An Efficient Fall Detection Method for Elderly Care System

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***Abstract*—**Fall detection is one of the challenging problems in elderly care system. The objective of this paper is to identify falls in elderly care system. In this paper, an efficient fall detection method is proposed to identify falls using correlation factor and Motion History Image (MHI). The proposed method is tested on URF (University of Rzeszow Fall detection) dataset and evaluated with some efficient measures like sensitivity, specificity, precision and classification accuracy. It is compared with other recent methods. The experimental results substantially proved that the proposed method achieves 1.5% higher sensitivity when compared to other methods.

***Keywords*—**Pearson correlation coefficient, motion history image, human shape identification.

I. Introduction

THE occurrence and detection of fall are increasing in elder people. This makes the researchers and health care professionals to create an efficient method in order to detect and prevent these uncertain situations. World Health Organization (WHO) stated that the effects of falls are growing worldwide [15]. From their report, it is clear that around 28-35% people of age 65 falls every year and within that, 32-42% of people are of age 70. The fall rate increases as number of elderly people increases. Approximately, in 2050 more than one in each group of five individuals will likely be aged 65 years or above. This will probably stimulate an increased fall rate. Hence it is necessary to develop fall detection system to avoid these incidents.

The elderly falls are caused by behavioral factors, person-related factors and environmental factors. To avoid these factors arising, there is a need for assistance. Foroughi et al. [1] developed a method for detecting falls using a combination of the eigenspace approach and Integrated Time Motion Images (ITMI). Feature reduction is done using the eigenspace technique. Feature vectors obtained from the feature reduction process are then fed to motion recognition and classification. Neural Network is the one that can deal with motion data robustly. Hence it is used for motion recognition.

McKenna et al. [2] automatically obtained spatial context models by the combination of Bayesian Gaussian mixture estimation and minimum description length model for the selection of Gaussian mixture components through semantic regions of interest. Foroughi [3] applied an approximated ellipse around the human body for shape change. Projection histograms after segmentation are evaluated and any temporal changes of the head position are noted. In order to extract optimized feature vectors, researches are made in projection histograms and temporal head position changes. The extracted feature vectors are then given to a MLP (Multi-Layer Perception) neural network like Foroughi's approach [1] for classification of motions and fall events.

Tao et al. [4] developed a detection system using background subtraction method and with an addition of foreground extraction. They used aspect ratio (height over width) as features for analysis, and an event inference module that uses image sequence data parsing. Rougier et al.'s approach [5] is based on a combination of MHI and human shape variation. Analysis of shape changes in combination with analysis of inactivity using the approximate ellipse is carried out. Fall incident detection in a compressed-domain is discussed in [6].

Object segmentation within the compressed domain is applied for the extraction of moving subjects using the combination of global motion estimation and local motion clustering. Rougier et al. [7] introduced a classification method for fall detection by analyzing human shape deformation. Gaussian Mixture Model (GMM) Classifier is implemented to detect falls. Ensemble classifier is used later to combine the results of all cameras. Wu et al. [8] uniquely identified velocity profile features between normal and abnormal activities, such as falls, for automatic detection.

Vishwakarma [9] followed an adaptive approach for the detection of moving objects using background subtraction and bounding box creation. The described fall model is based on the analysis, detection and classification of features. Features extracted include horizontal and vertical gradients, aspect ratio and the centroid angle to the horizontal axis of the bounding box. Cucchiara et al. [10] instead applied a multi-camera system for image stream processing. It includes recognition of hazardous events and behaviours, such as falls through tracking and detection.

In this paper, an efficient method is proposed to detect falls. This approach is based on a combination of motion history and human shape variation. The fall is identified by correlation factor. Sudden fall is identified by little motion and at the end of the fall, no or small motion is identified. The large and small motions are identified by Pearson Correlation Coefficient (PCC).

The remaining of the paper is organized as follows: Section II explains the proposed system architecture. Section III gives the explanation of MHI, correlation factor and human shape analysis of the proposed method. Section IV provides the

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experimental analysis followed by conclusion in Section V.

II. Proposed System Architecture

The overall proposed system architecture (Level I and Level II) is shown in Figs. 1 and 2. The proposed method is developed based on the fact that sudden fall will have large motion with its previous frame and at the end of the fall, the motion will be slow.

The sudden fall can be identified by correlation factor. Initially, large motion of the person in the video sequence is detected using the MHI. When a motion is detected, the shape of the person is analyzed. During the fall, the human form changes and at the end of the fall, the person usually has few and small body movements on the ground.

A change in the human form can be identified if the detected large motion is normal or abnormal. After conversion of MHI, the shape of the person is described as ellipse. The sudden fall and motion at the end of the fall in the human shape are identified by the correlation factor. The correlation factor used in this paper is PCC.

III. Proposed Method Description

This section describes how the motion history is obtained. The human shape analysis and correlation factor are also discussed.

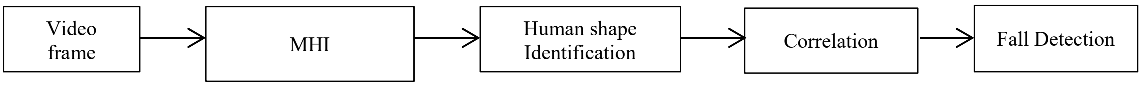

Fig. 1 Proposed System Architecture – Level I

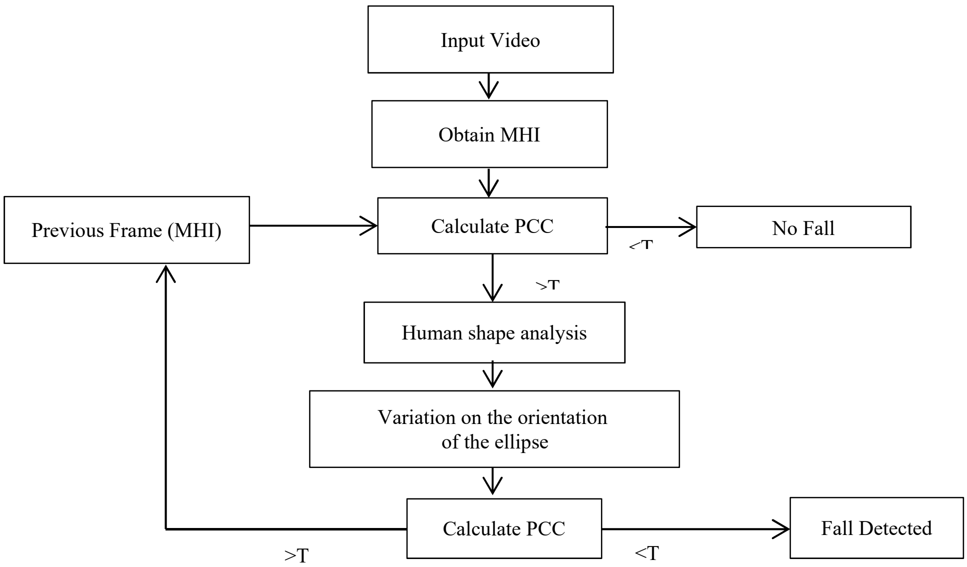

Fig. 2 Proposed System Architecture – Level II

A. MHI

Motion is very important feature for identifying fall. Serious fall occurs with a large movement. Hence, motion information is extracted from the video sequence to identify fall. To extract motion, MHI is used which was first introduced by Bobick and Davis [11].

The MHI is an image where the pixel intensity represents the recency of motion in an image sequence, and therefore gives the most recent movement of a person during an action. To define MHI, initially, a binary sequence of motion regions D(x, y, t) from the original image sequence I(x, y, t) is extracted using an image-differencing method. Then, each pixel in the MHI $H\tau$ which is a function of the temporal history of motion at that point occurring during a fixed duration τ (with $1 \le \tau \le N$ for a sequence of length N frames) [11], [12] is defined as

$$H_\tau(x,y,t) = \begin{cases} \tau & if\ D(x,y,t) = 1 \\ \max(0, H_\tau(x,y,t-1) - 1) & otherwise \end{cases} \quad (1)$$

The result is a scalar-valued image with brighter recent moving pixels. MHI is useful because motion quantification of the blob of a person is identified which is necessary for fall detection. The motion will be high in the case of a fall.

B. Correlation Factor

The sudden fall of the person is identified using PCC. It is a widely used measure for identifying similarity between two frames [13]. The value of PCC ranges from 0 (no correlation) to 1 (perfect correlation). The thresholds of PCC are given in the following subsections. The PCC is expressed as follows.

$$PCC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j)-f^m)(f_p(i,j)-f_p^m)}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j)-f^m)^2(f_p(i,j)-f_p^m)^2}} \quad (2)$$

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f and f^m specify the x-coordinates of the two frames for which the correlation is calculated. Similarly, f_p and f_p^m specify the y-coordinates of the two frames for which the correlation is calculated.

C. Human Shape

To analyze the human shape, the person is segmented using a background subtraction method, and then, the blob is approximated by an ellipse. The steps of the human shape extraction are explained below.

a. Foreground Segmentation

The moving person is extracted using background subtraction method which gives good results on image sequences with shadows and highlights. The segmented image is approximated to an ellipse. The approximated ellipse gives the shape and orientation of the person in the image.

The moving object is analyzed to detect a change in the human shape, more precisely in orientation and proportion. Next, the moving object has to be checked if there is a motion after the fall.

b. Analysis of Human Shape

If a large motion is detected (PCC < 0.8), the change in the human shape is identified as fall from another normal activity. For this purpose, two values are computed [14]: orientation standard deviation (σ_θ) and ratio standard deviation (σ_ρ) of the ellipse.

If a person falls perpendicularly to the camera, then σ_θ will be high. If the person just walks in the room, then σ_θ will be low. If a person falls parallel to the camera optical axis, then the ratio will change and σ_ρ will be high. If the person just walks, σ_ρ will be low. σ_θ and σ_ρ are computed for a 1s duration. A large motion is identified as a fall if σ_θ is higher than 15 degrees or σ_ρ is higher than 0.9.

D. Detection of Motion after the Human Fall

A last verification is carried out by checking if the person is immobile on the ground after a possible fall. As soon as a fall is detected, an unmoving ellipse is looked during the 5 seconds following the fall. If an unmoving ellipse is detected, then a fall is confirmed. If the ellipse still continues to move during these 5 seconds, this cannot be a fall. Hence five subsequent frames are checked if there is any movement. The PCC will be too high, if there is little or no movement. For this, the threshold of PCC is chosen as 0.3.

IV. Experimental Results

The proposed system is tested on URF Dataset which was designed to work with a single uncalibrated camera. In this dataset, the video sequences were acquired using a USB webcam with a wide angle of more than 70 degrees to see all the rooms. This dataset consists of activities like walking, sitting, crouching and lying. The latter activity has been included in order to train the classifier more specifically whether a person is lying down or not and to evaluate its detection performance. From the dataset, 612 images are selected. The selected image set consists of 402 typical ADL images, while 210 images represent a person on the floor. The depth images are also utilized to extract the features.

Fig. 3 shows the results obtained by the proposed method. It shows a forward fall of two different video sequences. The MHI is also shown in Fig. 3. To examine the classification performances, sensitivity, specificity, precision and classification accuracy are computed. The sensitivity is the number of True Positive (TP) answers divided by the number of positive cases (the number of true positive plus the number of false negatives). It is the probability of occurrence of fall and the classifier is therefore able to correctly identify a condition. The specificity is the number of True Negative (TN) decisions divided by the number of actual negative cases (the number of true negative decisions plus the number of false positives). It is the likelihood of non-fall, since a non-fall ADL occurred, and thus shows how good a classifier is to avoid false alarms. The number of right decisions divided by the total number of cases is used for accuracy calculation. The accuracy or positive predictive value (PPV) is equal to true positive values divided by the sum of true and false positive values. Thus, it shows how many of the positively classified falls are relevant. The accuracy, specificity and sensitivity and precision values are calculated as

$$Accuracy = \frac{(TP+TN)}{N} \tag{3}$$

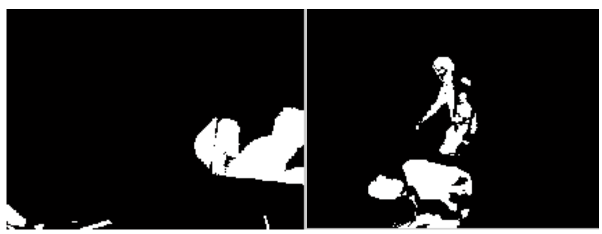
$$Specificity = \frac{TN}{F} \tag{4}$$

$$Sensitivity = \frac{TP}{P} \tag{5}$$

$$Precision = \frac{TP}{(TP+TN)} \tag{6}$$

where N is the total number of fundus images, F are actual false, P are actual true.

(a)



(b)

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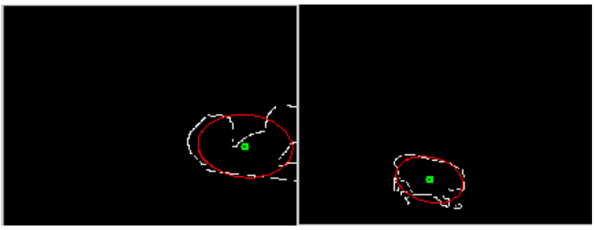
(c)



(d)

Fig. 3 (a) Original Video (b) Human Detection (c) MHI (d) Shape of the body of sample video sequence

Table I shows the results that were obtained by the proposed method for the aforementioned dataset.

TABLE I
RESULTS OBTAINED BY THE PROPOSED METHOD

Performance Measure	Results
Sensitivity	89.5%
Specificity	86.2%
Precision	88.1%
Classification accuracy	88.8%

From Table I, it is observed that the proposed method achieves very good results. A good rate of fall detection is obtained with a sensitivity of 89.5% and an acceptable rate of false detection with a specificity of 86.2%. Table II compares the results of the proposed method with a method described in [14].

TABLE II
COMPARISON OF THE PROPOSED METHOD WITH OTHER METHOD

Measure/ Method	Caroline et al. [14]	Proposed Method
Sensitivity	88%	89.5 %
Specificity	87.5%	86.2%

It is observed from Table II that the proposed method achieves 1.5% higher sensitivity when compared to other method. Fig. 4 shows the comparison of the proposed method with the method in [14].

V. CONCLUSION

In this work, a method is proposed to detect elderly person falls. The combination of MHI and correlation factor is used. The change in the human shape gives crucial information on human activities. The proposed method uses correlation factor to identify sudden falls and low motion at the end of the fall. The proposed fall detection system has achieved 88.8% of classification accuracy. The thresholds of PCC were chosen manually by logical reasoning on what is fall and what is normal. The proposed method can be further improved by an automatic method to define the thresholds using a training dataset.

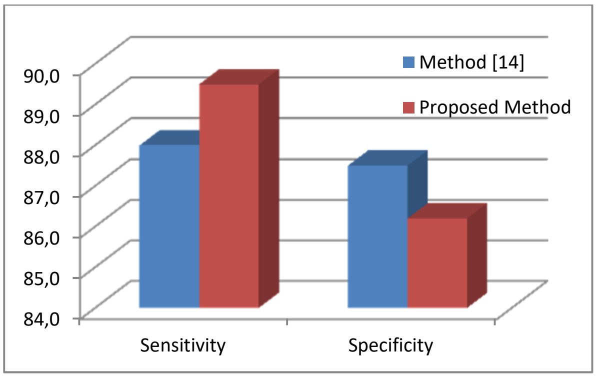


Fig. 4 Comparison of the Proposed Method Results with Method of [14]

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