Development Of A Two-Threshold-based Fall Detection Algorithm For Elderly Health Monitoring

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Abstract— Population aging has become a worldwide problem. Falls are considered as the first source of disabilities among elderly people. Fall detection algorithms are the key to distinguish a fall from daily activities, automatically alert when a fall occurred and significantly decrease the time of rescue when the monitored patient falls down. The algorithm presented in this paper uses tri-axial accelerometer outputs to discriminate between falls and daily activities. It is mainly based on a two-thresholds approach and inactivity posture recognition after falling. The algorithm showed prominent results compared to existing works and will be improved and implemented on a Zynq board for future applications.

Keywords—e-health; embedded systems; fall detection; FPGA; tri-axial accelerometer.

I. INTRODUCTION

Elderly population is expected to grow dramatically in the next years. Falling is one of the main public health problems among aging society, it is considered as a main cause of trauma, disability, hospitalization and in some cases morbidity. With the increased number of fall accidents of old people each year, it became urgent to find efficient ways to quickly detect falls and help the elderly population after falling.

Portable monitoring devices for chronic patients can be considered as one of the best answer to this problem thanks to the availability of wireless communication almost everywhere, miniaturization of electronic components and the reduced costs of MEMs accelerometers. A new trend in fall detection is designing a small, smart and wearable device with adapted fall detection algorithms. Multiples technologies like micro-controllers, FPGAs and smart phones have been used to detect falls and have shown prominent results [1].

Beside this, older people living by their own, need to be monitored during their daily activities including normal activities like standing, sitting, walking or during accidents like falling. If there is no assistance, it can result in serious injuries. Real-time and accurate fall detection algorithm can increase security for elderly population and supply help for timely assistance [2].

To accurately detect falls and send real-time alarm messages, it is important to develop an efficient fall detection algorithm that automatically distinguish falling among daily activities and to alert relatives in time to avoid more important consequences after the impact of falling [3]. This work aims to develop a robust fall detection algorithm using a two-threshold based method and a posture recognition after falling.

This paper is organized as follow. Section II gives an overview of the different works in literature dealing with fall detection algorithms. In section III, we will discuss more threshold-based algorithms and present our fall detection algorithm. Section IV shows our results and introduces our future fall detection prototype. Finally, discussion and conclusion are presented in the last section.

II. RELATED WORK

Different approaches and technologies like video-based approach, environmental techniques using pressure sensors and wearable devices have been used for fall detection.

Accelerometers are now more commonly used in the application of human activity monitoring for its low cost and convenience to set up [4]. In fact, accelerometer-based methods are more accurate and reliable compared to other methods [5]. Indeed, reliable fall detection systems with real-time alarm have been considered as the main challenge in designing health monitoring devices. Many studies have been undertaken in finding the right fall detection algorithm that can quickly and accurately detect falls [6].

A fall can be defined as a sudden change of body position from standing to lying. It lasts 1 to 5 seconds and occurs generally after a large negative acceleration [7]. Different researches use this acceleration particularity to develop fall detection algorithms.

Bourke et al. [8] showed very interesting results in threshold-based algorithms. In fact, their algorithm reduces the number of features, has low computational cost of extracted features and is compatible with an integration in embedded low power solutions (DSP, FPGA, μC).

Noury et al. [9] designed an actimeter by combining 3 sensors and develop an algorithm that once vibration is detected, determines if the vertical acceleration exceeds a pre-defined threshold and checks if the body is in horizontal state to alert that a fall occurs.

In [10], a wearable 3D-accelerometer at the waist has been developed using Shimmer device and Virtex V FPGA family. The FPGA runs two different algorithms, the first one estimates at a low sampling rate the patient's orientation and

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the second one detects if the acceleration crosses pre-defined acceleration.

Kangas et al. [11] showed that it is necessary to include posture detection after the fall. In fact, they demonstrated that by combining a simple threshold algorithm and posture recognition, false alarms have been reduced considerably .It results in a huge improvement in terms of sensitivity and specificity.

Q.Li et al. [12] introduced a wearable wireless accelerometer device for people fall detection where the algorithm follows a main rule: every time a fall occurs, the acceleration changes significantly resulting in the patient falling which changes meaningfully accelerometer's orientation with respect to the gravity.

Grassi et al. [13] designed an integrated system with 3 devices: MEMS wearable wireless accelerometer and a 3D Time-of-Flight camera to detect falls in a home context. Fall detection algorithms have been implemented on an FPGA which runs in parallel six different routines: the two first ones measure the stress in terms of fall energy while the seconds check the acceleration shape and the third ones estimate the orientation of the person after a fall.

In our paper, comparing to the related works, we proposed an algorithm where the thresholds have been refined depending on the results obtained while testing the existing algorithms so that the new fixed thresholds are more adapted to real-time accelerometer outputs and theoretically, the number of false alarms will be reduced.

In this work, we have developed a two thresholds-based algorithm with INACTIVITY detection after the fall which will be more described in the next section.

III. FALL DETECTION ALGORITHM

A. Threshold-based fall detection algorithms:

Threshold-based methods are the most commonly used in fall detection for elderly people. In this technique, fall is reported when the acceleration reaches pre-defined thresholds.

In this kind of algorithms, it is necessary to start by defining several parameters depending on the accelerometer and gyroscopes outputs, used for the definition of the movement [14]. The impact detection is calculated by using vertical accelerometer output or angular rate measurements. Finally, a fall alarm occurs when all the test conditions are true.

Threshold-based algorithms have low computational cost and low complexity which is a main advantage as it became easy to implement it for real-time applications [10].

During a fall, a person experiences a significant change in acceleration (Fig.1). It corresponds generally to a reduction of acceleration, called a "FREE-FALL" and is followed by a large pike which corresponds to the "IMPACT" with the ground [8].

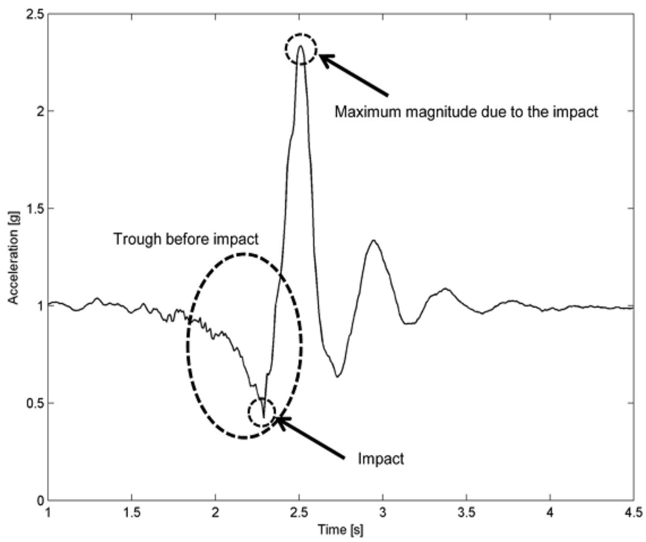

Fig. 1. Prototypical acceleration sum vector of a fall [8]

Based on the acceleration profile during a fall and a set of simulated fall values, we managed to fix 2 thresholds.

When a person starts falling, the acceleration decreases from 1g (corresponding to Earth gravity) to around 0,5g [15]. We chose then 0,6g as the lower threshold in our algorithm. And we also noticed that upon the impact with the ground, a short strong increase in the acceleration [16] is measured and this sudden change in acceleration corresponds to the upper threshold equal to 1,8g. According to this analyze and different existing algorithms, we are able to fix the two thresholds of our fall detection algorithm.

Beside this, the parameters tested in the proposed algorithm are mainly time interval length and large acceleration threshold. It was necessary to consider that changes in angles and accelerations can be part of everyday activities such as picking something from the floor, stretching or sitting down and therefore must not be selected as a fall or it will cause a larger number of false alarm. That's why we managed to fix to 0,6g and 1,8 g respectively corresponding to the lower and upper threshold to avoid false alarms and be more adapted to real life conditions.

B. Fall Detection Algorithm Design

For our fall detection algorithm depicted in Fig.2, we chose to use as the first parameter the sum-vector (SV) of the 3-axes acceleration to detect the different phases of the fall. The use of the sum vector of 3-axis accelerometer outputs as the main parameter provides robustness to the system [11].

$$SV=\sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

The second parameter used is the body tilt θ. It corresponds to the tiled angle between the accelerometer y-axis and the vertical direction. SV and θ are determined by equation 1 and 2 respectively.

$$\theta = \tan^{-1}\left(\frac{\sqrt{(A_y^2 + A_z^2)}}{A_x(i)}\right) \times \frac{180}{\pi} \qquad (2)$$

where A_x , A_y and A_z corresponds to the x-axial, y-axial and z-axial accelerations respectively.

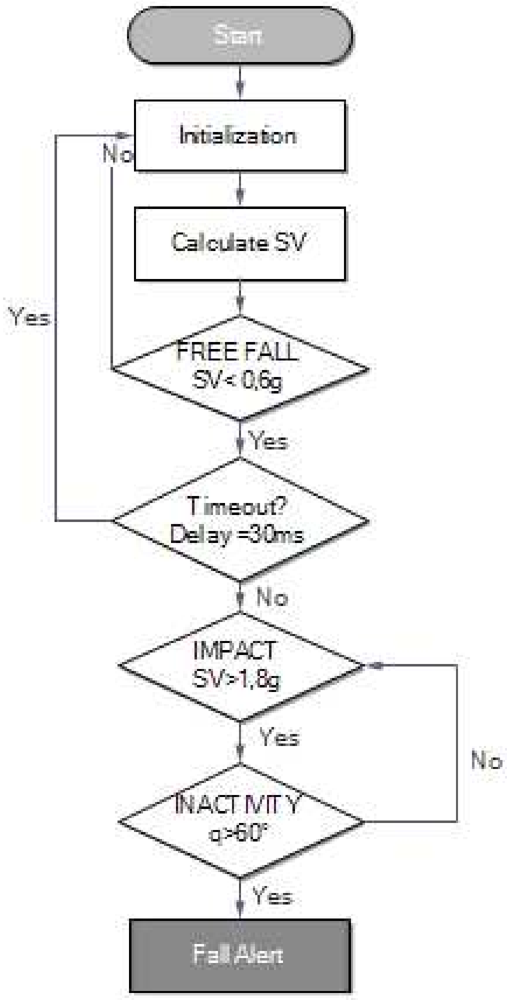

Fig. 2. Fall Detection Algorithm flowchart

The first threshold fixed, detects the FREE FALL phase and the second one corresponds to the IMPACT. We added to this algorithm a posture recognition phase in addition to thresholds comparison.

The posture recognition phase checks if after breaking the thresholds, the patient's position is lying (Fig.3). In fact, some daily activities like sitting on a sofa or going down the stairs can have SV values similar to those for falls. So it will be interesting to detect the INACTIVITY phase after the fall which corresponds to a lying posture by checking if the body tilt θ exceeds 60° [17].

In this algorithm, as there are various calculation operations and comparisons, we managed to write a C function for each step to avoid computational complexity. The C code is then executed, as a first experimentation, as a standalone code on the ARM processor of the Zybo board.

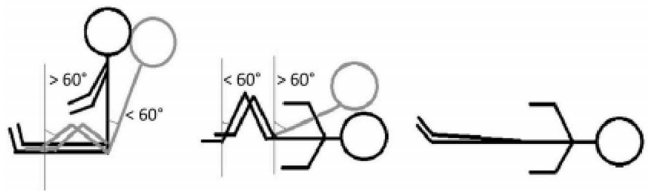

Fig. 3. Lying posture after falling [19]

To test the fall detection algorithm, available experience values are used. These acceleration values are data collected from a tri-axial accelerometer ADXL345 during different daily activities like lying down on a bed, sitting down on a hard surface like a chair and for 3 types of falls: forward, backward and lateral. Our experimental results are shown in the next part.

IV. Results and Prototyping

A. Results

For the experimentation, we used available 200 samples of daily activities including forward falls, backward falls, lateral falls, sitting on a sofa or a bed and going down the stairs.

In our algorithm, data are read from a file where accelerometer outputs have been saved and all the calculation operations are coded in C. This source file is then added and simulated on the Zybo board using Vivado and Xilinx SDK. Every time a fall occurs, a message is sent alerting a fall has happened and a LED of the Zybo board is flashing. This first software (SW) implementation on the Zybo board is just for testing and validating the proposed algorithm.

To evaluate the proposed fall detection algorithm, we will compare sensitivity and specificity values of existing algorithms. Sensitivity (SE) is the capacity of detecting real falls (Eq. 3): it's defined as the ratio between the number of falls properly detected (true positives) and the falls that really happened (true positives plus false negatives).

$$SE = \frac{TP}{TP + FN} \qquad (3)$$

Specificity (SP) is the capacity to filter false alarms and corresponds to the ratio between fall properly discarded (true negatives) and the total number of discarded actions (true and false negatives) (Eq. 4).

$$SP = \frac{TN}{TN + FP} \qquad (4)$$

We tested first our approach without posture detection and after, test the three steeps{START OF FALL + IMPACT + POSTURE} to show how results are improved (TABLE I).

TABLE I. SENSITIVITY AND SPECIFICITY OF FALL DETECTION ALGORITHMS

	{ START OF FALL + IMPACT}		{START OF FALL + IMPACT + POSTURE}	
	SE (%)	*SP (%)*	*SE (%)*	*SP (%)*
Proposed Algorithm	89,5	98	96	97
Bourke et al [8]	83	97	95	100
Kangas et al [11]	90	98	95	100
Chen et al [18]	-	-	76	94
Charlon [17]	-	-	98,33	97,77
Zavala et al [19]	-	-	95.6	99,6

Our results showed encouraging values in terms of specificity and sensitivity compared to other works. The samples used are experienced values available for research. The data set used contains only a limited number of falls and daily activities.

Additional changes have to be done in the future prototype to have experimental values from simulated falls. To be more accurate, we have to use real-time outputs from the tri-axial accelerometer, add a feature extraction and data classification steps in the fall detection algorithm and implement it on an FPGA platform. More works will be done in this thematic and will be presented in future papers.

B. Proposed Prototype

The idea is to use an FPGA platform to have a reconfigurable and flexible architecture in a single chip which bypass the problem of power consumption and can be reconfigurable depending on the parameters introduced and the patients specifications.

It will be very interesting to parallelize the different operations of calculation necessary for determining the vector sum of the of the 3-axes acceleration to detect the different phases of the fall and to have a real-time system that detects a possible dangerous fall with the smallest time of reaction.

The proposed prototype shown in Fig.4 will be composed by a tri-axial accelerometer ADXL345 connected to a Zybo board via I2C connection. We chose ZYBO (Zynq Board) as it is a low cost development board powered by Xilinq Zynq-7010 SoC featuring a dual core ARM Cortex A9 processor and FPGA fabric. Its dual ARM Cortex-A9 cores are at the center of a microcontroller packed onto the same chip as an FPGA.

This prototype will be a portable fall detection system that detects and informs automatically relatives via a Wi-Fi module that a fall has occurred. This work will be experienced and presented with more details in future papers.

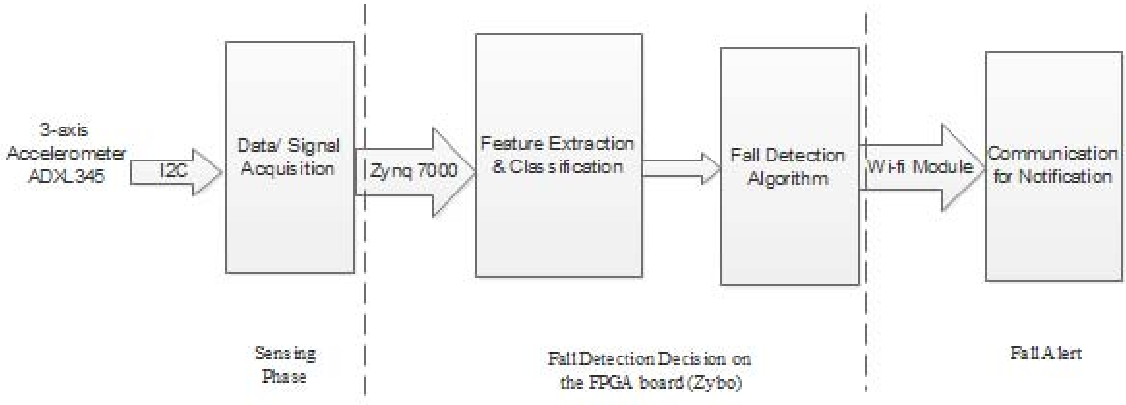

Fig. 4. Proposed Fall Detection Prototype

V. CONCLUSION AND FUTURE WORK

We have presented in this paper, a fall detection algorithm based on two thresholds: the lower one which detects the start of the FREE FALL and the upper which corresponds to the IMPACT detection. The two thresholds have been selected based on the basic trade-off between detecting the maximum number of falls and avoiding false alarms. For efficiency purpose, an INACTIVITY posture detection has been added.

The proposed algorithm showed encouraging values in terms of specificity and sensitivity compared to other works. But, to reduce false alarms, it will be interesting to add in the fall detection algorithm, methods like vertical velocity estimation, posture and pattern recognition. This advanced techniques will show better performance results in terms of sensitivity and specificity.

This algorithm introduced in this paper is limited as the outputs used are experimental outputs from available samples for research purpose. In the next steps, it will be more interesting to implement our two-threshold-based fall detection algorithm on an FPGA board connected to a tri-axial accelerometer through I2C to have real-time values and to achieve our goal in monitoring elderly people during their daily activities.

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