ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

A Study on Vision Based Fall Detection for Automated Geriatric Care.

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ABSTRACT

In our day today life, we see that most of the people fall down when the situations are not normal. The abnormal situations can be either due to sickness or due to sudden injury. Sickness can be a chest pain, faint, vomiting, headache, etc., and sudden injury can be due to sudden fall on the ground due to slippage, fire accident, etc., Analysis shows that most of the abnormal situations of the humans are accompanied by a fall from their original or normal position. The fall of elderly people has become more common and the injuries caused by fall may be so severe such that the person may not be in a position to ask for help, which may be life threatening too. Hence the detection of a fall which is an abnormal activity from the normal human activity is more important for automated geriatric care and health care systems. The algorithm used to detect the abnormal human activity should be accurate because the normal activities should not be detected as an abnormal activity. In this paper, a review is made on the automated fall detection systems used for smart home systems and for automated health care systems.

Keywords: Fall detection system, Elderly monitoring, Wireless patient monitoring system, Motion segmentation, Feature extraction, Event classification

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ISSN: 0975-8585

Introduction

Fall is defined as "a sudden body movement of a person towards the ground coming to rest inadvertently on the ground or other lower level" [1]. A sudden fall of a human being leads to injuries such as joint dislocations, fracture, and head injuries and sometimes these may be so severe that this may lead to the end of life. More than one-third of elderly people aged above 65 falls one or more times in each year [2]. More than two-third of the people who have experienced a fall is prone to fall again [3]. Hence for smart home systems or for automated health care systems, the detection of the falling activity of a human should be accurate so that it can be tagged to an alarm to alert other persons who can help them. Basically, the fall can be classified into three types based on the initial state of the person viz., fall from sleeping, fall from sitting, fall from walking or standing. Noury *et al* [4,5] has made a brief review on the fall detection methods and proposed different protocols to evaluate fall detection algorithms. The automated fall detection algorithms vary based on the device types used such as vision based sensor, wearable sensor, ambient-sensor-based to identify the abnormal activity. Perry *et al* [6] provided a brief survey on the methods for real-time fall detection using combination of sensors.

The recent advancement and interests of researchers in the field of video technology, provokes us to review the fall detection algorithms based on vision based sensor or a camera sensor. Also a camera based approach is much more reliable because a camera-based system can provide a high percentage of sensitivity and specificity [7,8]. But the major disadvantage of using a camera sensor is the lack of privacy. This can be overcome by the technique of using on-chip video processing and to alarm only if a fall is detected.

Vision Based Fall Detection System

In this modern world, most of the places are under CCTV surveillance and monitoring the video of all the cameras at the same time is not possible. Also the person who fell down might need the help immediately. So if there is an automated system to identify the abnormal activity of the human being, it can alert the rescuer for help. A typical fall detection system consists of a camera sensor connected to a processor or a computer, a network cable to alert the person in charge. The video i.e., a sequence of images captured by the camera sensor is processed so that, using a fall detection algorithm the sudden fall of a person can be identified and reported to the appropriate caregivers. Figure 1 shows a typical fall detection system and Table 1 lists the different fall detection algorithms used for camera sensor and their sensitivity, specificity and accuracy [1] based on the experiments done by the researchers. The performance of a fall detection algorithm is determined by the parameters like sensitivity and specificity as given below

$$Sensitivity(\%) = \frac{TP}{TP+FN} * 100 \qquad \text{.....................} (1)$$

$$Specificity(\%) = \frac{TN}{TN+FP} * \ 100 \qquad \text{.....................} (2)$$

TP: True Positive – A fall occurs and the algorithm detects the fall
FP: False Positive – A fall did not occur but the algorithm detects as a fall
TN: True Negative – A fall did not occur and the algorithm detects as normal activity
FN: False Negative – A fall occurs but the algorithm does not detects it

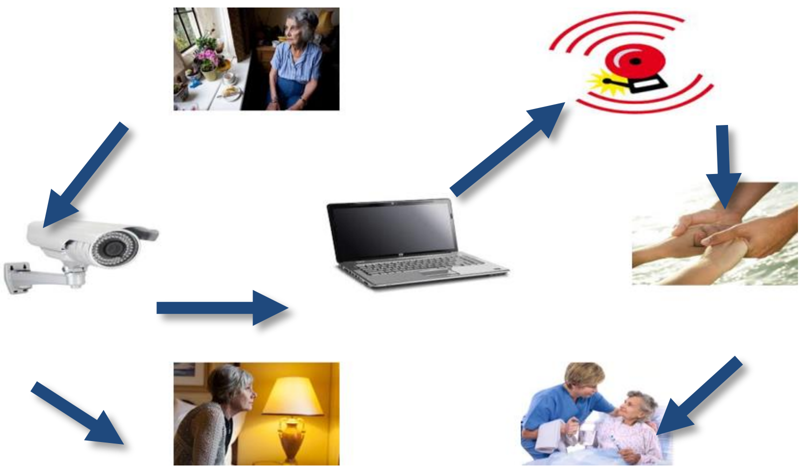
Some of the useful applications towards falls detection are wireless patient monitoring systems and elderly monitoring through video surveillance. Wireless patient monitoring system improves the quality of life by providing more freedom to continue their daily work. Elderly monitoring through video surveillance systems may be used in clinics or in nursing institutes. But monitoring through video surveillance affects the privacy of the person being monitored. Hence we have to employ some intelligent mechanisms to the monitoring systems so that they focus only on detecting the fall event without transmitting any other visual information and thus maintaining privacy [16]. Vision-based fall detection methods can be broadly classified into three categories: fall detection using a single RGB camera, 3D-based methods using multiple cameras, and 3D-based methods using depth cameras.

Table. 1: Results of different fall detection algorithms

Author	Method/ Algorithm	Accuracy (%)	Sensitivity (%)	Specificity(%)
[9]	SVM, extreme learning machine	86.83	91.15	77.14
[10]	On-ground event segmentation, ensemble decision trees	71	-	-
[11]	KNN, SVM	76–98	-	-
[12]	SVM, LR, ANN	-	92	95
[13]	HMM, LDA, KDA, RT, GPF	95.8	-	-
[14]	GMM, FST	51–100	36-100	83-100
[15]	RB	70–81	78-90	60-86
[7]	TB	-	97.83	100

SVM = Support Vector Machine
GMM = Gaussian Mixture Model
FST = Finite State Machine
kNN = k-Nearest Neighbor
RB = Rule-Based
LR = Logistic Regression
KDA = Kernel Discriminant Analysis
RT = R-Transform
ANN = Artificial Neural Network
HMM = Hidden Markov Model
GPF = Gaussian Probability Density Function

Figure 1: Typical Fall detection System



Fall Detection Algorithms for single RGB Camera

One of the key problems is to identify a fall among the daily life activities. The physical features proper to the fall movement can be used to detect a fall in our day to day life. The falling action is subdivided into four phases namely, prefall - linked to daily life motions; critical - loss of balance; postfall - final position after fall; and recovery - return to normal daily life [17] phases. The critical phase is too short which will be around 300–500ms. The velocity reaches a maximum value compared to the normal life activities typically around 2 to 3 times higher and the speed decreases down to zero. During the post fall phase, the main features are the change in the horizontal orientation of the body proximity to the floor, and the lack of body movements. Wearable devices placed directly on the body parts mainly chest [18], waist, or wrists [19] enable to capture the high velocities, which occur during the critical phase and the horizontal orientation during the postfall phase. Also these wearable devices require frequent recharging of the battery which is a limitation for

ISSN: 0975-8585

real time applications. A video based monitoring system enables the care giver to rapidly check if an alarm is linked to the fall detection system. According to this, several approaches have been proposed to detect falls which mainly focuses on the critical and the postfall phases.

SVM, HMM, GMM, k-NN are few algorithms that are used to detect a fall of a person in places where only a single RGB Camera is used. The aspect ratio i.e., the height to width ratio of a person changes when he falls down abnormally. Based on this concept, a simple background separation method is used by Mirmahboub *et al* [20] to create the silhouette of the person, and several features are then extracted from the silhouette area. In most of the video based fall detection systems three major process is performed. They are motion segmentation, feature extraction and event classification as shown in figure 2.

Figure 2: Steps in Fall Detection Algorithms

Motion Segmentation : Motion segmentation also known as change detection or foreground detection or background subtraction. Itis the fundamental step in most of the vision based algorithms. It is the process of seperation of the static background from the moving foreground. Motion segmentation or background subtraction is the widely used approach to detect the moving objects from the input video stream from a static camera. In a video stream, the difference between the current frame and the reference frame is called as the background image. It is an essential building block for most of the applications like robotics, metrology, video surveillance, video indexing, traffic monitoring and many other. Some of the methods used for background subtraction are

- Running Gaussian average
- Temporal median filter
- Mixture of Gaussians
- Kernel density estimation (KDE)
- Sequential KD approximation
- Co-occurrence of image variations
- Eigen backgrounds

Each method has its own advantages and disadvantages based on the applications. Also the accuracy of these methods varies with respect to the applications [21]. The reliability of motion segmentation increases proportionally with the number of stationary pixels in the concurrent frames. Few main attributes of the motion segmentation algorithm [22] are occlusions, robustness, missing data, camera model, prior knowledge and training data. Figures 3 and 4 show the flow of operations involved in the background subtraction.

The mathematical formula to represent the background subtraction is given as

$$\frac{|I(x,y) - \mu(x,y)|}{\sigma(x,y)} > Threshold \qquad \text{......................} (3)$$

If the above equation is satisfied, then the pixel(x,y) will be considered as the foreground or it will be considered as the background.

Feature Extraction: This is the second step in visual based fall detection systems. Fall detection is the action recognition where only one action of fall is most important for us. The widely used features in fall detection algorithms are aspect ratio of the silhouette and the orientation of silhouette [17]. A silhouette is the outline of something especially a human profile, filled in with a solid colour i.e., the outline appears dark against a light background. This silhouette is obtained from the first step of background subtraction. But if we consider the aspect ratio and the orientation alone, the action of a person sitting down will also be identified as a fall. Hence apart from these features, certain other features or characteristics should also be considered. Few characteristics are the person who falls down will hit the ground strongly; the vertical speed of the person increases, also the person fell down remains motionless if he had a severe injury. Feature extraction can be performed using three steps [23] namely, Radon-Transform (RT), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) as shown in Figure 5.

Figure 3: Flow of operations in background subtraction

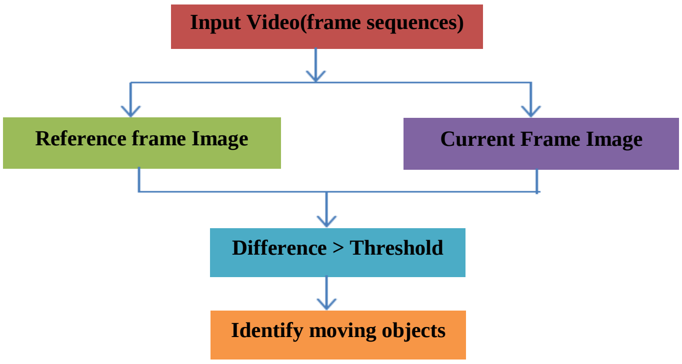


Figure 4 : Background Subtraction

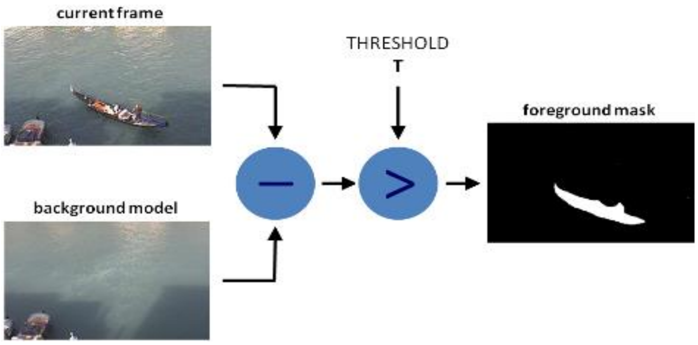
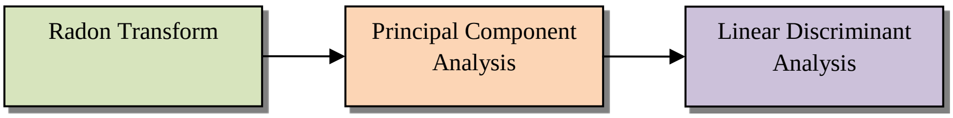


Figure 5 : Feature Extraction



Event classification: Once the feature is extracted event classification is done. Most of the algorithms that classifies the falling activity are based on machine learning and the below are the few algorithms used for feature extraction or classification.

1. SVM(Support Vector Machine) Classifier
2. GMM(Gaussian Mixture Model)
3. HMM(Hidden Markov Model)
4. k-NN (k-Nearest Neighbour) Algorithm

Support Vector Machine (SVM): SVM classifies the normal action from the falling activity based on the input samples. SVMs are a state-of-the-art classification technique where patterns can be described by a finite set of characteristic features [24]. This classification technique finds wide application in the fields of text classification, face recognition, genomic classification, etc. The SVM as a non-linear classifier and hence handles overlapping effectively. Also SVM has achieved a very good performance in lots of real-world classification problems [25]. The machine is trained with the silhouettes of different normal activity as well as the falling features. If most of the characteristics of the silhouette received are similar to the falling action then the activity is classified as a fall else it is considered as the normal activity.

Hidden Markov Model (HMM): HMM classification is probability based modelling which is successfully used in speech and handwriting recognition. In this model the falling acceleration of the human fall is acquired which has a regularity of a fall and then the motion features is acquired for a very short period before the collision occurs. Therefore HMM is a double random process, having a finite state transition with respect to acceleration and a visible state transition with respect to the motion features such as shrinkage of the silhouette area.

k-NN (k-Nearest Neighbour) Algorithm: It is one of the simplest Machine learning algorithms that is used for classification of features in real time. K-NN classifier is preferred over other algorithms because of its simplicity and effectiveness. The processing speed of the k-NN classifier is high compared to the other classifier algorithms like SVM or HMM. In k-NN classifier the machine is trained with the silhouettes of various activities. The received silhouette is compared with the characteristics of the nearest neighbours to classify the action as a falling activity or the normal one.

CONCLUSION

In this review, it is seen that different algorithms are employed at different levels to recognize the fall, which is one of the human activity. In addition, this review should have given a broad idea on how fall detection is performed. It is also noticed that these fall detection systems are implemented as the combination of hardware (camera) as well as the software. Also all these approaches generally use only one camera, which could fail to detect falls in case of occlusions. These occlusions frequently occur in real time applications at home because a room contains furniture and objects that could be placed between the subject and the camera. Dealing with occlusions is a key issue for using video systems in real world situations in order to avoid misdetection and false alarms. Using multiple cameras could overcome this limitation by offering several different points of view of the subject.

Field Programmable Gate Arrays (FPGAs) have become a very popular target technology for the implementation commercial applications of low or medium volumes. FPGAs are nowadays so technologically evolved and complex that they are able to host an entire system-on-chip. Hence, FPGA implementation of the fall detection systems are more advantageous compared to the above said approach because of its reconfigurable nature. It has faster processing speed, flexibility to advance to the next level and secure. Future work could be to make a survey or to study on the scope of implementing the fall detection systems in FPGA.

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