Automated Fall Detection Using Computer Vision

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Abstract. The population of elderly people is increasing day-by-day in the world. One of the major health issues of an old person is injury during a fall and this issue becomes compounded for elderly people living alone. In this paper, we propose a novel framework for automated fall detection of a person from videos. Background subtraction is used to detect the moving person in the video. Different features are extracted by applying rectangle and ellipse on human shape to detect the fall of a person. Experiments have been carried out on the UR Fall Dataset which is publicly available. The proposed method is compared with existing methods and significantly better results are achieved.

Keywords: Human fall detection · Computer vision
Background subtraction · Elderly care · Assisted living

1 Introduction

Caring of elderly or ailing people, who live alone, is one of the most important concerns in a family. One of the most dangerous situations is a person falling when alone at home. Approximately 60% injuries in the case for elderly in hospitals are due to falls. Falls affect the elderly people living alone because the person may not be able to call for help, such as if he or she is unconscious or paralyzed. In general, a person who is alone needs help if he or she has fallen. This is more necessary in case of ailing or elderly people. A fall at home can occur in many situations, like falling from bed, loss of balance, fall from walking and fall from a sitting or standing position.

According to the European Union Commission and the World Health Organization [1], the population of older people will increase threefold between 2008 and 2060. In this report, it is mentioned that every year approximately $28-35\%$ people over 60 and $32-42\%$ over 70 years of age, fall and these numbers are increasing. This increasing population of the elderly makes caring for old people a greater challenge. Not all falls create serious injuries but most of the time elderly people are unable to get up without help of others after falling and the time period which is spent lying on the floor can also create some health problems like dehydration, hypothermia, etc.

U. S. Tiwary (Ed.): IHCI 2018, LNCS 11278, pp. 220–229, 2018.
https://doi.org/10.1007/978-3-030-04021-5_20

There are many existing methods which are based on wearable devices [3–8]. These methods use an accelerometer and a gyroscope to detect a fall of a person. However, the person feels uncomfortable after wearing such devices for a long time and if the person forgets to wear it, falls can no longer be detected. Therefore, visual monitoring has greater advantages. Computer vision based approaches provide an inconspicuous and non-intruding way of observing objects, people and their activities, i.e., the person does not wear any device. Such approaches are not affected by noise, unlike other non-vision based devices which may be affected by noise. Some other advantages are as follows.

Computer vision systems use a camera that has the advantage of observing and storing vast amounts of information of the scene in its view. The other advantages are that the camera has the capability of identifying multiple events at the same time. Also, a camera is less intruding because it can be fixed in a structure and need not be worn by the person. The video recorded by the camera can be used for remote processing and verification. Moreover, a camera system may be easily installed and the user need not have any expertise in using the system.

In our framework, we process the video frame by frame. The processing step gives the contour representing the human body. We then extract features that describe a fall and use our learning based algorithm for fall detection in videos.

We continue the paper as follows. Section 2 provides discussion of similar work is presented. In Sect. 3, we describe the proposed method for detecting fall of a person. In Sect. 4 , we show our experimental results and compare the performance of our proposed method with the state of the art methods. The main findings and possible future directions are summarized in Sect. 5.

2 Related Work

The first fall detection system was proposed in the early 1970s [9]. It was designed in such a way that it can send an alert message when user pressed a remote transmitter button. Automatic fall detection method started appearing in 1990s [10] which was proposed by Lord and Calvin. This system was based on accelerometer.

Muheidat et al. [11] proposed a context-aware and real time fall detection system for elderly. The system consisted of sensors which are placed under carpet and the electronics reads the walking activity. Then smart phone is used to improve smart carpet for improving the efficiency to detect the fall. Joshi et al. [12] proposed a fall detection system using computer vision and internet of things. Single camera is used to capture the different activity of the person. Center of Mass, aspect ratio and orientation angle are calculated to detect the fall of a person and an email is sent with attached screenshot. Djelouat et al. [13] proposed a computer vision based fall detection system for elderly person. First, acceleration data is gathered for different activity of person. Then data is multiplied by a binary sensing matrix. KNN and extended nearest neighbor is used to classify fall from other activities.

In 2016, Merrouche et al. [14] proposed a fall detection method using computer vision techniques and camera. This system used human shape analysis, head tracking and center of frame detection methods. Relationship between time and distance, translated by covariance, is calculated for discriminating falls. The system achieved 92.8% accuracy. Wang et al. [15] presented a fall detection method using RGB camera. Background subtraction method is used to detect the moving object. Then contour of the body is extracted to obtain width and height of the human body. Speed of the human body is calculated using an optical flow method. Then fall of a person is detected based on magnitude and direction of body. Wang et al. [16] proposed a method for detecting fall of a person. A vision component is used to detect and extract the moving person in the video. Then histogram of oriented gradients, local Binary Pattern and feature extraction by the Deep Learning framework are used to detect the fall of a person. The system achieved 93.5% sensitivity and 92% specificity.

Rougier et al. [17] proposed a fall detection which is based on the analysing human shape in a video. A shape matching method is used to keep track of the posture of the person in the video. The shape deformation is quantified from these postures using shape analysis methods. Fall of a person is recognized using the Gaussian Mixture Model. Lazzi et al. [18] proposed a fall detection system using video. First, images are captured and then background subtraction method is used to detect the moving object in the video. They, then apply some processing method to improve the result. After that different features are extracted for detecting the fall of a person. Yajal et al. [19] proposed a fall detection method using directional bounding boxes. The method was evaluated in the video using RGB-D camera. Aspect ratio is calculated to monitor the movement of the person. Diaz et al. [20] developed a dynamic background subtraction method for detection of fall of a person using 2D camera. Background subtraction method is used to detect the moving object from the images. Then movement detection method is used to detect the fall of a person. The system achieved up to 85.37% accuracy.

Ma et al. [21] proposed a fall detection system via shape analysis using a camera. Two computer vision techniques, shape-based fall characterization and learning based classifier, are used to detect the fall form other daily living activities of a person. The system achieved 91.15% sensitivity and 77.14% specificity. Chua et al. [22] proposed a fall detection method using uncalibrated camera. The method combined human shape and human head detection together to recognize the fall of a person. Different features are extracted from fitting the ellipse to detect the fall. The head detection method is used to differentiate fall from other daily living activities of a person. Dumitrache et al. [23] presented a fall detection method which is dependent on triaxial accelerometer data. This algorithm was designed to be implemented in a mobile system that uses a micro controller for data processing and a tri-axial accelerometer for data acquisition. Xiao et al. [24] proposed for detecting fall activities by using Gaussian mixture model (GMM) and spatial temporal analysis of aspect ratio. First, GMM is used to get background and foreground part of image. Then aspect ratio feature are calculated from the minimum external rectangle of person. By using spatial temporal analysis of aspect ratio, the system output the fall behaviour more robust. Khawandi et al. [25] developed a framework of fall detection which uses different machine learning algorithm. The algorithm easily learned the data, classified the data and identified falls from data which is received by a multi sensor monitoring system. Then decision tree is used to classify fall of the person.

Yun et al. [26] developed a fall detection system based on analysing human shape by applying unified Riemannian manifold. It represented dynamic shapes as points moving on a unit of n-sphere and computed velocity corresponding to manifold points which are based on geodesic distance. The proposed system achieved 96.77% detection rate and 10.26% false alarm rate.

3 Fall Detection Method

We detect the fall of a person in a room environment. Here, we assume that a camera is mounted in the room in such a way that it can cover a large area of room and there are no major occlusions in the room. We also assume that the focal length and field of view (FOV) of the camera does not change. The camera captures the scene frame by frame and sends it to the on board computer. Again, the input image is of size 320×240. The experiment is done on UR Fall dataset [2] which is publicly available.

3.1 Background Subtraction

In a video sequence, identifying moving objects is the fundamental and critical task. The most common method to detect moving objects in the video is background subtraction. Background subtraction which is also known as foreground detection is a technique to detect moving objects in the video sequence. Here, we use the Mixture of Gaussian (MoG) method to detect moving objects (which includes the person) in the video as shown in the Fig. 1

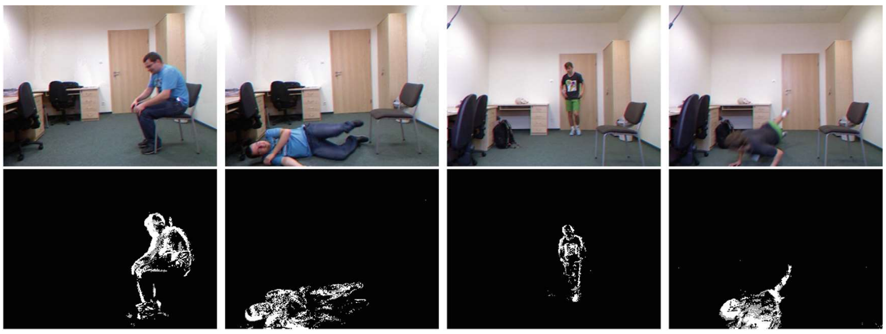

Fig. 1. Result of background subtraction.

3.2 Morphological Operations

Morphology is a large set of image processing operations that process the image which is based on architecture. These operations take input image and then apply a structuring element to that input image and generate output image which is of similar size. In these operations, every pixel value in the resulting image is based on correlation of the related pixels for the input image with its adjoin image. Erosion and dilation are the most basic morphological operation. We have taken the output of background subtraction technique and applied dilation and erosion on those images to get the proper connected components which may be lost during foreground segmentation.

3.3 Extraction of Connected Components

This method scans the images and combines the pixels into component which is based on pixel association, i.e. all pixels in a connected component divide same pixel values and these values are connected to each other. Once all clusters are calculated, every pixel value is marked with a colour or gray level based on the component it is allowed to. Connected component trademark works by searching an image, pixel by pixel in order to find connected pixel areas. Here, we have used 8-connected component so that whole human body could appear all together. A big contour is most probably caused by a large area for human body. A small contour is also found due to some noise i.e. lighting effect, moving cutting, etc. Upon this observation, a filter is applied on the list of contours to extract those contours that fall between two limits. A suitable range of these two limits are found experimentally.

3.4 Extraction of Contours

The contour extraction stage has been able to remove a significant amount of noise and unwanted objects. A big contour is most probably caused by a large area for human body. A small contour is also found due to some noise. Upon this observation, a filter is applied on the list of contours to extract those contours that fall within a threshold. A suitable range of the thresholds are found experimentally. At this stage, we have a list of contours that are most likely to represent actual human body shape.

3.5 Our Proposed Method

We process the video frame by frame. First, we apply background subtraction method to detect the person from the video. Then we extract those contours that represent the actual human shape in the video. After recognizing the contour, we fit the ellipse and rectangle as shown in the Fig. 2 After fitting ellipse and rectangle, we calculate the area and orientation of the ellipse and the aspect ratio of the bounding rectangle frame by frame and apply incremental clustering to it. In the first frame, we create the first cluster using the aspect ratio of

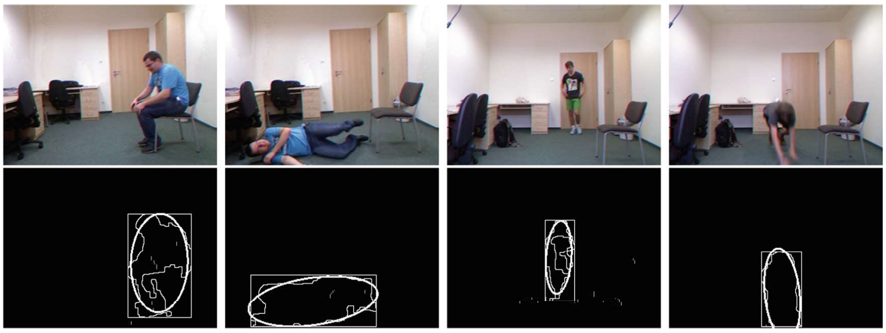

Fig. 2. Results of ellipse and rectangle fitting on the segmented foreground.

bounding rectangle, area and orientation of the ellipse as the features. When a new frame comes, we again calculate these parameters and compare it with the feature values of the existing clusters, for each feature separately. If there exists similarity with an existing cluster, we put it in the same cluster. Otherwise we create a new cluster, with these features as the first element. For more than one element in a cluster, the average of the feature values are used for comparison with the new features.

Let X_1,X_2 and X_3 are the three variables where X_1 is the angle of ellipse, X_2 is the area of the ellipse and X_3 is the aspect ratio of the rectangle. First, we find the height and weight of the ellipse and then area of the ellipse is defined as

$$X_2 = PI * (H/2.0) * (W/2.0) \tag{1}$$

Here, we divide H and W by 2.0 for maximum and minimum radii. After fitting the ellipse, now we fit the rectangle. Then, we find the aspect ratio of the rectangle, which is calculated as:

$$Aspect\,Ratio = \frac{width\,of\,the\,rectangle}{height\,of\,the\,rectangle} \tag{2}$$

Now, we take these parameters and apply clustering method to detect the fall of a person in the video. Three conditions are applied together:

1. The angle of ellipse lies between 5 to 40 or between 70 to 100 i.e. $0 \leq X_1 \leq 50$ or $70 \leq X_1 \leq 100$.
2. The area of the ellipse lies between 4000 and 12000 i.e. $4000 \leq X_2 \leq 12000$.
3. The aspect ratio is greater than 1 i.e. $X_3 > 1$.

4 Experimental Results and Discussion

The proposed algorithm has been implemented using C++ and OpenCV open source computer vision library version 3.0 on Linux operating system. In the dataset [2], there are total 60 video segments which are taken for fall detection and 40 video segments for daily activities like bending, sitting, walking, etc. In this system, only RGB-dataset is taken for detection of fall of a person. There are some healthy person and old person in the dataset and there is no large occlusion occurs in the room. The implemented algorithm runs on Linux operating system of type 64-bit with clock speed of 2.4 GHz, 6 GB of RAM running at 1333 MHz. Before measuring the frame per second on each dataset, CPU scaling was turned off to ensure that it runs at constant 2.4 GHz all the time on all these datasets. The proposed method detect fall either from walking or from chair. When a person falls, it shows red rectangle and write fall on the image as shown in the Fig. 3.

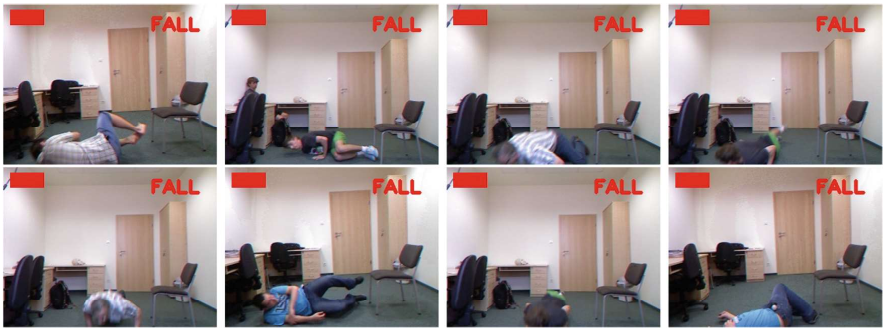

Fig. 3. Fall of a person in different situations. The red box indicates that the fall is correctly recognized. (color figure online)

For daily activities, it shows green rectangle on the image as shown in the Fig. 4. Again, comparison is made with 3 existing methods in terms of the sensitivity and specificity as follows:

$Sensitivity = TP/(TP + FN)\, and$
$Specificity = TN/(TN + FP)$
where TP, FN, FP and TN is defined as:
$TP(TruePositive)$: the number of falls correctly detected.
$FN(FalseNegative)$: the number of falls not correctly detected.
$FP(FalsePositive)$: the number of normal activities detected as a fall.
$TN(TrueNegative)$: the number of normal activities not detected as a fall.
Here, high sensitivity means most fall activities are detected correctly. Similarly, high specificity means that most daily activities are not detected as fall.

The proposed system achieved 99.10% sensitivity and 97.10% specificity (Table 1).

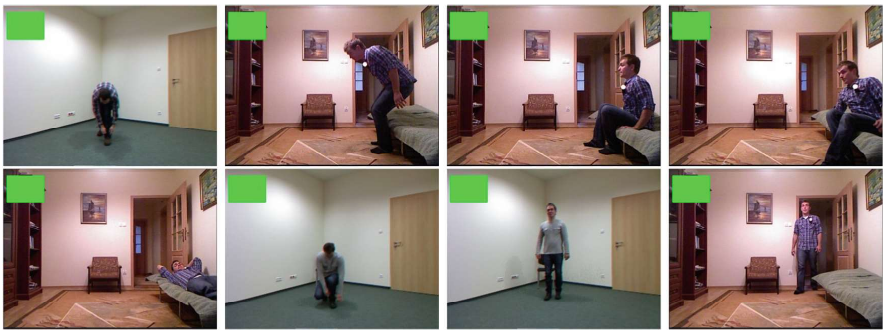

Fig. 4. Daily living activities of a person. The green box indicates that the activity is correctly recognized as "Not Fall".

Table 1. Comparison of different methods in terms of sensitivity and specificity.

Method	Sensitivity(%)	Specificity(%)
Rougier et al. [17]	95.40	95.80
Ma et al. [21]	99.93	91.67
Yun et al. [26]	96.77	89.74
Proposed method	**99.10**	**97.10**

5 Conclusion and Future Work

In this paper, we have proposed a novel framework for automatic fall detection of a person in the room. In our framework, first contours are extracted from video frame by frame through a series of low image processing methods. After that rectangle and ellipse are applied on human body shape and by taking three different features, falls are recognized. The experimental result shows that our algorithm gives good result. Our proposed system assumes that there is no large occlusion in the room. In the future, we will attempt to recognize fall in more challenging conditions as well as different daily living activities of a person.

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