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Analysis of Fall Detection Systems: A Review

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ABSTRACT

Since falls are a major public health problem among older people, the number of systems aimed at detecting them has increased dramatically over recent years. This work presents an extensive literature review of fall detection systems, including comparisons among various kinds of studies. It aims to serve as a reference for both clinicians and biomedical engineers planning or conducting field investigations. Challenges, issues and trends in fall detection have been identified after the reviewing work. The number of studies using context-aware techniques is still increasing but there is a new trend towards the integration of fall detection into smart phones as well as the use of machine learning methods in the detection algorithm. We have also identified challenges regarding performance under real-life conditions, usability, and user acceptance as well as issues related to power consumption, real-time operations, sensing limitations, privacy and record of real-life falls.

KEYWORDS: *Fall detection, Review, Smart phones, Assistive technology, Health care*

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I. INTRODUCTION

According to a report of World Health Organization, early fall detection is an active problem in the old age group people. The report revealed that the fall detection problem affect 28-35% people for the people around 65 years of age and 32-45% for those over 70 years[1]. In the past few years, various research studies have been conducted on the fall detection problem. Objective of these research studies is to develop a system to provide a timely medical assistance to an old age Recent studies have suggested that early detection of fall could higher, unless preventive measures are not taken in the quick future. Therefore, it is necessary to devise a system which handles the fall of elder peoples. Report further forecast that by the year 2030, the number of injuries caused by falls are anticipated to be 100%. Fall may be caused by some neurological disorder or age-related biological changes. A fall detection system is an assistive gadget whose principle objective is to notify when a fall event has happened. [2]. All the fall detection systems designed for the common purpose, particularly it detects fall events from activities of daily living (ADL) [2]. not only minimize the damage in terms of head, spinal or any similar major bone injuries. In A highly-accurate automatic fall detection system is likely to be a significant part of the living environment for the elderly to speed up; and improve the medical care provided while allowing people to retain autonomy for longer [3]. Automatic fall detection system is one of the recent topics in the field of preventive health care since the last decade. In recent years, automatic fall detection system is working on the analysis of images, video, audio as well as inertial sensor data from various sensors including an accelerometer, gyroscope and magnetometer[2] [34]. According to [3], fall detection system is categorized into three approaches: wearable devices based, ambience sensors based, and vision based. Various techniques are required for examining several types of falls possibly from walking, running, jumping or even climbing stairs etc. There are different methodological approaches are introduced for fall detection on the basis of deployment of sensors as a camera based, wearable device based and ambience sensor based. The paper is organized as follows. The next section provides a detailed description on various fall detection approaches. This section covers three important approaches being used for detections; ambient based approaches, vision based and wearable device based approaches. We also present the open challenges in the fall detection problem followed by the conclusion in the last section.

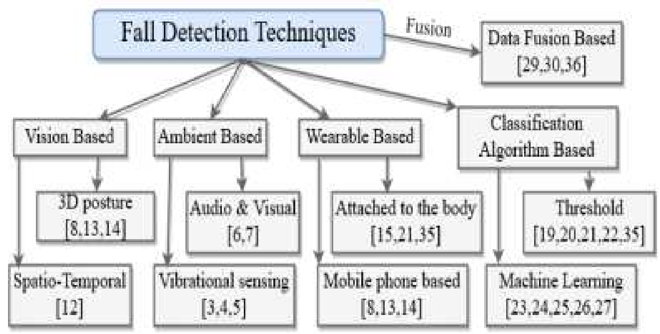

Figure 1: Fall Detection Taxonomy

II. AMBIENCE BASED APPROACHES

Ambient-based fall detection systems are based on using proximity and floor sensor to collect the data of the activities of daily living. This data is used for the fall detection. The research work presented in [24] uses numerous sensors installed to collect human data when a person gets close to them. What's more, ambience based devices endeavor to combine sound and visual information and identify the occasion through vibration information [3]. Ambient based approaches are the simplest techniques for detecting a fall event as it does not use any wearable device and just use motion, light and vibration sensors. Figure.1 depicts how ambient based solution is used for fall detection.

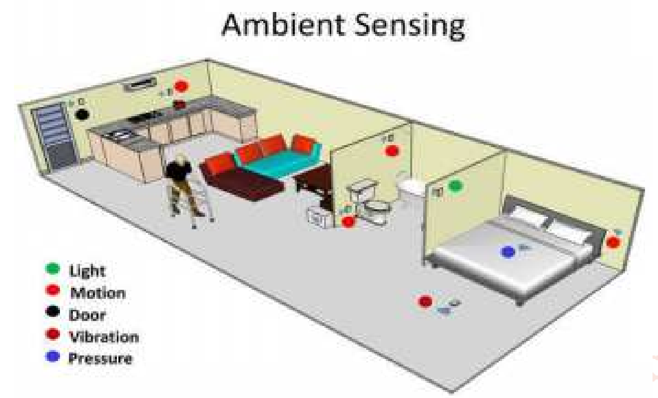

Figure 2: An example of the usage of ambient sensors in monitoring activity patterns

A. Audio and Visual
Ambient based models tend to be based on combined determination associated with audio visual signals along with some other specific information including floor vibrational data or even microphone signals through the channel of environmental sensors. Toreyin et al.[6] utilized audio and video data in order to detect fall of a person and attempt to separate falling from walking and sitting down using wavelet processing and Hidden Markov models(HMM). In another research work, Toreyin et al. [7] used a HMM model to detect a fall using audio data and passive infrared (PIR) sensors Event sensing using vibrational data.

B. Vibration Sensing
The detection associated with activities as well as utilizing vibrational data can be essential in any way, for instance, monitoring, tracking and localization etc. [3]. Alwan and Majd et al. [4] focus on a floor vibration based fall detection system. The daily activities of peoples can produce the floor vibration. The system uses the vibration patterns of the floor and matches vibration pattern technique to detect fall events. Yazar et al. [5] used PIR and vibration sensors and deployed winner-takes-all (WTA) decision algorithm to distinguish fall from the normal activities of daily living.. Alwan and Majid further revealed that these ambient based solution leads to a high rate of false alarm, limited accuracy and the high cost of installation [4].

III. VISION-BASED APPROACHES
The vision-based approach uses single or multiple cameras in an indoor environment to track a person's movements and the body shape during the whole falling period [8] [9] [10]. Anh Nguyen et al. [10] proposed a single camera based fall detection system, and the system works on the tracking of the motion characteristics and the body shape during the whole falling period, not at a certain point in time. Zhen-Peng Bian et al. [9] proposed single depth camera based fall detection system. This system is independent of illumination of lights, and the system can also work in the dark room. Yu et al. [11] proposed a fall detection system using vision-based technique by applying background subtraction to take out the frontal area human body; and the data is imported into a directed a cyclic graph supporting vector machine (SVM) for classifying different human poses. Different methodologies as to image examining have been proposed including spatiotemporal features and 3D head position analysis [3].

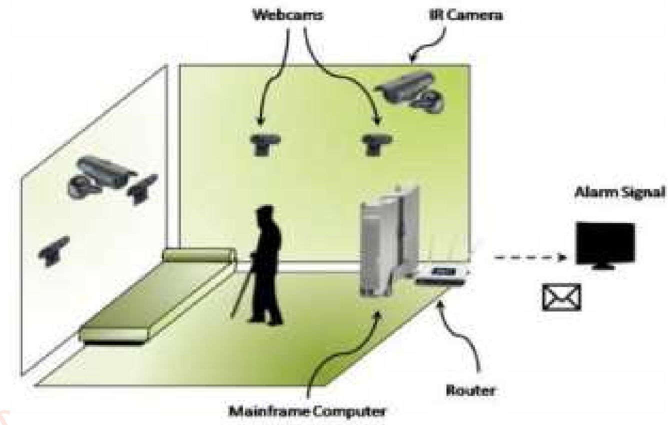

Figure 3: Camera based fall detection system example

A. Spatio-temporal Shape modelling using spatio-temporal features gives human activities important data which are used to detect different events. Foroughi et al. [12] proposed a method to fall detection by merging the eigen space approach and integrated time motion images (ITMI). Time of motion event and Motion information that are contained in spatiotemporal database can be described as ITMI. Feature reduction is applied using the Eigen space technique, and the neural network classifier which is used for classifying the fall events.

B. 3D head position analysis Head position analysis relies on the head monitoring that controls the event of large motion inside the video sequence. Different state models are utilized to monitor the head based on the magnitude of the movement information [3]. Auvinet et al. [8] mentioned a several approach to the technique in [13] by means of Occlusion-resistant algorithm and Vertical volume distribution ratio (VVDR). Hence, they proposed fall detection system on the basis of multiple cameras fuses reconstructed 3D shape of the person and, they have reached sensitivity of 99.7% and specificity or in other way four or more cameras works better. The drawback of the multi-camera system is must be adjusted, and video sequence from different camera must also be synchronized. This procedure makes the implementation of a system to be more complicated and costly.

The main advantage of the vision-based approach is that the person does not suppose to wear any extra device for the falling detection. Nonetheless, the operation of this approach is restricted to those spots where the sensors have been beforehand deployed [14].

IV. WEARABLE DEVICE BASED APPROACHES
The wearable device based methods requires the subjects to be dress in some devices or garments with embedded sensors such as magnetometer, gyroscopes, and accelerometers to track the user's motion of body or posture,

the data collected by the inertial sensors are used as motion signals to analyze the state of movement.

Accelerometer
An accelerometer is a device that used to measure the acceleration, changes in position and velocity. It is the most widely utilized techniques applied for determining physical activities in order to observe activity patterns.

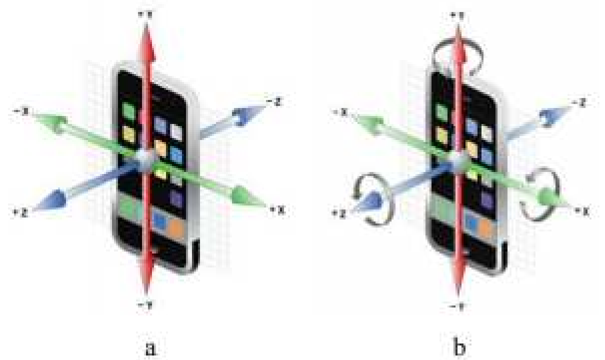

Figure 4: Three axis accelerometer (a) and gyroscope (b) in a smartphone device (source: Apple Inc.)

Gyroscope
A gyroscope is a device that used to measure change in orientation and rotational velocity.

Magnetometer
A magnetometer is a device which measures a magnetic field. Either the sensor attached to the body or embedded in smart phone generates the inertial sensor data.

A. Wearable Device attached to the body
The sensor attached to different part of the individuals' body to collect the data during the fall. Huynh et al. [21] [35] used wireless sensor system (WSS) based on accelerometer and gyroscope, and the senor is attached to the human body at the center of the chest to collect real-time fall data. Lai et al. [15] integrated different sensor devices such as, tri-axial acceleration for joint sensing of injured body parts when an accidental fall take place. The model transmits the data encouraged by the sensors which are dispersed over different body parts.

B. Wearable Device Built-in Smartphone
According to [16], today's Smart phones accompany a rich set of embedded sensors, namely an accelerometer, digital compass, gyroscope, GPS, microphone, and camera. Todays, many researchers are using the advantage of this fact to develop Smartphone-based fall detectors. For instance, Bai et al. [17] illustrated Smartphone with GPS function which is based on 3-axis accelerometer sensor to detect falls. Andò et al. [18] developed a Smartphone based ADL and fall detector system by using accelerometer sensor. Rakhman et al. [19] used accelerometer and gyroscope sensors integrated into an Android-based smartphone and evaluated some threshold based algorithms and sensor data to determine a fall.

V. CLASSIFICATION ALGORITHM BASED ON WEARABLE APPROACH
The classification algorithm is applied to classify activities of daily living (ADL) and several fall events. According to our literature review, a wearable based fall detection algorithm can be categorized into two approaches namely Threshold based [19]-[22] and machine learning based [23]-[27]. A. Threshold Based Threshold-based approaches use single or multiple threshold values to classify events. The system compares real time sensor data with the given threshold values, and if it exceeds, the system notifies the occurrence of a fall. For instance, Bourke et al. [22] proposed a threshold based fall detection algorithm using a bi-axial gyroscope sensor and, they have identified three threshold values. Rakhman et al. [19] used accelerometer and gyroscope sensors integrated into an Android-based smartphone and evaluated some threshold based algorithms and sensor data to determine a fall. Guo et al. [20] and Huynh et al. [21] [35] used a wearable device with built-in tri-axial accelerometer and gyroscope for fall detection, and they have utilized a threshold based algorithm. This algorithm has three threshold values: lower acceleration, upper acceleration, lower angular velocity in order to check whether the person is fallen or not. B. Machine Learning Based In Machine learning based approach, different types of falls and ADL patterns are trained by a learning algorithm and then classified the event by evaluation algorithm[23]-[27]. The machine learning algorithm includes Hidden Markov Model (HMM) [23,24], Support vector machine (SVM) [25], Decision Tree [26]. Tong et al. [23] proposed a low-cost fall detection and prevention system by using HMM and tri-axial, and the results of experiment indicated that falls could be expected 200–400 ms earlier the accident, and could also be accurately identified from other regular activities. Cao et al. [24] proposed fall detection system by using acceleration data and Hidden Markov model (HMM), and the data collected by tri-axial accelerometer integrated on a wearable device. Aguiar et al. [26] proposed a Smartphone based detection system by using accelerometer sensor embedded on the device, and they have checked three machine learning algorithms such as Decision tree, k-nearest neighbour (K-NN), and Naive Bayes, but among those algorithms, Decision Tree has appeared good performance. Pierleoni et al. [25] proposed support vector machines (SVM) based fall detection system by using accelerometer and Magnetometer sensors. In recent years, numerous papers were published that discuss different aspects of the fall detection techniques based on the combination of threshold-based and machine learning based algorithms. Lim et al. [28] applied the combination of simple threshold and HMM algorithm and using 3-axis acceleration, the combination of simple threshold and HMM have decreased the complexity of hardware. Yodpijit et al. [27] used accelerometer and gyroscope motion sensors to detect the fall, and focused on threshold-based and ANN algorithm to distinguish between ADL and falls in order to minimize the number of false positive outcomes.

VI. DATA FUSION APPROACH
Andò et al. [29] presented multi-sensor data fusion approach, which fuses data from a gyroscope and an accelerometer; and they have worked on smart algorithms for the activities of daily living (ADL) and fall classification, which utilize the data provided by inertial sensors embedded in a mobile phone, and installed on the user device. This algorithm uses a threshold based method applied to the features extracted from the average of the magnitude of the three acceleration and angular velocities components. The system automatically sends the notification to caregivers as soon as the fall event detected. Wang et al. [30] presented multi-sensor data fusion approach for fall prediction of the older peoples by using the walking

assistant robot, which uses acceleration, gyroscope and tactile-slip sensors to acquire the elder's falling data and extracts its features, and they used BP neural network algorithm for fall prediction. In the following tables I and II, we present a summary of different works with corresponding researchers. This summary depicts the types of sensors used, the methodology applied and final outcome of each work.

VII. OPEN CHALLENGES

In the previous sections, the paper provides a detailed survey on various fall detection techniques. Each technique tends to offer certain benefit for fall detection. There are following ongoing challenges with regard to various fall detection techniques covered in this survey: A. Challenges with vision-based fall-detection Vision-based fall detection is using rich set of features extracted from the sequence of frames captured from the video data. To be able to exploit the full potential of vision based solution for early fall detection, we believe the real challenge still lies in terms of cost of GPU based processing at the local node and use of improved ANN algorithm for fall predication and anticipation on real-time data. B. Challenges with ambient based approaches Though ambient based solutions are the simplest compared to other techniques, as it makes use of vibration sensor to detect the fall. However, as reported by previous research work, ambient-based solutions lead to increased false alarms thus limited in accuracy. But, ambient-based approaches are quite appropriate for Ambient-Assisted Living application wherein data can be continuously collected and stored on cloud for further analytics. Real challenge is to preserve the privacy data of an old age person who may be reluctant to share the data of daily activity living. C. Wearable based ongoing research challenges. The recent advances in the wearable space is attracting many researchers to address range of problems. Most of these problems are related to our activities. There activity recognition using wearable is drawing lot of attention. Wearable devices use embedded sensors to recognize the activities It is used to measure changes in orientation, position and velocity in order to detect the physical activity so that can identify the fall event. Previous research work suggests that an accelerometer and gyroscope data can be collected and processed for fall detection. It's worth that gyroscope has a practical problem of drift therefore further research work should be focused on minimizing the drift issues while using gyroscope data independently or in fusion with accelerometer.

Table I: Comparison of Different Fall Detection Systems

Article	year	Types of sensors	Methodology	Performance
Zigel et al. [33]	2009	Microphone, Accelerometer	Feature extraction, and Bayes decision rule classifier	Sensitivity: 97.5% Specificity: 98.6%.
Bianchi et al [31]	2010	Accelerometer, air pressure sensor	heuristically trained decision tree classifier	Accuracy:96.9% Sensitivity: 97.5% Specificity: 96.5%
Auvinet et al. [8]	2011	Camera	Occlusion resistant Algorithm Vertical volume distribution ratio (VVDR)	Specificity: 99.7%
Ariani et al [32]	2012	(PIR)motion detectors and pressure mats	heuristic decision tree classifier	Sensitivity: 100% Specificity: 77.14%. Accuracy: 89.33%
Aguiar et al [26]	2014	Accelerometer	Decision Tree	Sensitivity:99% Specificity:97%
Huynh et al. [21]	2015	Accelerometer and Gyroscope	Threshold based algorithm	Sensitivity =96.3% Specificity=96.2%.
He et al. [34]	2017	Accelerometer and Gyroscope	Kalman Filter and Bayes Network Classifier	Accuracy:95.67% Sensitivity:99% Specificity:95%

Table II: Various Categories Of Fall Detection Techniques And Comparison

Techniques	Category	Cost	False alarm rate	Result	Setup
Ambient based	Audio and visual	Low-cost to Medium	High	Scenario dependent	Easy/Medium
	Vibration	High	High	Scenario dependent	Medium
Vision based	Spatio-temporal	Average	Low	Higher/non-specific	Medium
	3D-head change	Average to high	Low	Higher/non-specific	Medium
Wearable based	Device attached to the body	Low-cost	Low/dependent	Scenario dependent	Very easy
	Device built-in Smartphone	Low-cost	Low/dependent	Scenario dependent	Very easy

VIII. CONCLUSION

To sum up, fall detection is an interesting problem which has been discussed widely but still requires further attention. The fall detection system intended to anticipate a fall event by analyzing the data of daily activity living. This paper reviews various research studies being conducted on the fall detection systems for elderly people. Mostly studies focus on the identification of elderly falls from their normal activities. There are three majors fall detection approaches such as wearable, vision and ambient based to classify fall events. Among the major approaches of fall detection system wearable based system is rapidly increasing. Recently a number of studies prefer Smart phone based method which uses built in sensors for detecting falls.

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