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Fall Detection Procedures and Their Common Drawbacks – A Review

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ABSTRACT

Slumps are a major cause of physical trauma to the aged. These falls mostly occur due to the inability of the elderly in physically coordinating themselves. When falls are detected early enough, then proper medical assistance can be given to the victims. As such, several kinds of fall detection systems have been developed overtime. A study of these fall detection systems can be utilized as a standard for assessing subsequent research efforts in this area. This inquiry provides a survey of various fall detection systems over the past one decade, including some of the general challenges they face.

Keywords: Activities of Daily Living, Assistance, Challenges, Elderly, Fall detection, Health, Injury.

1. INTRODUCTION

A majority of people who are beyond the age of 65 years is skyrocketing and the United Nations World population prospects, 2010 has speculated that by 2030, their proportion to the people between the age of 20 and 64 years will arrive at 35%. Falls constitute much of the perils that people go through at old age. When the elderly experience just a single fall, a permanent fear of falling is created in their sub-conscious minds and as such, they may develop a level of phobia that may affect their careers negatively (Age UK- Stop Falling, 2019). Since the physical health and careers of the elderly are at stake, improving the process of detecting falls will be a step in the positive direction preserving the elderly. When falls occur, fractures, several kinds of physical injury such as: abrasions on the skin, breakage of bones and sprains, occurrence of dislocations and muscles strain has been identified as some of reasons for sudden death amongst the elderly (Alves et. al, 2004).

The major reasons why fall detection systems were invented are to study the users of these systems and help them in alerting their caretakers when a fall occurs as most of them are often incapacitated after the fall and may not be able to press an alarm (Lord, Sherrington & Menz, 2007). The aim of most FDS developers is to increase the rate at which the system can identify the occurrence of an actual fall and lower the false alarms of fall detection that occurs as a result of the system misinterpreting an Activities of Daily Living (ADL) as a fall. Although research on detecting falls has many issues, there is rather a lot of studies in this area have however been encouraging.

One of these issues is that falls have been universally defined as events which suddenly brings an individual to the level of the floor or ground (Fleming J. & Brayne C., 2008).The World Health Organization Report of 2009, however claims that this sort of definition is could make it difficult to differentiate between a real fall and some ADLs as there are deliberate actions that can resemble a situation where an individual falls suddenly the floor. One other issue with research on falls is that, it is difficult to for most researchers to obtain real fall data for studying and analyzing fall occurrences. This is due to the fact that falls are hazardous events. Some researchers have however taken up this daunting challenge and obtained useful results (Ma et. al, 2014; Igual, Medrano & Plaza, 2013; Noury et. al, 2007; Mubashir, Shao&Seed, 2013; Habib et. al, 2014; Perry et. al, 2009). A lot of research has resulted from the advent of new technologies in recent years.

This study examines studies carried out on fall detection from the year 2005 to recent times. To examine improvements in fall detection systems afterthe year 2014, we conducted a detailed searched on search engines such as “Google Scholar” keywords such as “fall detection”, exacting one hundred and fifty-two most cited papers from 7460 related papers. Then, based on the most relevant papers to our work, we analyzed three main areas of fall detection research, which include: revolutions of sensors, changes of fall detection algorithms and performance of fall detection systems. Finally, we examined and summed up issues and problems emanating from this field and gave suggestion on future direction for the research work. This paper is organized as follows: Section 2 shows related research work to this study. Section 3 analyzes the various improvements in fall detection systems after 2014. Following the analysis, the challenges, related to fall detection systems are outlined in Section 4 and finally, the paper ends with a discussion on the conclusion of the study and future work.

2. RELATED WORK

Chen et al. (2005) utilized the connection between static motes and a wearable device, worn on the waist and in developing a fall detection system with the aim of creating the possibility of independent living for the elderly. An inexpensive and low power consuming Micro Electro-Mechanical System (MEMS) accelerometer is mainly used in detecting the fall. The scientists demonstrated the possibility of making use of a wireless sensor network in detecting fall occurrences. They found out that each ADL activity has a specific profile of acceleration. They also discovered that depending on the size and body weight of the wearer of the fall detection device, the frequencies and the amplitudes of the movement of an individual differs from another individual. This gives room for improvement on the fall detection device if it is specially designed for each user.

Lee & Mihailidis (2005) developed a fall detection system which can help to bring about immediate response to fall victims at home. The developed system locates the user when he or she enters the room (from the celling where it is mounted) and analyses his or body posture continuously in order to detect a fall. It makes used of image based sensors and computer vision. Williams et al. (2006) proposed a model that uses the concepts of finding on object and detecting a fall. The model proposed by the scientists mainly relies on data acquired from video unlike other solution which mandates the user to wear a device. In their experiment, certain features are extracted from the video camera, transferred to a processing unit where machine learning techniques are applied on them in detecting a fall. Miaou et al. (2006) utilized a camera in capturing 360 degree scenes from which different images where extracted and thereafter processed these using the personal information of each individual in the series of images. This personal information is passed into a system which is designed to detect a fall for any individual that experiences a fall.

Cucchiara et al. (2007), proposes a method for detecting falls using by classifying posture of an individual, using Hidden Markov Models (HMMs) in order to detecting falls. In their experiment several cameras are used to acquire images from different rooms in the home where the individual lives. When a fall is detected an alarm is raised and a short message service response is automatically sent to caregivers, notifying them of the fall event. Doukas et al. (2007) proposed a system for detecting fall victims by monitoring their activities of daily living.

A machine learning algorithm (Support Vector Machine) is used to classify the ADL data in order to detect a fall. Nasution &Emmanuel (2007) utilized the k-nearest neighbor (k-NN) algorithm and evidence accumulation technique analyzing the postures of individuals in order to detect a fall. In their experiment the bodies of individuals were segmented and the projection histograms of their bodies were analyzed and their postures classified in order to detect a fall. Hazelhoff (2008) proposes a fall detection system which utilizes principal component analysis in an analyzing the direction of the major axis of an individual's body and the proportion of the variances of the different directions of the body in detecting the occurrence of a fall. Anderson et al. (2009) presented model for detecting fall occurrences using fuzzy logic. The model consists of two stages. The first stage of the model deduces the condition of the individual in each image as to whether he or she has fallen or not. In the second stage the linguistic summarizations of the individual's condition is examined in order to detect a fall.

Sposaro & Tyson (2009) presents developed a system to detect falls using an Android-based tri-axial accelerometer on a smart phone together with an integrated tri-axial accelerometer. Threshold based algorithms and position data were then used to analyze data from the accelerometer in order to determine a fall. Rimminen et al. (2010) proposed as system for detecting human falls using floor sensors, near-field imaging (NFI), and pattern recognition. In their experiment the scientists detected the position of individuals on floor using floor sensors and detects if they have fallen or not, using their body patterns by measuring impedances with a matrix of thin electrodes under the floor. Rougier (2011) proposed a system for detecting falls by examining changes in the human body shape in a video sequence. A technique for comparing and matching different shapes is used to analyze an individual's silhouette along with the video sequence. The changes in the shape of the individual are measured from the silhouettes and then the Gaussian mixture model is used in detecting falls from normal ADL activities.

Zhang et al. (2012) proposed a fall system to foster the independence of older people by using RGBD cameras for detecting activities and the Support Vector Machine in their analyzing ADL data in order to detect activities that resemble fall occurrences. Yuwono et al (2012) utilized a tri-axial accelerometer worn on the in detecting falls. The accelerometer helped to detect falls employing techniques such as Gaussian distribution of ensemble of classifiers which included a multilayer perceptron and Augmented Radial Basis Function (ARBF) neural networks, Discrete Wavelet Transform and Regrouping Particle Swarm Optimization. Albert et al. (2012) carried out their research in order to expound methods used in carrying out fall detection. In their work, the scientists were able to detect falls by using machine learning techniques such as logistic regression and Support vector machines in analyzing ADL data to detect falls.

Kwolek & Kepski (2014) proposed an inexpensive fall detection system which has a low rate of false alarm. The system utilized depth maps and data from a tri-axial accelerometer in detecting falls. The accelerometer performs the function of detecting when a fall is about to occur and when the user is moving. Once the accelerometer detects an acceleration that is higher than a certain threshold value, algorithm in the accelerometer obtains the user, examines the features of the user and uses an SVM classifier to determine if there is a fall occurrence.Aguiar et al. (2014) utilized data acquired by a smart phone with an in built accelerometer and carried in the user's pocket with in detecting falls. The system made use of decision trees and machine learning techniques in classifying this data in order to detect a fall.

Bian et al. (2015) developed a system for detecting human falls using data obtained from tracking the key joints of the user who is observed, using a single depth camera. One of the key points as regards the achievement of the system is that it is capable of working in a dark room. The system uses a Randomized Decision Tree (RDT) algorithm for extracting data from key joints of the user and Support Vector Machine (SVM) is used in classifying this data to determine if a fall has occurred. Zerrouki et al. (2016) used the Exponentially Weighted Moving Average (EWMA) with Principal Component Analysis techniques in detecting anomalies in human body postures in order to detect a fall.

One of the merits of the system is that it is very fast and the features extracted are categorical enough to portray the postures of the user in detecting a fall occurrence. Triantafyllou et al. (2016) utilized camera tracking technique which uses features such as area variance and vertical velocity in characterizing a fall and the Human Markov Model in modeling the fall process. While retaining the privacy of the user, the system monitors in real-time, any area within its camera view range using multiple depth sensors. Wang et al. (2017) used data acquired by a cardio tachometer, an accelerometer and a smart sensor to analyze the movement of users putting on smart body sensors in order to detect fall occurrences in homes. The system is capable of distinguishing normal ADLs from actual falls, thereby reducing the false alarm rate.

Iuga et al. (2018) used a drone for monitoring the position of the elderly within a specific area using a simple maneuvering method and deep learning techniques in order to detect if a fall has occurred. The algorithm used was successfully able to control the movement and positioning of the drone in following the individual being monitored in a precise manner, so that proper monitoring can be achieved. Hussain et al. (2018) performed experiments on extracted features from an ADL dataset and used these features to train and test machine learning classifiers such as Support Vector Machine (SVM).Logistic Regression, K-Nearest Neighbor (KNN), Decision Tree (DT) and Logistic Regression (LR) to ascertain which one gave the highest level of accuracy in detecting falls. The SVM emerged as the classifier amongst the ones tested, with the highest level of accuracy in detecting falls.

Oliver et al. (2018) developed an algorithm which uses the K-Nearest Neighbor technique for analyzing human body postures after tracking them, in order to detect a fall. The system utilizes a blend of numerical data in order to increase the reliability and accuracy of the system. Musci M., (2018) developed an algorithm for on-line detection of falls. ADL data is gathered from the user with a wearable device and classified accordingly, in order to detect falls, using the Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) algorithms. Yacchirema (2018) developed and system for detecting falls for the elderly in indoor environments, using an IoT-based system. The system utilizes sensor data obtained from the usual ADL of the elderly and analyses these data using a decision tree model embedded on a Smart IOT router in detecting a fall. The system sends reports to the caregivers of the elderly whenever a fall is detected.

Shahzad & Kim (2019) developed a smart phone-based system for detecting falls. The system uses a Multiple Kernel Support Vector Machine and a threshold based method to detect the occurrence of falls from an accelerometer embedded on the smart phone. The algorithm is capable of properly distinguishing actual falls from fall-like events, thereby reducing the rate of generation of false alarm. Theodoridis et al. (2019), designed a human fall detection technique by using Recurrent Neural Networks (RNNs) in processing an encoding data involving the measurement of acceleration obtained from sensors worn on the body. The scientists also examined the process of augmenting data acquired from three-dimensional rotations.

Harrou et al. (2019) used pixel-based characteristics depicting changes in the body shape of an individual in identifying fall occurrences. In their experiment, areas of the parts of the body were calculated and used as input data for classifying and detecting falls, using the Generalized Likelihood Ratio (GLR) technique. Due to the inability of the GLR technique distinguish between real falls and fall-like occurrences, the scientists used SVM on features of ADL data to determine whatever kind of fall occurred at any point in time.

3. GENERAL CHALLENGES

While the future of fall detection technology appears bright, and a lot of prolific effort has been made on it, there still exist some problems that attempt to stall its improvement. Some of these problems are evaluated as follows:

3.1 Describing Falls Based on Their General Characteristics

In defining human falls, different researchers have adopted several methods, with the most common ones being based on thresholds, shapes or rules. Machine learning-based methods have been employed by researchers in for distinguishing between a fall incidence and other day-to-day activities in addition to providing definite findings after carrying out complex processes, such as extracting features from the action and performing classification tasks.In the process of detecting a fall, some vision-based fall detection systems send images acquired from a video camera over a network to other systems for further processing. Image compression techniques such as the one utilized by Akinrotimi & Mabayoje, (2019) can be incorporated into vision based fall detection systems so as to facilitate the process of feature extraction from such images, before further processing is carried out to detect a fall occurrence.

In spite of the efficacy of these methods, a system used in detecting falls, is often insensitive to changing environmental conditions(such as those that result from the mode with which experimental data is gathered or the nature of the experimental data used. Oftentimes, the fall detection algorithm and the system that emanated from it cannot be used again, once a change occurs in the conditions directly associated with the experiment. It is therefore important that the process of building fall detection models and analyzing fall incidences should be done in such a ways as to indicate the essence of the fall.

3.2 Transforming fall detection algorithms into 'Real-World' Systems

There is very little indication that most fall detection algorithms which function well during laboratory testing, or with datasets that are simulated, can actually be successfully utilized in reality. In order to successfully use the systems developed in the laboratory and their associated theories in solving real world issues, then some of the problems that could be initiated by these systems and their associated algorithms, should be examined. Kinect for instance, has been used by many researchers of fall detection systems, basically because it has the ability to easily obtain three-dimensional information from tracing the human subject. One of the limitations associated with its use is that it can only trace the subject effectively within a distance of 0.3meters to 4meters. As a result, a Kinect cannot practically cover a whole room. Therefore, the use of sensors (either body-worn or strategically placed around the room) should be further investigated.

Machine learning-based systems are more commonly used in building fall detection systems; however their performance depends on the nature and source of the datasets. The datasets used for building most fall detection systems is simulated due to the difficulty in obtaining real fall data, thereby making them less realistic. One common problem with fall detection systems is that, most of the data used in developing them are 'unbalanced' , in that, the data related to falls is usually in a smaller ratio to that of non-falls. As such, even when very efficient algorithms are used in classifying the dataset in order to detect falls, there is usually a high rate of false negatives as the fall detection systems often answers to the class with a larger dataset. This gives the fall detection system a false rate of accuracy (which is usually high) but makes it very unreliable. There is therefore a need to carry out cogent research in forestalling this problem in order to make most fall detection systems more reliable and fit for use in 'real - world' scenarios.

3.3 Privacy Concerns

Generally, people express some level of discomfort when they are being monitored with cameras. As such, fall detection systems which make use of vision-based algorithms encounter a lot of challenges as regards their acceptability, since their deployment often requires the installation of cameras in the users' room. This was part of what led to the use of Kinect, (in spite of its deficiency in real world application) in developing fall detection systems. The Kinect collects information (depth image and skeleton data) about the subject in a blurred form, thereby hiding the private details of the subject while providing cogent information. In addition, Wi-Fi-based fall detection systems appear promising in terms of preserving the privacy of the user, as they are ubiquitous and demand the use of fewer devices, compared to those that make use of sensors worn on the body. However, it is often difficult to use them in detecting falls from more than one person, due to the interference experienced by the Wi-Fi signals.

4. CONCLUSION

As one of the major threats to the well-being and even the existence of the elderly, fall detection related studies has attracted the interest of many researchers. This attention has been sustained for the last two decades, with diverse kinds of findings emanating from the subject matter. The current challenges faced by fall detection systems, however indicate that there is need for further research in this area so as to bring about more viable innovations. This study therefore conducts a review of some fall detection systems that have been developed and also presents some of the general problems encountered by fall detection systems.

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