment. Elderly people who live alone are usually exposed to health risks which in some cases may cause fatality. In fact, fall incident among the elderly is considered one of the major problems worldwide, and often result in serious physical and psychological consequences [1]. Research pointed out that 30% to 45% of the persons older than 60 years fall at least once a year. People who experience a fall event at home, and remain on the ground for an hour or more, may suffer from many medical complications, such as dehydration, internal bleeding, and cooling, and half of them die within six months [2]. The delay in hospitalization increases mortality risk. Studies have shown that the longer the person lies on the floor, the poorer is the outcome of medical intervention [3-4]. For that reason, it is imperative to detect falls as soon as they occur such that immediate assistance may be provided.

Current health monitoring systems are based on necklace or wristwatch with a button that is activated by the patient in case of an accident. However, in emergency situations, this imposes an important risk factor. In fact, the person may forget to wear the device, or likely may no longer be able to press the button. The ideal solution is therefore a contactless approach that avoids the need for actions by the elderly person. Systems under investigation in the latter category are based on video cameras, floor vibration, and acoustic sensors. In the case of the video camera method, researchers are currently trying to address challenges related to low light, field of view, and image processing, but also privacy is a concern [5]. Floor vibration and acoustic sensors have limited success due to the environmental interference and background noise [6].

Due to the disadvantages of existing fall detection technologies, there is a need for further solutions. An alternative approach based on radar techniques has been demonstrated by the authors [7], [8]. The system uses a machine learning technique to distinguish fall events from normal movements as described in [9].

In this paper an automatic fall detector based on microwave radar measurements is presented. In comparison to [9], where the technique is applied to classify signals consisting of one single activity whose starting and ending points are known, a sliding window is now introduced to estimate and to process signals consisting of multiple activities. The size and the overlapping among sliding windows have been optimized for this application.

In Section 2 the automatic fall detector is presented, and the experimental results are discussed in Section 3.

2 Automatic fall detector

The health monitoring system used to design the automatic fall detector has been described by the authors in [8]. It consists of a sensor, combining both radar and wireless communications features, and a base station for data processing (Fig. 1). The sensor integrates a radar module, a Zigbee module, and a microcontroller, while the base station consists of a Zigbee module, a microcontroller, and a laptop.

A Continuous Wave (CW) waveform at 5.8 GHz is generated and used to detect the speed signals produced by the test persons during four different activities, namely falling, walking, sitting down, and no movement. The resulting baseband signals are digitized and transmitted to a base station to be processed using Matlab.

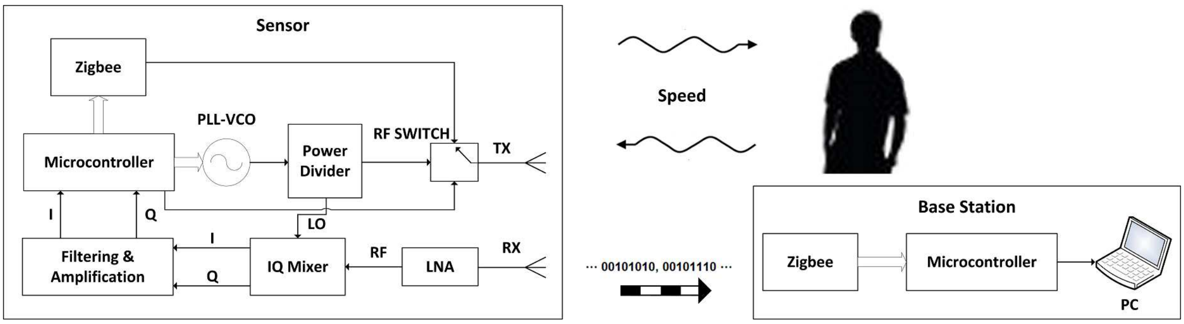

Fig. 1. Simplified block diagram of the health monitoring system.

A movement classification based on a Least Squares Support Vector Machines (LS-SVM) approach combined with Global Alignment (GA) kernel [9] is applied to analyze the digitized baseband speed signals in order to distinguish falls from the other activities. The fall detector aims at assessing the changes in speed experienced during a fall or a normal movement. During a fall, in fact, the speed continuously increases until the sudden moment when the movement stops abruptly. During a normal movement, the Doppler signal experiences a controlled movement. More precisely, while a person is sitting down, the speed first gradually increases, and then decreases to a smooth stop, whereas during a walk, instead, the speed is quite constant over time.

The developed algorithm consists of two stages of data analysis, namely the training phase and the testing phase (Fig. 2). Both phases use the digitized speed signal as input.

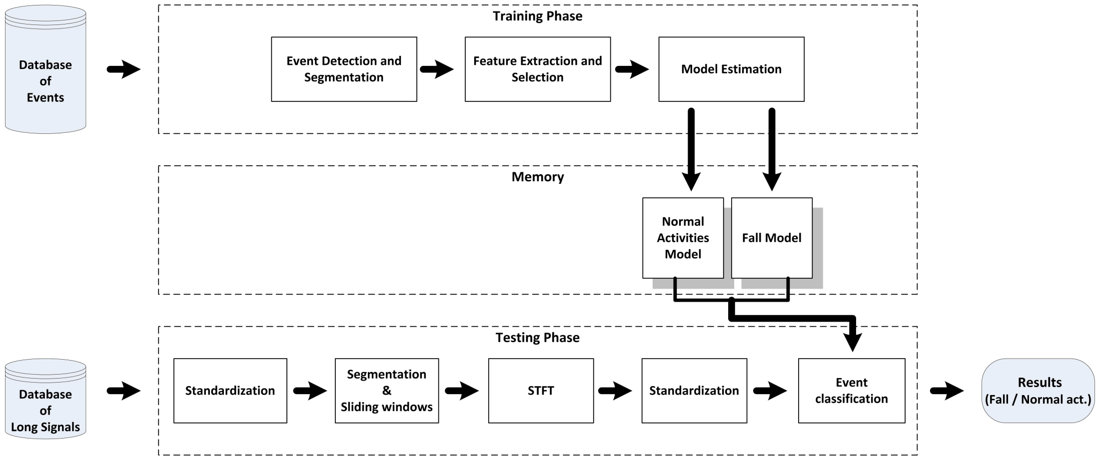

Fig. 2. Automatic fall detector block diagram.

A. Training phase

The training phase consists of activity detection and segmentation, feature extraction, feature selection, and model estimation. Two classification models have been estimated for the different types of events. More precisely, the four activities are divided in two main groups, namely fall events and normal movements (i.e., walking, sitting, and no movement). These acquired activities are used to build a data set. However, before learning a model, each activity is grouped in a segment of 2 seconds, considered sufficient to cover the details of the activities and mainly the fall event. This operation of segmentation consists in the detection of the activity energy's peak and in cutting the signal around this peak. Given such segments, the data is preprocessed, namely it is first standardized, such that each dimension has zero mean and unit standard deviation, and then transformed using the Short Time Fast Fourier Transform (STFT) from which only the magnitude spectrum is retained. As opposed to the FFT, the STFT can represent time dependent structures and therefore results in higher performance in case of signals that experience a gradual change in velocity. The STFT is performed by cutting first the segments into 50% overlapping frames which are each multiplied with a Hamming window after which the FFT is computed on each of these frames. Prior to the learning phase, the data is again standardized. Once the learning process is finalized, the model is created and stored in a memory to be used in the validation stage.

B. Testing phase

To validate the classification models, an independent test set, with data not used in the training phase, is needed. For this purpose, the stored test signals consist of multiple activities invoked at unknown instants.

The algorithm performed in this phase presents a structure similar to the data processing of the training phase (Fig. 3). However, the main difference lies in the segmentation stage where the sliding window principle is applied due to the fact that the starting and ending points of the activities are unknown. The size of the sliding window is fixed to 2 sec., to be consistent with the length of the activities' segments in the training phase, while the overlapping should be optimized in order to be sufficiently adequate to distinguish a fall from normal movements taking into the account the number of required recourses and the computational burden in achieving the algorithm. Experimental tests have demonstrated that a sliding window of 2 sec. with 75% overlapping is adequate to cover the details of the acquired signals. The segments are then re-preprocessed and subsequently arranged to build the test set that is compared with the classification models.

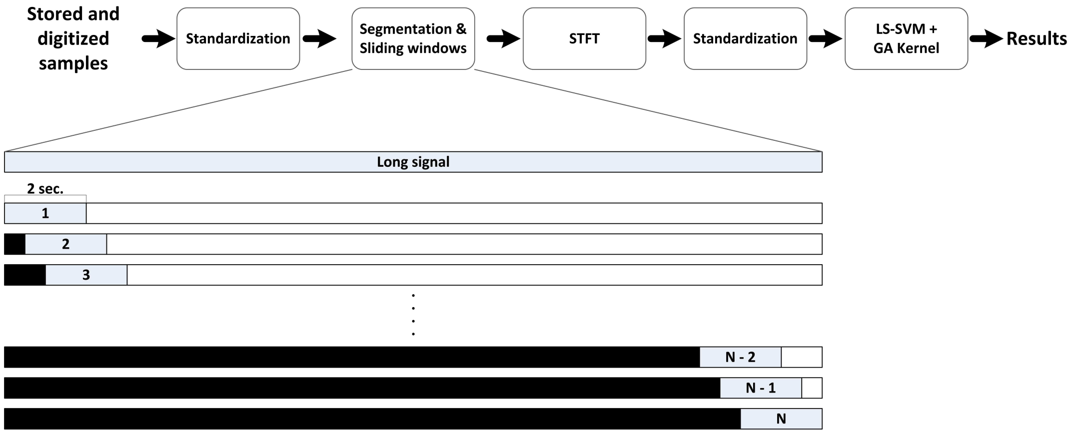

Fig. 3. Block diagram of the testing phase. In the sliding windows stage, the signal is cut in segments of 2 seconds with an overlapping of 75%.

3 Experimental results

A training set containing 50 activities executed by a single test person is used to estimate the activity classification models. The models have consequently been tested on 20 speed signals containing multiple activities acquired on 3 different test persons, whose total durations varied from 10 to 30 seconds. Each of these signals was acquired with a single volunteer in the room at a time, and who had not contributed to the training model. Moreover, each signal contains only one fall event invoked in a random instant. The success rate of the algorithm was calculated as the percentage of detected falls.

The results have indicated that the fall detector was able to detect 19 falls, with a success rate of 95%. Moreover, no false positives have been reported.

Fig. 4 shows a test signal of 10 seconds. It consists respectively of a walking movement in the first four seconds, a no movement, a fall event starting at about 6 seconds, and another no movement. The results show that the fall detector detects the fall when the sliding window intercepts the event.

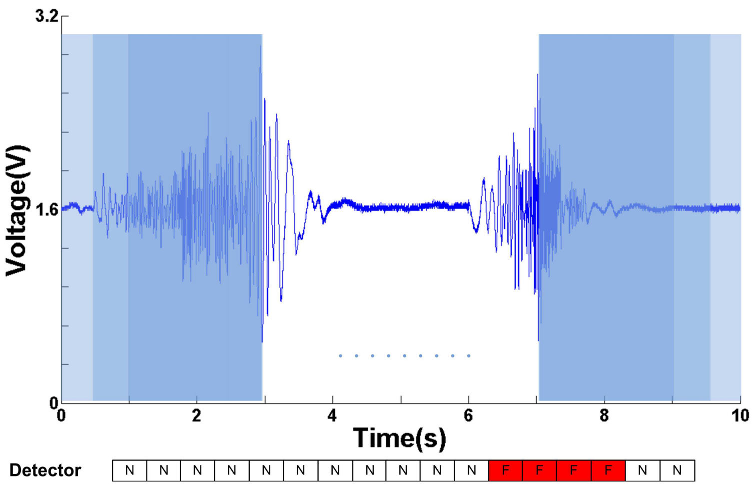

Fig. 4. Speed signal including a fall event (F) and normal movements (N). The frequency of the signal is proportional to the radial velocity of the person during the movement. Each detector box corresponds to a window of 2 seconds, dividing the full signal in 17 windows.

4 Conclusions

This paper shows the feasibility of an automatic fall detector based on machine learning techniques and sliding window's principle. Speed signals, acquired from a human volunteer, have been used to learn an activity model to distinguish automatically fall events from movements (i.e., walking, sitting down, and no movement). The evaluation was performed on data acquired from different persons that have not contributed to the learning of the activity classification model. Experimental results have shown a success rate of 95% in detecting fall events.

Future research will focus on a larger set of activities and on achieving the validation test in real time.

Acknowledgements

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