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A Review on Recent Developments on Detection of Fall

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Abstract

Remote patient monitoring has always been a difficult problem in the medical field. Fall detection during monitoring is essential because falls are unexpected behaviors that can seriously affect a person's health, particularly those who are older. Accidental falls have moved to the top of the lists of general health issues in the past few decades. A fall detection system, with the emerging development of the technology, aims to decrease the number of deaths, injuries and the economic burden on the healthcare system. This study presents an in-depth analysis of the latest published research on vision-based detection of falls. It also covers the merits, demerits, and challenges of the previous works of vision-based fall detection, and the future scope of the research is also summarized.

Keywords: Fall detection system, Vision-based, Machine learning, Threshold-based, Pose estimation

1. Introduction

[1] Falls are among the main causes that may lead to severe health issues such as mental status, balance instability, functional impairments, chronic disease, and sometimes even death. The chance of falls in the elderly can rise by 31%, which is mentioned in statistics [1], as a result of medical conditions like Parkinson's disease and medicines like sedatives and antidepressants. The facts about falls are mentioned in Fig. 1. Based on the data [2], falls among older Indians can occur at a rate of 14% to 53%. To offer prompt assistance, a fall monitoring technique is vital. It can reduce the severity of the injury as

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well as death in most cases.

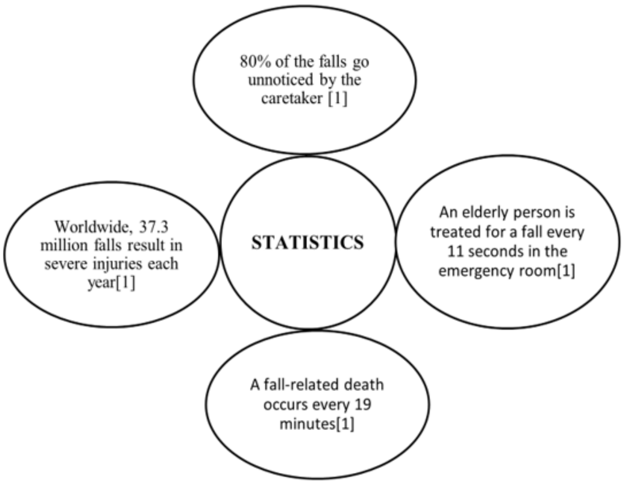

Figure 1. Statistics on Fall

The mechanism for detecting falls can be classified into three types, as shown in Figure 2.

- Systems that make use of sensor-equipped wearable devices
- Systems that rely on context-aware devices (non-wearable devices)
- Systems combining computer vision capabilities as well as machine learning algorithms

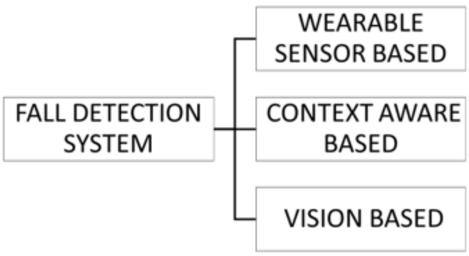

Figure 2. Classification of system which recognizes falls

Wearable accelerometers, barometers, inertial sensors, and gyroscopes, which may be embedded in cellphones, necklaces, or smart wristbands, are used in sensor-based fall detection approaches [42] in order to detect slips. However, because the participants' bodies must have the devices implanted, they are often painful and impractical. The detection of falls using sensors is divided into two main groups. They are, respectively, threshold-based and fall detection based on machine learning. Both approaches entail gathering and extracting motion data from sensors. The retrieved features are utilized in machine learning techniques [3] to train models that are then used to categorise new motion data. Threshold-based systems [4] group the motion data by comparing its calculated features with defined values.

In context aware fall detection methods [5], detectors are installed in the person's surrounding environment. Pressure sensors, floor sensors, infrared sensors, and microphones are some of the sensors used to detect the fall. A dedicated PC is connected to them, and the acquired data is transferred to the computer for further processing and analysis.

The main issue with wearable and context aware based methods [42] is that they require bulky hardware components, which results in high costs. Some systems rely on base stations and radio frequency. This base station, which is strategically located in one's home and hardwired to a phone line, then contacts a call center for assistance. The disadvantage of these systems is that they all require an intermediary call service, which costs a lot of money every month.

Vision-based techniques [38] observe a person's real-time movement using a standard video camera or a depth video camera, and an algorithm is performed in the background to identify the person's posture. When a falling posture is recognized, an alarm is issued to call for help. The main advantages of vision - based fall detection methods are more user-friendly and environmentally friendly. They may be used to monitor multiple people at once, and a single video can capture more detailed information than any other sensor deployed in the surrounding area.

This study focuses on the positives and negatives associated with employing vision-based techniques to identify falls. This document is structured as given below. The overview of the literature on fall methods for detection is included in Section 2. Section 3 contrasts the approaches used today. The proposed suggestion for potential implementation is presented in Section 4 to wrap up this survey.

2. Literature Survey

Numerous techniques for detecting falls based on vision have recently been developed. The primary benefit of computer vision-based solutions is that they are,

- Non-intrusive,
- Non-invasive, and
- Not easily affected by noise.

The following sections cover the most widely used methods to identify the fall.

2.1 Fall Detection using Threshold based Algorithm

The threshold-based technique operates on a predefined threshold value which can be compared with the real time value. Based on the result, the actions are identified.

Caroline Rougier et al. [6] devised a novel threshold-based fall detection system that is based on movement past data and human shape alteration. A calibrated camera was used to capture videos and the history of motion and variation in human shapes were extracted. A manual method was offered to select the threshold using logical reasoning. The supervised method obtained 88% sensitivity and 87.5% specificity on the collected videos containing 24 normal activities and 17 simulated falls.

Another method used the one calibrated camera to extract the 3D head trajectory of a person in a room, and a hierarchical particle filter was used to track the individual using a 3D ellipsoid that represents the head. This method was suggested by Rougier C et al. [7]. The 3D locations were approximated, which is enough for the majority of activity recognition based on trajectories. A mean inaccuracy of 5% per 5 meters was obtained using the Human Eva - I dataset.

Yoosuf Nizam et al., [8] proposed a vision-based system that uses a Kinect sensor to collect the necessary depth image for computing the subject's velocity and position. These data from each successive frame were utilized to compute the velocity of the body in order to detect any unusual activity that occurs continually inside the sensor's field of view. If abnormal action is recognized, the subject's position is estimated from the next few frames to establish that the activity resulted in a fall. If there is no abnormal velocity detected, the process will display the coordinates and restart. The velocity pattern from the activities aided in classifying potential fall movements. The experimental findings demonstrated that this can distinguish human falls from other activities of daily life with an average accuracy of 93.94%.

2.2 Fall Detection using Background Subtraction Method

Most of the existing methods uses the background subtraction methods [37]. Background subtraction [37] is an approach for separating objects that move from their surrounding space. Some of the methods of background subtraction are given in Figure 3.

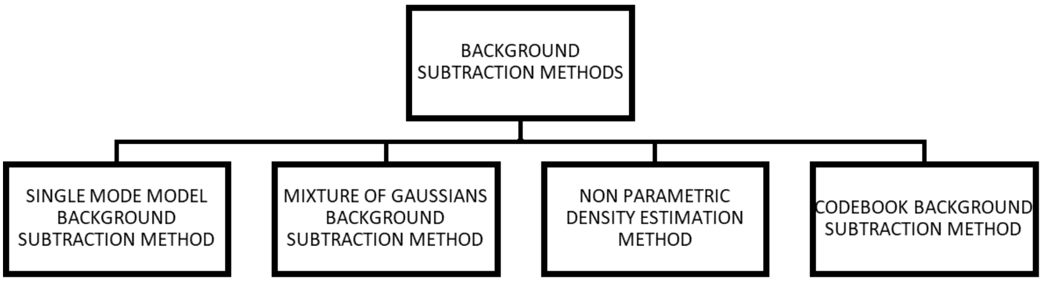

Figure 3. Background Subtraction Methods

The commonly used background subtraction method [37] is the codebook background subtraction method because of its advantages mentioned in [13]. The advantages of codebook subtraction methods are resistance to acquisition, adaptability to lighting, adaptable and compressed background models, and unconstrained training.

G. Debard et al. [9] analysed the performance of a fall detection algorithm when simply background subtraction is used, when a particle filter was used to track the person, and when a hybrid method was used. Five wall-mounted IP cameras were used to record 70 videos, 46 of which were fall videos and 24 of which were ADL videos. The hybrid technique improved the fall detection algorithm's sensitivity and reliability, yielding a sensitivity of 76.1% and a PPV of 41.2%. G. Debard et al. [10] demonstrated an innovative method based on background removal and basic metrics extracted from the foreground object, that include aspect ratio, fall angle, and head speed.

The method developed by Debard et al. in [11], is the development of [9] and [10]. [9] was used to detect the person in each video frame, and five fall detection features were combined into feature vectors for each second in the video stream. Further, optional steps were added to evaluate whether the algorithm could be improved. Precision-recall curves and Areas Under the Curve (AUC) were utilized to measure the accuracy of camera combinations as explored on the fall dataset along with a combined set of fall and ADL activities. It was reported that using the average of the confidence levels from five cameras produces the greatest results, with an AUC of 0.445, a 218% increase.

2.3 Fall Detection using Machine Learning Method

Machine learning methods works well in detecting fall. Nicholas Thome et al. [12] developed a Multiview method for finding falls whereby motion is given by a Layered Hidden Markov Model (LHMM). Dual cameras were used, and a fusion unit was performed for posture classification by merging the decisions provided by individual cameras which were working independently in a fuzzy logic context. The final decision was made by using a LHMM. The works were experimented on the dataset, which contains 50 fall and 50 non fall videos. A detectability fall rate of 82% for a single view and 98% for a multiview system were obtained.

M. Yu et al., [13] recorded the videos by using a USB camera. Background subtraction was applied to extract the foreground human body, and post-processing was used to improve the result. For the task of posture classification, ellipse fitting and the projection histogram were employed as characteristics that may be fed into the Directed Acyclic Graph Support Vector Machine [46]. The algorithm obtained an excellent fall recognition rate (97.08%) and an extremely low false-positive rate (0.8%) on a 15-person dataset that encompasses 3200 postures from the recorded videos.

A. Abobakr et al., [14] introduced a method that is a combination of both posture recognition and the spatio-temporal method. A calibrated background frame was subtracted, a Random Decision Forest model was applied to the foreground body pixels, and an SVM model was used to detect fall events. The video clips were captured using the Kinect sensor, and the datasets utilized were synthetic and live, reaching 99 percent sensitivity. Research [15] stated that supervised fall detection systems do not provide an individual-specific solution, demand a big dataset, and are negatively affected by occlusions. These difficulties can be solved via unsupervised approaches.

The ceiling-mounted broad-angle camera was put into use by H. Nait Charif et al. [16]. Over two days of changing weather, 97 sequences at 30 Hz with a resolution of 480 x 360 pixels were considered. Two entrances to the room, a chair and a sofa, were labelled as semantic zones. The authors tracked the overhead of the human body with an elliptical model using the particle filter approach. 13 annotated sequences were created, and an expectation maximization method was used when a person's position was outside the usual activity region for longer than the preset time threshold.

C. Rougier et al., [17] presented a new GMM classification method using human shape deformation analysis. 75 different events were collected, and it was found that the edge point matching step was robust to occlusions and other segmentation difficulties, and the addition of edge points within the silhouette (the Canny filter) generally helped to improve the results. The important key points that the peak representing the fall is an important feature to characterize a fall, but the lack of movement after the fall is also important for robustness when occlusions occur, were defined. The system can run in real time at 5 frames per second. But the disadvantage of unsupervised methods is that these models are not updated regularly.

A semi-supervised vision-based fall detection approach was published by M. Yu et al. in [15]. The authors used a single USB camera to extract the three features—ellipse features, shape-structure features, and position feature and the codebook, the best background subtraction model was employed. By combining the One Class Support Vector Machine (OCSVM) classification result with two criteria that quantify the movement amplitude and duration of an unusual posture, a standard OCSVM technique was developed and updated live using the extracted features.

2.4 Fall Detection using Pose Estimation Methods

Pose estimation techniques were used to extract the individual's skeleton's characteristics. In the pose estimation, there are two methods, as illustrated in Figure 4. While bottom-up techniques like Alphapose [30] and Dcpose [43] first locate the keypoints and then identify the objects, top-down approaches like Openpose [31], Openpifpaf [44], and Movenet [45] immediately identify the keypoints.

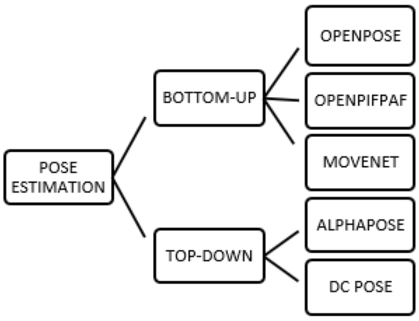

Figure 4. Approaches of Pose Estimation

The keypoints are gathered, and then they are tracked from frame to frame. Action recognition can be done from the extracted skeleton features. The basic workflow using human skeleton features are mentioned in Figure 5.

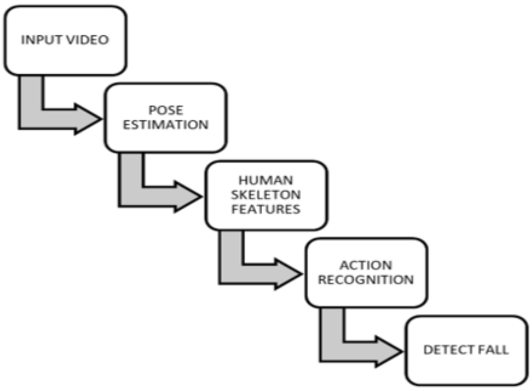

Figure 5. Methods to detect fall using human skeleton features

Openpose [31] was successfully used by Chen, et al. [18] to extract people's keypoints. By using this method, the author extracted 12 key points. The fall was identified using three important parameters: hip joint speed of descent, centreline angle with the ground, and width-to-height ratio of the human body's external rectangle. 100 videos with 10 experimenters were recorded, and also took into account people standing up after falling, with a 97% success rate.

Using video footage from a normal camera, H. Ramirez et al. [19] estimated the human skeleton using Alphapose [30] and applied four classifier models to identify the motion, including random forest, support vector machine, multilayer perceptron, and K-NN. When compared to other fall detection and activity identification algorithms, this technique outperformed on the UP-fall public dataset.

Alphapose [30] is the most accurate human posture estimator, while Transformer outperformed LSTM in the action recognition task, according to [20], which was the investigation of the benefits of using human pose estimation algorithms from five different methods, including Dcpose [43], OpenPose [31], OpenPifPaf [44], and MoveNet [45]. The real-world videos were gathered and were turned into the artificial intelligence hub dataset, which is a synthetic dataset. Experiments were run on that dataset and very good results were obtained.

3. Dataset

The dataset used in the existing systems are shown in Table 1.

Table 1. Dataset used in the existing systems

Ref. no.	Name of the dataset	Year	Total
[21]	Le2i	2013	191 videos
[22]	University of Rzeszow Fall Detection	2014	70 videos
[23]	High Quality Fall Simulation Dataset	2016	Recorded video of 2:25:54 hrs
[24]	Fall Detection Dataset	2017	22,636 images
[25]	UP fall Dataset	2019	296,364 samples of raw sensor signals and images.
[26]	AI hub dataset	2020	2500 videos

4. Comparative Analysis

Table 2 contains the methodology, devices and the dataset used in the existing systems.

Table 2. Summary of the existing methodology

Ref. No.	Year	Methodology	Dataset	Result
[6]	2007	Motion history and human shape variation features compared with threshold value	24 normal activities and 17 simulated falls	Sensitivity- 88% Specificity- 87.5%
[7]	2010	3D head trajectory features compared with threshold value	Human Eva-I	Mean error 5% at 5 meters
[8]	2016	Velocity and position features compared with threshold values	Videos of simulated fall & ADL activities	Accuracy 93.94%
[9]	2015	Background subtraction + Particle filter	70 videos of 46 fall and 24 normal activities	Sensitivity 76.1%
[11]	2017	Background subtraction (5 features extracted)	Fall dataset	AUC-0.445
[12]	2008	Layered Hidden Markov Model	50 fall and 50 non fall videos	Detect fall rate of 82%-single view, 98%- Multiview
[13]	2011	Directed Acyclic Graph Support Vector Machine	3200 postures collected from 15 people	Fall detection rate 97.08%

Although the threshold-based method is straightforward, selecting the appropriate values as a threshold is quite tough. If the threshold value is too low, it may frequently anticipate incorrect results. The background subtraction method [37] is effective and fast; nevertheless, the fundamental problem is that it is confined by leaving the background unaltered and not applying appropriate foreground object models, as stated in [27].

The machine learning techniques [38] require time since human activities take place in a matter of seconds. Moreover, it can take only few features to decide whether the fall has occurred or not. But the pose estimation approaches work well since it can extract all the human keypoints. Particularly Alphapose [30], works well for detecting the fall because it is a top-down approach that can quickly detect complicated poses and is free of ambiguous appearance. Table 3 contains the existing system that uses pose estimation methods.

Table 3. Pose estimation methods

Ref. no.	Year	Method	Dataset	Result
[14]	2018	Openpose [31]	100 videos	97% success rate
[28]	2020	Alphapose [30], Openpose [31], LCRNet++ [32]	Toyoto Smart home dataset [34]	Cross subject 62.1%, Cross view 54%
[19]	2021	Alphapose [30]	UP-Fall dataset [25]	99.34% Accuracy
[29]	2020	Alphapose [30], Openpose [31], Posenet [33]	URFD [22]	94.5% sensitivity and 99.5% specificity

5. Conclusion

This study provides a comprehensive analysis of the existing methodologies and algorithms for detecting falls utilizing various machine learning algorithms, background subtraction algorithms, threshold-based algorithms, and pose estimation approaches. This study found that pose estimation approaches combined with action recognition perform well because it is capable of extracting a greater number of human body keypoints which are very efficient for the fall detection task. The main problem with most of the methods is that it can detect only a single person at a time. In future, Alphapose method might be used to track multiple people at a time and ST-GCN might be the best method for action recognition since it works on non-Euclidean data and has the capability of predicting each person’s action separately.

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