A review of Approaches and Principles of Fall Detection used in Diverse Human Safety Systems

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A review of Approaches and Principles of Fall Detection used in Diverse Human Safety Systems

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Abstract – **Fall detection is of interest to health care providers and researchers in recent and past decades since it can be used to reduce emergency response time. In fact this is can be used to reduce health care cost. Extensive research has been done to detect fall in all possible conditions. The research has generated many different algorithms and application to automatized fast alarm to reduce the consequences of the fall. This article gives an inclusive review of different research of fall detection systems, identify the existing approaches and principles methods used to detect the fall. Fall detection categories can be scattered into the following: wearable device based, vision based and ambience device based. These categories were analyzed and compared for each published work. At the end of this work we proposed some ways to improve the presented systems and some future work.**

Keywords – **Fall detection, Approaches, Wearable, Vision, Ambient**

I. INTRODUCTION

Sudden falls can cause damage to the body of human, especially for elderly and sometime harmful falls lead to death. Based on recent statistics the number of major injuries among the edge people, are the results of the falls [1], [2], [45] and in the remote areas most of the time because of either late or missing alarm to receive help, the unfortunate person can die. Therefore the surveillance systems demand for fall detection has increased, especially vision-based systems [3]. Fall can be defined as " unintentionally coming to ground, or some lower level not as a consequence of sustaining a violent blow , loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure" [4]. Many studies used this definition, however, "as it is general enough to be extended to include falls resulting of dizziness and syncope, consequences of an epileptic fit or cardiovascular collapses, such as postural hypotension and transient ischaemic attacks." [5].

The falls are considered among the most dangerous accidents may happen at home. The statistics show in Canada before 2006, 62% of the injuries were the result of falling according to senior's hospitalizations [6], [49]. The fallen person should receive an immediate treatment as soon as possible to avoid bad consequences and it is very critical issue [7]. According to [8], since 1900 life expectancy has dramatically increased in the United States and the causes of death have changed. After 20th century the death rates dropped down for all age categories. Same article asked "What are the leading causes of death for older Americans? [8]." Jian Liu and Thurmon answered: "The National Safety Council reported that in 2007, 21 600 Americans met their death by falling, and of these deaths, the majority (over 80%) were people over 56 years of age [9]."

In this paper, we present a survey of the academic studies which have discussed different methods of fall detection based on their principles and approaches. Because it is not permissible to subject the old people in such experiments, the most of researches and studies have simulated falls from young and healthy people and that may affect the result of these studies [40]. The paper is organized to illustrate each approach based on its technique. We conclude this paper by presenting a common evaluation method and suggest possible future directions of the fall detection applications.

II. CHARACTERISTICS AND DETECTION CLASSIFICATIONS OF FALL

In order to understand any fall detection algorithm and/or find a way to improve or design new algorithms, an optimal definition of the various kinds of falls is required.

The fall can be classified as the transition from a controlled to a non-controlled body positions, and it has two main scenarios: one from a stable situation to fall. For example, falls while standing falls while sitting on a chair or falls while lying. The second kind of falls is from motion. For instance, falls from walking, falls from bed, fall from stairs or from any other daily actions [3], [47]. For these scenarios, fall has different characteristics ending by lying down on the ground either with conscious or the unconscious situation. Xinguo Yu [7] listed all possible characteristics of the fall and he divided them into three sets of classifications. According to that we agree that most of the elderly’s fall are the result of the second kind of falls. Though each kind of fall has different characteristics based on its possess.

Finding optimal solutions to detect each type of fall has two main steps. First, propose an algorithm that responds to the posture classifier which is dealing with a variety of changes in view of point that can professionally contact with part of occlusions and cover a maximal area of the view. Next, recognizing the motion features by the proposed algorithm is very suggestive for fall detection [10].

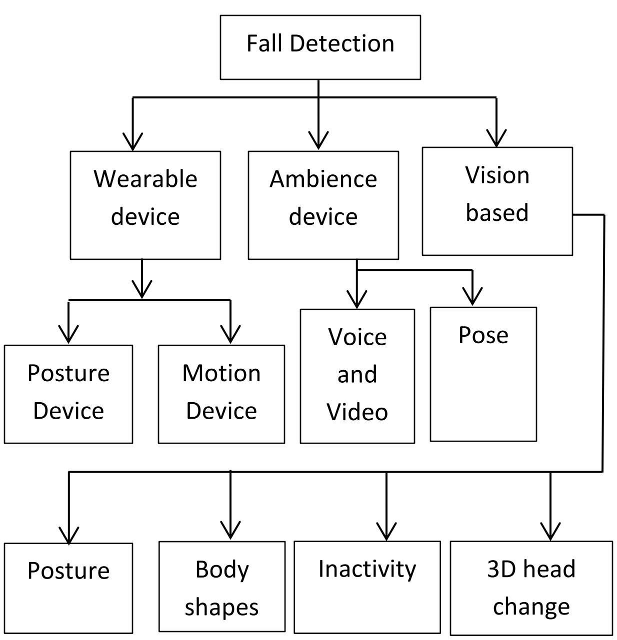

Fig. 1 Fall detection methods classification [7].

Basically, the proposed methods can be distributed into three categories as it is presented in Fig. 1: wearable device based, vision device based and ambience device based. Fig. 2 illustrates the processing framework of existing approaches. Data acquisition comes from the sensors, while the video stream comes from the cameras.

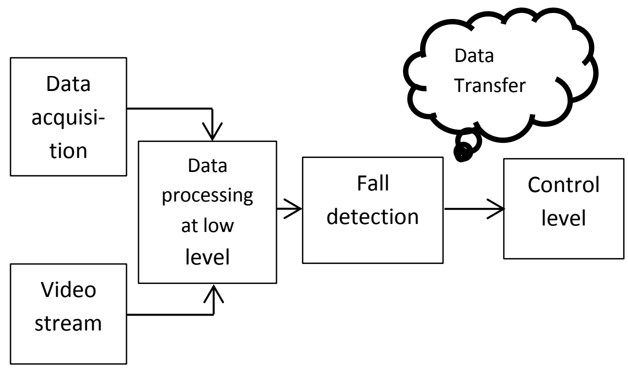

Fig. 2 Framework of existing approaches [3].

III. WEARABLE DEVICE BAESD APPROACHES

Wearable devices are the devices can be worn or attached to the body or dresses with embedded sensors used to sense the motion and the orientation of the subjected body to discover the fall when it occurs. For instance, P. Pierleoni et al used acceleration scale based on smartphone application to detect the fall [42], [45], [50]. In this section we summarized different methods used in these approaches. High rate of fall among the elderly generates a need of developing a reliable fall detection system. There are many systems that came to real life and some they just have been proposed. However, the wearable devices have the highest number in this field, and their claim of fall detection precision above than 90% relying on the accelerometers and gyroscopes [11], [46], [48], [50], [52]. They all have a common advantage which is the mobility. “By changing physical environments and creating unique integrated interventions across various disciplines, they can improve the mobility of older adults [1]”. Nowadays smartphones are available in the market with various sensors and gyroscopes. Furthermore, using cell phone comparing with other traditional wearable detector devices, is easy and low cost [30]. This technology inspired many researchers think about it as wearable device with the mobility and could be used to detect the falls of elderly people like [12], [13], [14], [15], [31], [36], [37]. Most often falls occur during intentional actions introduced by the persons. During a fall is in process a fallen person will be unbalanced. The person will initially try to rebalance by taking some movements forward or backward, thus increasing these movements; for example, by fanning his or her arms, will perhaps resulted to fall in the end [5], and at the same time these amplified movements could be detected by the wearable sensors [16].

Fall detection can be done in many ways. The very basic technique is obtained by push-button controlled by the person that depends on whether he or she still is conscious. However, this technique completely fails when he or she is unconscious [17]. Another technique commonly used by identifying high acceleration compared to daily living activities [12].

A. Posture Device

Olukunle et al [11] presented a wearable device system for human fall detection based on gyroscopes and accelerometers. The researchers employed, particularly decision trees and machine learning to detect four categories of fall: left, right, frontward and backward. Two SHIMMER[1] sensors were used to attain the acceleration and angular velocity in order to transfer data from subjects to a distant PC. Both sensors consist of a microcontroller, 3D gyroscope, 3D accelerometer and Bluetooth device and NSP430F1611. The team concluded with a description of a decision trees-based method for fall detection from the proposed methods. By using from three to seven subject sets the training task was accomplished. Four kinds of falls were clearly identified with acceptable performance rate of 72% for training set of the three subjects and up to 81% aimed at the remaining seven subjects training set. Non-real time implementation with low complexity was implemented.

B. Motion Device

Yanjun et al [18] designed a detection method under the Neyman-Pearson detection framework. They used TelosW: “an ultra-low power platform for wireless sensor network [19]”, mounted with accelerometer as the detector, which was attached to the waist of the targeted person to detect the movement data. The work presented the fall detection system based on sensor system design. The researchers developed the test experiments to distinguish fall acts from regular activities to specify the characteristics of each activity. Detection threshold was calibrated by using Neyman-Pearson model. Data collection has done of five people, including three males and two females. Total trials were 200 for each activity and computed the acceleration peak values. Detection performance used training data to obtain the threshold for any given false alarm rate. The performance showed a good match between training data and test data based on ROC (receiver operating characteristic). Finally, a proposed detection method was tested and obtained an optimal detection, which met the specified false alarm rate and maximized the detection probability.

IV. AMBIENT DEVICE BAESD APPROACHES

This section will summarize the main idea of ambient device approaches. Basically the main idea of these approaches is to combine multiple installed sensors; for instance, the visual data, the audio data and the event sensing in one set through vibration data [3], [7], [20], [21], [39], [43]. These methods be can considered as real-time investigators.

A. Voice and Video

Transferring image data and camera data can be done by good communication environment like cord or cordless transmission line that connects them with the controller unit. The fall detection system can also detect the falls based on voice signal [22], [49], [50].

Kofi et al [21] proposed a system based on ceiling-mounted video sensor for intelligent activity monitoring. The system was able to learn how to test locations, calculates global levels of activities and detects falls. The algorithm was build one, two sections: detection sub-system for training and detection, and behavioral sub-system for location

[1] SHIMMER: Is small type of sensors wireless based platform uses for wearable health applications.

testing and K-mean clustering. The result showed that proposed method is low cost, easy to implement and has the ability for training. Also, it is a location projective geometry system using block-base vertical and horizontal histograms. However, it is basically applicable to track a single object.

B. Vibration Sensors

Falls can cause vibration on the ground, so connecting multiple sensors to the ground can obtain fall detection. Furthermore, falls cause change in air pressure; indeed, it is possible to track and sense that change and one way has been successfully used to detect the falls as shown in [23].

Majed Alwan et al [24] presented a working method based on a floor vibration-based for fall detection system, nevertheless, the system was entirely inactive and unremarkable to the tenant. The performance of the used detector was assessed by leading controlled workspace examinations using anthropomorphic models. The results of their study exhibited 100% fall detection rate, and minimum false rate alarm. While M. Cheffena, achieved 98% of accuracy by using smartphone application [51].

V. VISION BAESD APPROACHES

The last approaches set presented in this paper are the vision based approaches. Actually, this approach has grown very fast recently. Cameras have many advantages over other sensors because they can detect multiple events in the surrounding area at the same time with less interruption. Automatic vision based fall detection systems are more dependable and robust than other available fall detection methods [25], [38], [33], [41].

A safety can be improved by using appropriate and smart monitoring system which could be helpful in different situations without needing to be connected to the body. In fact, vision applications based do solve this challenge [33]. The research area in vision-based approaches are increasing. However, it is complex, difficult and most of the time expensive to be applied for real time applications and difference life conditions [33], [34], [35], [44].

Vaidehi et al [25] proposed two main parameters to determine whether the person is falling or not. In fact, he proposed an aspect ratio and inclination angle. Aspect ratio computes the height and the width of the person, and finds a relationship in between to decide a fall. However, they observe that the aspect ratio doesn't work for motion objects and gives ambiguity value when the person bends down. Using inclination angles is another method to decide the fall and be more optimal for different kind of fall. They concluded their proposed application extracts the static features of persons and doesn't work for motion. Proposed method involves less computation than most existing methods.

Martin Humenberger et al [26] used Bio-Inspired Stereo Vision with neural network and embedded hardware to detect the fall. They defined that the Bio-Inspired means: "the use of two optical detection chips with event-driven pixels that are sensitive to relative light intensity changes only [26]." Each chip uses a stereo configuration for 3D representation. The fall detection platform was designed using four main components: a stereo sensor to capture the area, FPGA computer for 3D representation, black-fin DSP to detect the fall based on neural network processing and voting probabilities and alarm unit. The most evaluation results given in percentage were based on a true positive (TP), and false positive (FP) and they showed a fall detection rate of more than 96% for dataset involving 679 fall scenarios.

Yun Li et al [27] proposed an acoustic fall detection system algorithm (acoustic FADE) using a Microsoft Kinect. The system used a microphone array to detect the fall signal based on the number of interferences exceeds FADE's ability. Extracting the fall indication from the interferences has been done by consuming two blind source separation (BSS). Microsoft Kinect used to collect the acoustic data from the real environment. The results showed that in a high interference and the noisy background environment, the performance of the proposed system was good.

Pengming Feng et al [28] used deep learning methods in computer vision to analyze the postures in smart indoor environment for detecting fall activities. The proposed method covered the three main levels of processing. First stage, background modeling and foreground extracting. Next, classify the human binary image. Then deep learning approaches based on a Boltzmann machine and SVM classifier. Heart rate and oxygen in the blood can be measured by a ring sensor as illustrated in [29]. Similarly, [28] showed that such system may identify the fall that have happened. Furthermore, in their paper showed that video detection has more advantage upon the other approaches such as: a few facilities' system with little interference from the surrounding environment is more convenient for older people. The experiments included 15 persons, used 2904 different postures to train the classification system and 294 postures used to test the system. The classification results based on restricted Boltzmann machines (RBMs) and deep belief networks (DBNs) classifiers showed that, for 500 hidden layers, classification rate 84.3% and 86% and false detection rate 5.09% and 3.7% respectively as best situations.

Xin Ma et al [32] presented a new vision based fall detection that used a low cost depth camera. Therefore, using low cost Microsoft Kinect camera improved extreme learning machine and resulted in 91.15% sensitivity, 77.14% specification, and 86.83% accuracy. They also built a dataset that included six types of actions: walking, sitting, bending, squatting, lying and falling. Kinect camera uses infrared sensor which is used for the depth sensing, and it doesn't require any visible light to project the human or any other sin. Segments the background from the image frames stream can obtain tracking moving person in the real time events [44]. Thus, the experiments and data collections showed human silhouettes were successfully extracted even in a dark room, and this came as counted advantage by using this camera over color camera [32],[44].

VI. CONCLUSION AND FUTURE WORK

Comparing different approaches is extremely difficult since they use different types of data set. In this paper, we have summarized different approaches and techniques for fall detection algorithms. We also presented the characteristics of high falls and how they have been detected by addressing two main parameters: the sensitivity and specificity. The main categories were illustrated under three approaches. Table (1) shows the salient points for each method, and it gives overall point of view to all used approaches in this area of study. This paper could be counted as a reference for the interested researchers and readers. Also it gives some good background for future work and it shows the current thread of research in this area.

Approach / Category	**Methods**	**Environment of use**	**Area/Persons**	**Setup**	**Response time**	**Price**
Wearable Devices	Transducers	Anywhere	Y	Easy	Fast	Moderate
Ambient Devices	Transducers/Cameras	Indoor (high) Outdoor (Medium)	Y/N	Easy/Medium complexity	Fast/ Very fast	Expensive
Vision Based	Cameras	Indoor (high) Outdoor (Low)	N	Complex	Real time	Expensive

Table 1. Salient points for each method, and overall point of view to all used approaches in this area of study

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