A Vision Based approach for Fall Detection System for Elderly People

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Abstract—**There is a surge in the aging population, it is important for doctors and guardians to be conscious of issues related to health, which could impact majorly to the health of the elderly. Falling is one of the significant concerns that lead to fatal health problems in the case of the older population.. The proposed system is especially for elderly people who are living alone in their homes or for old age homes. A vision-based fall detection approach has been used below in a home environment. A UR dataset of kinetic sensor's output videos is used which classify into two categories i.e. fall and activities of daily living which are considered for experimentation. The MOG2 algorithm is used for background subtraction to focus on the human object and ignore the rest of the surrounding environment. The Shi Tomasi algorithm is used for finding interest points that are tracked using the optical flow method: Lucas-Kanade algorithm. Using interest points we compute its maximum displacement along with direction and speed of motion. For fall activity the last positions of interest points were observed. So the system detects a person in the environment, keeps tracking the person, and calculates the optical flow in case of a fall. If the fall is above the threshold point, an alert is sent to the concerned people and medical authorities.**

Keywords— fall detection, shi-tomasi algorithm, MOG2 algorithm, elderly people fall, optical flow.

I. Introduction

The fast growth of technologies has made life easier for the elderly population, especially the ones staying independently. Fall can be defined as "moving from a higher level to a lower level [1], rapidly and without a sense of control over the body". According to the World Health Organisation (WHO) global report on fall prevention, people aged 65 years and above **fall** about 28 to 35 % each year, and there is an increase in the proportion as age and frailty level increase [2]. The prevalence of falls in **India** for people above the age of 60 years has been reported to be between 14% to 53% [2]. After a fall if the person still remains on the floor for more time, may face medical complications, such as dehydration, internal bleeding, and cooling, and half of them die within six months [3]. There has been a major need in the market for a system that helps in detecting and alerting a fall. Abundant research has taken place in recent years to evolve a fall detection system that helps in recognizing and immediately alerting help for the elderly and patients. However, despite multiple efforts made to attain a definitive and meek system for fall detection, the currently implemented technologies do not meet the needs of the elderly population. The major reason for the refusal of the currently available technologies for the elderly is the generation of many false alarms in the existing devices. These in turn lead to considerable exasperation in the older population. Also, the privacy and accuracy are not preserved or maintained in the existing devices adequately. In recent years, a wide range of sensors (individual and in combination) have been used in a lot of research for detecting falls.

There is a high social and commercial value in the technology market for assistive technology for the home care of the elderly population. Since elderly people do not have to change their living style while staying at home, this proves to be a ground-breaking benefit. Through research, it is found that after a fall event if the person lies on the floor for a longer time then this can result in fatal health conditions or death too in certain cases when there is a delay in providing immediate medical assistance. So to prevent such life and death situations, the need for immediate medical attention is very crucial. The delay between the occurrence of falls and the approach of medical assistance has to be reduced to overcome the grave injuries. The proposed system is mainly helpful to provide faster alerts to the medical staff and the near-dear ones or guardians when the fall has happened. There are a lot of non-vision-based approaches proposed earlier by several researchers in recent years but these suffer from certain disadvantages like causing distress by wearing the device or carrying the device at all times, etc. We believe that a vision-based system is the required hope for faster and accurate detection and controlling of fall detection in the elderly population.

We have implemented a vision-based approach in this paper. The publically available UR fall dataset [4] is used in the implementation. In this UR fall dataset [4], the fall activity has been performed by a few young volunteers in a home environment. Further efforts can be made to build a new dataset and test the system in real-world scenarios.

II. Literature Survey

Various methods used for fall detection systems have been proposed by various authors. This analysis study presents different methods and approaches used to clarify the understanding of the planned work.

Ogawa et al. [5] have developed a system that uses an infrared sensor and using different machine learning algorithms such as linear discrimination with 92.0% accuracy, the k-neighbors classifier with 93.0%, support vector machines give 39.75%, Naive Bayes with 66.35%, AdaBoost with 68.0% and random forest give 64.57%. Learning data is collected and action patterns are recorded but it does not classify a changing state from standing to lying.

Harrou et al. [6] developed a system using the vision-based approach for human fall detection using GLR chart and SVM algorithm. The combination of GLR and SVM techniques gives a result with lesser false-positive falls than the other techniques, which makes it a more accurate fall detection technique. It has some privacy concerns as it uses an RGB camera.

Abobakr et al. [7] proposed a system that uses vision-based fall detection using input depth frames passed through several processing modules. It is done in three phases, first is foreground segmentation. Second, a Random Forest Algorithm (RDF) is used on datasets and third, an SVM classification model is used for analyzing the change in the posture for fall occurrences.

Huang et al. [8] developed a system that uses a novel 2D video-based fall detection method with help of human pose estimation using feature augmentation. First, they use OpenPose to extract the key points of the human body in raw RGB data. Secondly, this data is used as input of a convolution neural network to extract multi-layered features. In the third step, binary classification is done using a neural network. Using SVM as the classifier a comparison is done with the result of neural networks.

Tolentino et al. [9] has aimed to develop a system that will recognize emergency situations based on body gestures. With the help of Kinect Sensor, a skeletal tracking system will be generated to acquire the gesture of the human subject. After which the gesture will be passed to a decision tree algorithm which will determine the severity of the emergency.

S. Moulik et al. [10] proposed an IoT-enabled fuzzy inference-based fall detection system that takes input from the accelerometer, which is a wearable device and uses infrared sensors and ultrasound sensors. It is an alarm generation system that generates alarms whenever a fall is detected. It generates 16% fewer alarms on average in comparison to the existing single sensor threshold-based approaches. It produces efficient results and handles different complex situations, it produces fewer false alarms than the existing approaches.

Barabas et al. [11] developed an application that uses Microsoft Kinect sensors for fall detection. It captures the data from the sensor and stores a wide range of image data, positional information is stored in CSV files for further processing, and calculates the angle between arbitrary joints for simple gesture detection. The data is processed in real-time and using that fall is detected.

S. Badgujar et al. [12] use a wearable sensor-based fall detection system, suitable for elderly people. Machine learning algorithms to detect falls from a set of daily activity activities. A decision tree algorithm is used as it has better accuracy than SVM and also prediction time is less than SVM. The models are evaluated using parameters such as specificity, accuracy, sensitivity, and confusion matrix. The accuracy obtained is 96% using decision trees.

Nguyen et al. [13] In this smartphone data has been used to evaluate a fall. This paper measures the rapid change in the acceleration in the standing axis, The configuration of the application was dependent totally on the type of smartphone the user uses. The data collected in this paper was collected from a single source which may lead to a limitation.

Comparison table of existing fall detection systems.

Table 1. Comparison table of existing fall detection system.

Detection Technique	Method	Type of Sensor	Remarks
Extremities have been used to acquire the signals Thresholding Method,Wavelet transform.	Wearable device used	Accelerometers	Provides false alarms and irritation
Waveforms of vibration are being extracted to get a feature vector with the help of complex wavelet transform (CWT) and then classified using a support vector machine (SVM).	Ambience sensor based	PIR (Passive Infrared) and Vibration sensors	The performance gets degraded during reverberant and noisy scenario
Application vector magnitude of 3-axis accelerometer ,orientation of the sensor and absolute vector magnitude are used .	Smartphone based	Smartphone built-in accelerometers	The smartphone must always be carried.Proper usage of smartphones is found to be difficult in case of elderly people.Low battery life.
A mobile robot system is used with Microsoft Kinect to follow a person and detect fall events.	Vision based	Microsoft Kinect	Expensive and need for a mobile robot system.
1st stage - Vertical state characterisation 2nd stage- On ground event features, ensemble for fall confidence	Vision based	Microsoft Kinect	Degradation in the resolution during fall makes the foreground detection difficult to recognize
Canny algorithm , Contour Approximation method	Vision based	Microsoft Kinect	Raspberry pi and opencv 1.0 are used

III. PROPOSED SYSTEM

An important distinction to make is that many systems consist of wearable devices which makes it a huge dependency as it may make the older person uncomfortable; also regular recharging of the devices is required. Considering all this, a sensor-based independent system is proposed which requires minimal maintenance and maximum robustness.

Our system functionality will be divided into steps classified below.

A. Data Preprocessing/Collection

A stream of video is collected with the help of a Kinect sensor. The sensor is attached to the ceiling of the room at the best possible position considering maximum area coverage. The video frames which are received are capped at an fps limit called "threshold_fps". The frames received are then converted into Grayscale format. The importance of this step is that the MOG2 Algorithm [14] which we are using in this system only accepts a grayscale frame. The received frames are then passed to the MOG2 algorithm [14] which is a better version of the MOG algorithm. One important feature of this algorithm is that it selects the appropriate number of gaussian distributions for each pixel. It provides better adaptability to varying scenes due to illumination changes etc. Fig.1 represents the foreground detection algorithm. As we can see, the system filters out the human subject from all other components present in the environment.

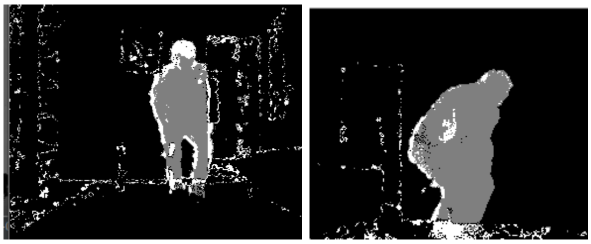

Fig 1. MOG2 Algorithm.

B. Data Segmentation

In this step, the Shi-Tomasi Algorithm is implemented. The grayscale frame which is received from the previous stage is then processed to calculate the best features of the parameters required to calculate a fall. Good features include the position of the human subject in the room, his posture, and his state. For each and every frame the features new good points are recognized. Shi-Tomashi algorithm [15] is a slightly better version of the Harris corner detection algorithm as the scoring formulae are tweaked a bit.

Equation (1) represents the calculation of 'R' in the Harris Corner Detection algorithm.

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2 \qquad (1)$$

Later in the Shi-Tomasi algorithm [15] equation (2) was changed to

$$R = \min(\lambda_1, \lambda_2) \qquad (2)$$

Hence all the good features of the frame are detected which is used for further calculation. A constant parameter called 'R' is kept as a threshold which helps in classifying the point as useful or not. The value of 'R' is kept according to the environment the system is in. Also, it can be changed or altered on the basis of system requirements. The processing of the frames is then carried out in the next phase of the algorithm. In Fig.2 we can see the important points highlighted that help in the calculation of the optical flow of the human subject.

Fig 2. Shi-Tomasi Algorithm.

C. Silhouette Tracking

This is considered the most important phase of the system. All the important features which are received in the previous phase are then used here to calculate the optical flow of the object. In this method, we use 2 consecutive frames to determine the change in motion of the feature points which are extracted in the earlier phase. This method creates a 2D vector where each vector is a displacement vector showing the movement of points from previous to next. The main principle of this algorithm is that a set of points are given to the Lucas-Kanade algorithm [16] and in return, we receive the optical flow vectors of those points. Depending on the displacement points with respect to time a threshold 'm' is kept to determine the change in position of the subject which has been tracked. If the threshold is broken it is determined a huge change in optical flow is measured resulting in the detection of a fall.

D. Flow Diagram

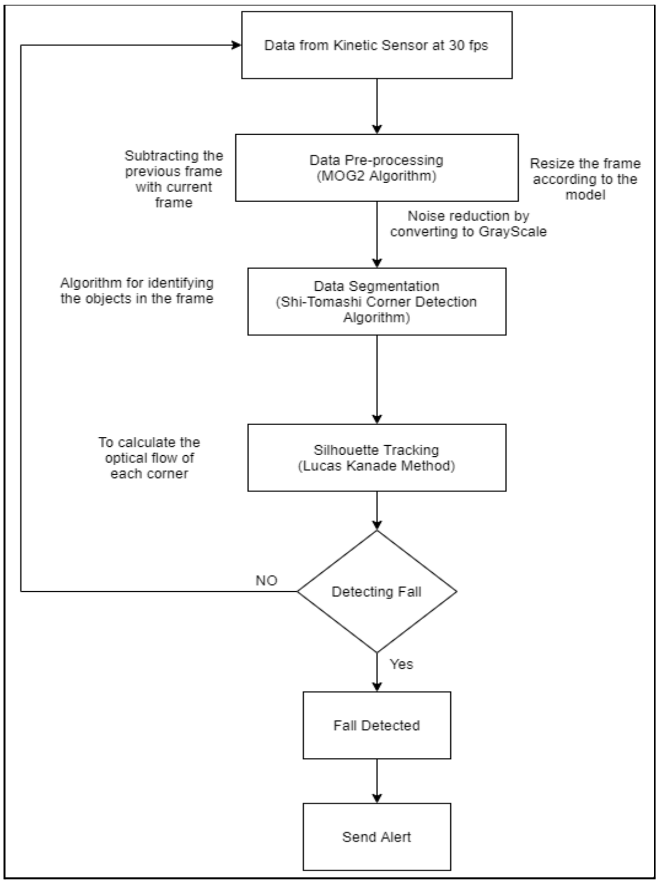

Fig 3. Flowchart of the System.

IV. Results

The first step in the process is data segmentation. The dataset which is available is then passed through the MOG2 algorithm [14]. In this, the algorithm for each frame foreground is detected. All the unnecessary pixels are blacked out for proper clarity of the human subject. Once foreground is obtained, all frames will be available for the next algorithm.

The Shi-Tomasi Algorithm [11] was successfully implemented and the desired outputs were retrieved for further analysis and tests. Using this 2D vector of points the optical flow of each point will be calculated. On the basis of the flow and considering the environment a suitable threshold will be considered.

In the next step, once we get all the good points of all the frames, we track them. The optical flow of all good features will be tracked. This will be done with Lucas-Kanade optical flow algorithm [16]. The algorithm will keep a track of the optical flows of all the good points and on the basis of it, it will detect a fall. Fig.4 shows the change in the position of the tracking points. It is represented by a yellow line. Based on which, the optical flow is dependent.

Fig 4. Optical Flow Calculation.

V. Conclusion

The fall detection system proposed above is mainly developed for the elderly population in a home environment. We have implemented algorithms on a UR fall dataset [4], available to us in the public domain. This dataset has been captured in a home environment. Background subtraction, computation of the interest points, speed and direction of motion, optical flow are the important steps. The system does not require any kind of supervision and hence is an unsupervised system. The work can be extended further with higher resolution depth videos as well as with a combination of other sensors/datasets. Also, the algorithms used will be tested on real-time videos.

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