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Review on Fall Detection Systems using Artificial Intelligence

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ABSTRACT

Day by day, aged 65 and above global population is increasing rapidly, and up to 2050, it will reach 1.5 billion. So, the fall detection system is a trending research area where the research community is showing interest day by day. Research in fall detection has seen an upward movement in the recent past. Falls to the elderly can be life-threatening or might cause severe injuries if the person remains on the ground for a longer duration without proper medical care. This paper summarizes comprehensive research that has taken place in the last decade to help new researchers in this field. These articles are taken from primary sources, and the selection criteria are mentioned. This paper summarizes each article's various algorithms, input parameters, classification, and limitations. The performance criteria and publicly available datasets were analyzed to access the performance results. At last, we found that the field is slowly but constantly moving towards its implementation in Machine learning, CNN, and Deep learning. There is a lack of well-organized and real-world data to train the classifiers in the event of an actual fall of an older person.

KEYWORDS:Artificial vision; neural networks; fall detection; fall classification; fall dataset, CNN, Deep Learning.

1. INTRODUCTION

The primary cause of death in the elderly falls and on average, 26% to 33% fall once a year [1-2]. The physical and mental strain at this age can lead to depression and mood swings apart from the injury caused. In the event of long-life where a person cannot call for help immediately after a fall can lead to even death over some time. The elderly develop a fear of falling syndrome. They tend to think that now and then, they might fall. A state of anxiety develops. The elderly must be constantly monitored for their safety. The visit from family members is not enough as they must be monitored 24X7. Appointing a full-time home nurse or getting admitted to an elderly home is not a solution and is expensive. The elderly have a strong desire to stay in the home they built. The development in sensors and the integration of the data collected with machine learning algorithms has prompted many manufacturers to produce fall detection systems. Older people are constantly monitored in the fall detection system based on the sensor data generated. The ultimate goal of all fall detection systems is to detect a fall and provide medical help at the earliest. Detecting a fall is a challenging task as the false-positive cases are on the higher end. The sensor would recon a sudden movement of the body as a fall and raises a false alarm. Falls are defined as any non-controlled movement from upright or sitting to ground level movement. During falls, the acceleration is too high and it is also a challenge when trying to provide computational solutions to falls. The occurrence of falls can take place any time anywhere.

The fall detection system is classified as Wearable, Ambient and Machines. Figure 1 gives the classification of the fall detection system used for the article. In wearable systems, the sensors are worn by the elderly. Ambient systems use the nearby environment like vision, waves and pressure. The machine fall detection systems in the broad category are supervised and unsupervised based on their algorithm. Further, it can be classified as of type CNN, Deep learning.

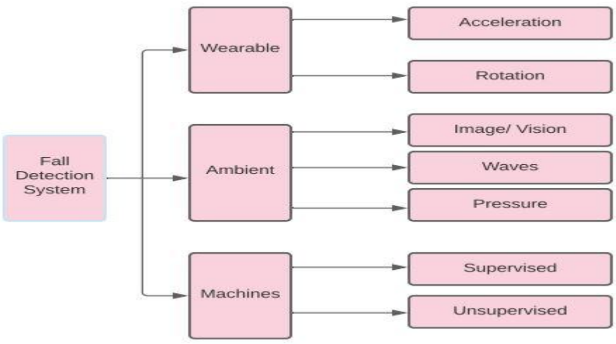

Figure 1: Classification of Fall Detection System

Figure 2 shows the criteria of article selection for the review process. All the articles were selected from primary sources. A total of 105 articles relating to fall detection were downloaded. Some articles were available in more than one source and after careful analysis of the author name, journal name and contents, duplicate articles were removed from the selection.

A total of 19 articles were found to be duplicated. The records selected for the review proposes were 85. On checking for the subject criteria and eligibility, 31 records did not qualify, and on further checking for full text, another 21 records did not qualify. A total of 32 records passed our selection criteria. This paper gives a review of the selected 32 papers.

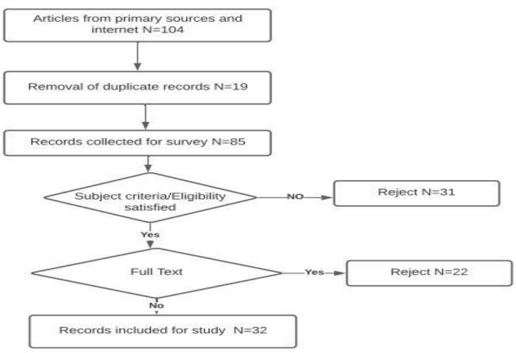

Figure 2: Article selection criteria

2. LITERATURE REVIEW

The Hoopster method is used for background subtraction [3] which is a different approach. It employs a computational color model that separates the chroma-ti-city and brightness components. When light disturbances are present, it is possible to segment the foreground much more efficiently than with earlier approaches, reducing light change sensitivity in the process. Pixels are also clustered by similarity in this approach, which reduces computational complexity. Some methods, shown in [4], use a filter to establish silhouette contours. A Sobel filter is utilized in this scenario, which determines a two-dimensional gradient for each image pixel. The system segments the foreground using the technique given in [5]. The optical flow (OF), which will be discussed in more detail, is computed to detect which objects in the image are moving, a feature employed for foreground segmentation. After that, pictures are binarized and morphological operators are applied to minimize noise. Finally, lines connecting the points denoting the center of the head and the feet form a triangle, the area/height ratio will be employed as the characteristic categorization feature. In [6], the method described in [6] mainly integrates the region-based data on color and brightness in different cod words, every code is memorized in a codebook area. Pixels are then checked. In every frame,pixelsaredeclaredforeground if their color or brightness does not match the region codeword, which encodes area brightness. Otherwise, the codeword is updated, and the pixel is declared area background.

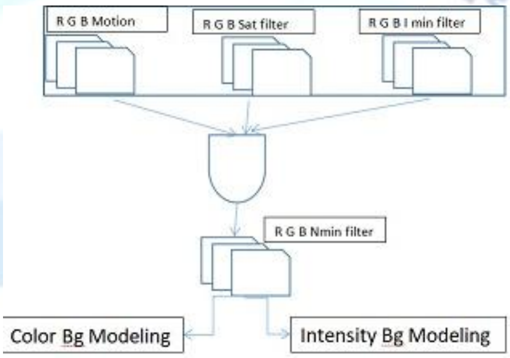

Figure 3: Hoopster methodused for background subtraction

Based on the GMM process described in [7], a human silhouette is segmented by using depth information and its curvature scale space (CSS) features are calculated by sing procedures outlined. The CSS calculation method converts the human silhouette into a parametric model. The Gaussian function is then applied to the arc length vs. curvature to represent the arc length vs. curvature.

Then, silhouette features are encapsulated with the Gaussian mixture model from the CSS process into a single Fisher vector for calculation purposes. In the final step, a block of systems creates volumes using distributions constructed around point clouds. These distributions are called voxels, and descriptions are extracted from voxel clusters. Implementing vision-based fall detection systems has traditionally been the province of ambient systems. However, robots can make them mobile,[12]and smart glasses or contact lenses could bec ome part of the future. Cloud computing may not be an option for these applications, so the computational cost will need to be considered, and low power consumption will be an essential factor. Finally, although this review has solely focused on vision-based fall detection systems, optimal performance comes from fusion-based systems that complement vision-based technologies with alternative ones.

The method adopted in the proposed work [21] is considered three main components: the height considered the maximum point of real-time accuracy and the blob area extraction of a person right from the depth frame. Thirdly from the depth data, many features can be extracted. SVM models definitions were mentioned. Multiple test performances gave the concept more accurately, that is, to 98.6%, which is acceptable and more significant than the system accuracy. The efficient fall detection is done in a statistical study mode [23] and classified in GLR chart and SVM classifier. Five partitions were made in the human body to represent five occupancy areas. For each area, input data is collected based on the area ratios. The feasibility of the deviated area is calculated using the input data in two formats GLR-SVM fall strategy is a comparison between the natural and unexpected falls, and the missing data is encrypted comparisons are made in classifiers including neural network, decision tree, K-nearest neighbor, and naïve Bayes classifiers. The most significant finding was that the combination of SVM and GLR techniques provided a method with rarer false-positive falls than other methods, making it a more exact fall-finding technique. As for upcoming work, there was a plan to integrate evidence from Kinect photographic camera (instead of RGB camera), which operates on depth imagery and preserves privacy for people being monitored.

3. LIMITATIONS AND GAPS

In [3] the authors used pixel clustering method to perform background segmentation and modelling and also used feature thresholds. Here the limitation is dataset is specific and the gap is the color camouflage in the foreground and background layer is not discussed. In [4] the approach is Gaussian mixture model along with Sobel filtering for extracting the foreground using the background subtraction method. The vision system is also able to detect Anaesthesia. The limitation is dataset is specific and the accuracy is 81% and the gap is Machine Learning approach is not used. In [5] the approach uses support Vector Machines (SVM) and robot vision images and a flow-based approach for extracting foreground. The input is in RGB and the limitation is the dataset is not available and is specific to the application. The system accuracy is 90% and the gap is only base level SVM classifier is used, No classifier is proposed. In [6] A publicly available multi-view fall dataset is used. The homo graphic projections using multiple cameras are made to the ground plane. The pixel coloring approach is used for extracting the foreground. The estimation of foreground pixel is made using polygons and the gap here is Machine Learning approach is not used. In [7] the SVM classifier is used to detect falls. The depth feature is used for fall detection and Fisher vector encoding and Curvature Scale Space (CSS). The system accuracy is 88.83%. SDU Fall dataset is used. The limitation of this approach is only single camera capture is used and the representations of fall can be mined using deep learning. In [8] the depth parameter along with SVM to extract silhouette. The torso rotation characterization is used and the limitation is the dataset is not available and is specific to the application. The system accuracy is 95.8%. Only single depth camera is used. In [9] the approach is the feature threshold method to extract the foreground through background subtraction using Gaussian Mixture Model. The system input is in RGB and the limitation is the dataset is specific and the accuracy is of the model is not specified. Here also the gap is only a single camera is used. In [10] the difference in depth frames and the position of head tracking gives the foreground extraction of the image. The public SDU Fall dataset is used and the accuracy is 92.98%. The limitation is head localization was not discussed and Only 20 scenarios were taken into consideration. The backward fall and fall threshold was not discussed.

In [11] SVM library LIBSVM is used. The features are extracted using the Deep Learning framework by combining histograms of oriented gradients and Local binary patterns. SIMPLE Fall Detection Dataset ND Multicam Fall Dataset is used with an accuracy of 93.7%. The data size is small in this reference and the gap is it falls in different directions was not mentioned. In [12] the system selects fall using GMM to analyze shape change in human silhouette. The foreground is extracted by the method of background subtraction. The accuracy of the system is 92%. Dataset is specific to the system and the gab is fall behind static object only detected in this reference. In [13] it uses the gestures of the human body for fall detection along with segmentation. The human upper body database is created and based on human height and width, the fall is detected. It Uses the feature threshold approach. The dataset used is LE2I and the accuracy is 81.55%. The limitation was not used in natural video surveillance system. The gap is Machine Learning approach is not used. In [14] the ma thematic morphology technique removes the foreground from the background in the image. The motion vectors are computed using optical flow compute the motion vectors. Mean directions were found using the von-mises distribution. The accuracy of the system is 91%. The limitation is only CHARFI2012 Dataset is used and the gap is fall direction and classifier not used. In [15] it was used a depth Skeleton joint tracking model to predict the fall. The bounding box polygon technique are also used. Here the Dataset is specific and the gap is with constant depth change, the bounding box cannot track the object. In [16] the GMM technique is used for extracting the foreground. The K Nearest Neighbour (KNN) algorithm is used on the silhouette. The input signal is in RGB. Dataset is specific and the gap is occlusion, state differentiation and illumination changes are not mentioned. In [17] the approach uses the Hidden Markov Model (HMM) to extract the foreground from the background. The input signal measures the depth. The accuracy of the model is 84.72%. Here also dataset is specific and occlusion, state differentiation and illumination changes are not mentioned. In [18] depth is used for the extraction of the silhouette. Foreground segmentation takes place. Depth difference is used to create a feature vector. The classifiers random forest is used for pose recognition at the pixel level. The SVM is used for the identification of movement. The limitation is the sensor which is used to determine to standing, sitting and falling posture. The data is input to random forest and the gap is the sensor is used to determine to standing, sitting and falling posture. The data is input to random forest and the gap is Illumination changes are not specified. In [19] the depth information along with the threshold is used to identify head velocity. The system works with occlusions. The limitation is only rigid fall is modeled and the gap is not used in any other type of sensors. In [20] the silhouette is extracted using depth information and an ellipse is bound around the silhouette. The SVM classifier is used. The dataset used is Depth and Accelerometric Dataset. The limitation falls in all scenarios like sofa and bed not covered.

In [21] depth information along with SVM classifier id used to extract out the foreground from the background. The limitation is only a single device is used and the gap is more number of sensors was not used to cover more area. In [22] an optical level image sensing system is specified using Conventional neural networks; The facial boundary is anonymous to protect privacy. The training and test dataset are public-ally available. The hold-out validation strategy is used for evaluating the accuracy. The limitation is the rate of false alarms is high and the gap is depth information was not used. In [23] The pixel-based feature is extracted for detecting falls. The generalized likelihood ratio (GLR) is used. The SVM is used to overcome the drawbacks of GLR. Classification is performed using SVM. The limitation was having the accuracy 93.3% on public dataset Unfall detection and Fall detection dataset and the gap is depth information was not used. In [24] the method uses depth information and performs segmentation. The features are extracted and the map is created using CNN. Soft-max is used in the CNN model. The limitation dataset is specific and the gap is behavior impact on fall was not analyzed. In [25] the method describes two states as fallen and falling. The perceptron (MLP) and Random forest are used for classification. The other classifier used is KNN. The pixel points are identified using CNN. The limitation is fall detection in an outdoor environment not specified and the gap is the baseline classifiers like Random Forest was only used. In [26] CNN is used to identify the critical pixel points of humans and was based on linear logistic classification. Here the usage of dataset is specific and the gap is occlusion, state differentiation and illumination changes was not mentioned. In [27] the input signal is

RGB and the feature points are generated using CNN. The artificial Neural Network uses soft-max in the last layer. The architecture is VGG 16. The YOLO is used for tracking. The limitation was that all direction fall was not specified. Depth information was not considered. In [28] the threshold-based system uses CNN to identify human pose. The feature is extracted using a vertical velocity of the hip and ground angle plane. The limitation is only side action is captured and was not from all directions and also depth information was not considered. In [29] The method integrates IoT with machine learning techniques. The findings were that the KNN classifier is better than the other classifiers tested. The k fold validation technique on two datasets was used. The limitation is the rate of false-positive is high and the gap is an optimal algorithm in machine learning not specified for fall detection. In [30] the approach uses AlexNet Neural Network and wearable devices to detect falls. The system does not specify optimized learning algorithms. In [31] a pipeline approach to detect falls is made with classifiers. It is found that simple machine learning classifiers perform better. The experiments were performed on six publicly available datasets. In-depth machine learning technologies are not used and deep learning approach was not mentioned. In [32] An approach in CNN is presented in LSTM network acceleration and angular velocity sensors. The CNN uses ResNet18 architecture. The limitation was the network which is used is redundant and deep learning approach was not mentioned.

4. FINDINGS

In today's worldwide the elderly population is increasing at faster age and will soon overcome the number of teenagers. Countries like Japan and Canada are facing this problem. Many resources will be made available to the elderly community, and unmanned 24 hours fall detection systems will get much attention. In the elderly community, 28% experience fall in a year and some of them are related to deaths. Of all the technologies available, deep learning using complex machine learning classifiers has made a remarkable impact. The use of depth information than the conventional RGB has its own advantages. A deep learning system using high-class complex machine learning classifiers and depth information and camera data from multiple angles is required for an effective fall detection system.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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