Design and Implementation of Anomaly Detection in Video Surveillance using Foreground Detection

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Abstract

Abnormal event detection is now a challenging task, especially for crowded scenes. Many existing methods learn a normal event model in the training phase, and events which cannot be well represented are treated as abnormalities. It fails to make use of abnormal event patterns, which are elements to comprise abnormal events. Moreover, normal patterns in testing videos may be divergent from training ones, due to the existence of abnormalities. Anomaly detection finds extensive use in a wide variety of applications such as fraud detection for credit cards, insurance or health care, intrusion detection for cyber-security, fault detection in safety critical systems, and military surveillance for enemy activities. The proposed detector treats each sample as a combination of a set of event patterns. Due to the unavailability of labeled abnormalities for training, abnormal patterns are adaptively extracted from incoming unlabeled testing samples. It detects the moving object using Gaussian Mixture Model based on foreground detection and the abnormalities in the videos are detected.

Keyword- Cyber Security, SVM, GSM, Buzzer

I. INTRODUCTION

Nowadays, different methods have been proposed for detecting falls; when classified by tools they use, such anomaly detection systems can be divided into the following three kinds: methods using wearable sensors, acoustic sensors and video cameras.

Physiological measures of interest for use in rehabilitation are heart rate, respiratory rate, blood pressure, and blood oxygen striation and muscle activity. From the biological indicator of a human being extracted from the sensor, we can obtain indication of abnormality in the biological signal as a precursor to a fall. The sensor integrated a novel height sensor based on two manufactured micro electro mechanical systems (MEMS) accelerometers for measuring the hydrostatic pressure offset of the photo plethysmo graphic (PPG) sensor relative to the heart. The mean arterial blood pressure was derived from the PPG sensor output amplitude by taking into account the height of the sensor relative to the heart. If such a system detects abnormality in the heart rate, then the system may determine that a fall may have occurred.

Some researchers use acoustic sensors, for example microphones, to detect falls based on the acquired audio signal, which can collect the audio signal from the environment. If the detected human being has fallen, there will be anomalous sounds; by detecting this kind of signal, we can get an alarm when the human being has fallen over. For example, fall detection system based on a floor vibration sensor and a microphone; the vibration and sound signals were obtained from the hardware equipment and temporal and spectral features were extracted from the obtained signals. A Bayes' classifier was then applied to classify fall and non -fall activities based on the extracted features.

For computer vision based systems, some researchers have extracted information from the video and set a threshold to determine whether there is a fall or not, some researchers have extracted some important features from the frames and perform classification of fall and non - fall events. For example, proposed a system which is based on posture recognition using a single camera to monitor the person in the room environment. In this work, firstly, the features were extracted from an ellipse fitted to the human profile and a projection histogram, then a multiclass support vector machine was used for classification purpose, which is a scheme to combine multiple SVMs, it can be used to solve two – class classification problems, to achieve multiclass classification.

II. RELATED WORK

It is well known that anomalous behaviour detection and group behavior analysis is an important problem in video surveillance. This can be noticed by the number of papers that addressed the problem in the last ten years [1], [2]. In this paper, as in the majority of existing studies, we consider as abnormal events that are rare in the scene, and which are different from the majority. In the literature, there are basically three main categories of work for anomalous behavior detection in videos. The first category is based on the explicit event modelling using supervised techniques, where the model of abnormal behavior is learned from the training set and the system should detect the abnormalities defined in the model [1].The problem of these approaches is that the abnormality

detection really depends on previously collected and annotated videos. The second category includes approaches developed for specific applications using knowledge-based systems, representing a specific abnormal behavior manually defined by the user, as for instance, detecting threats for cargo video surveillance [3].The third category of work, which is the focus of this paper, is about unsupervised approaches that can detect abnormal behaviors not restricted to prior knowledge, and without the need of training. However, in this category, most studies detect only simple abnormal events such as cars and bicycles among pedestrians. They analyze the optical flow and acceleration, which is very discriminative among these objects [4]. Other approaches simply classify the objects that are not grouped into clusters, representing the outliers, as abnormal [5][7], or detect objects that move in different speed or directions unusual events [8]. In this class of work, there are two main categories: trajectory - based [9] and pixel-based [10][12] approaches. We claim that there are abnormal behaviors that cannot be detected by using either trajectory-based or pixel-based methods. Abnormalities in speed and direction can be easily detected. From trajectories. However, abnormal actions such as jumping or fighting may not be detected from the analysis of the spatio-temporal trajectory points, as these actions are related to the body movements of the person, rather than global movements. Similarly, pixel-based approaches may not detect a terrorist or a thief which is loitering, since this activity is related to global movement of the person rather than the finer body movements. In most unsupervised approaches, normal events are learned in a clean video sequence which does not include any abnormal event [13], [14]. However, this is a certain limitation in many aspects. In many applications, it is very likely that the training set will include abnormal events. Therefore, these unsupervised approaches may not learn an appropriate model to correctly classify abnormal behaviors, mainly when there are several abnormal events in the training set. In addition, the learning is limited with the normal trajectories that are present in the clean sequence. If there are other types of normal trajectories that appear in a different part of the video, the algorithm cannot learn these normal instances and will detect these normal trajectories as abnormal events. On the other hand, since we run our unsupervised learning framework over the whole video, it learns all the types of normal events present in the video and distinguishes the abnormal events. We evaluated the proposed approach on three different categories of datasets: Subway [8] and Mind's Eye [15], which are two popular public datasets that have been used by a large number of approaches in various applications, and Vanaheim Metro [16], which is a European project dataset collected in Paris metro stations.

III. PROPOSED SYSTEM

In this project, first we detect the moving object using Gaussian Mixture Model base background subtraction. In this method of background subtraction not need prior knowledge (reference background). This foreground method efficiently detects the foreground from varying environmental condition like, camera calibration, illuminance changes. Then we are use Kalman Filter to track the objects. Kalman filter estimator of object location and velocity with robustness to measurement occlusion and spurious measurements. We will show that our formulation successfully tracks and identifies multiple similar objects under dynamic camera movement and partial object occlusion. Our Kalman filter tracking algorithm successfully tracks objects of interest even in the presence of spurious and missing measurements and partial occlusion.

A. System Architecture

Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus, it can be the considered to be the most critical in achieving a successful new system and in giving the user, confidence that the new system will work and be effective. The implementation stage involves careful planning, investigation of the existing system and its constraints on implementation, designing of methods to achieve changeover and evaluation of changeover methods.

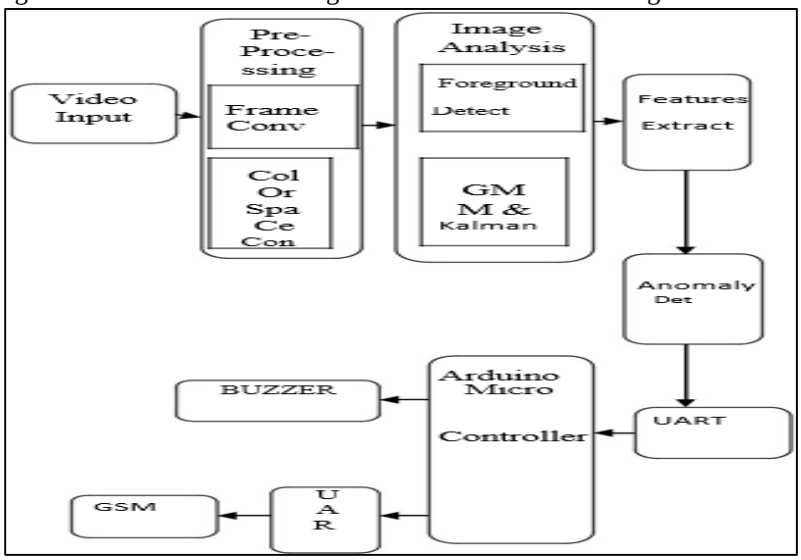

Fig. 1: Block diagram

B. Video Frame

Video is nothing but a sequence of images, each of which is called a frame. In this scenario we take video as an input and generated a number of frames determined by the frames per second property of video. Then detect moving objects.

C. Background Modeling

The proposed background model utilizes block-based and the statistical characteristics of a pixel in order to extract the static image (background image). The block-based background model generation including the matrix representation and the probabilities calculation is presented as follows.

D. Matrix Representation

Our background model development consists in dividing the T initial images of the sequence into blocks of n pixels where n can be in the range of 2, 4, 8, 16.Therefore, each formed block has 2 pixels. After that, each block (i,j) of the sequence are combined to form a matrix Mbi, j. Consequently, we have M, N / n^2 matrix of blocks, such as each image of the sequence has M rows and N columns. Probabilities calculation: After the matrixes of blocks are formed, the probability density function (pdf) of pixels intensity into each matrix is computed. The probability density function of each pixel's luminance is of the matrix Mbi, j can be expressed as follows:

$$pdf(l) = nl / (T \times n)$$

The pixel that has the highest value of pdf is classified as background. The same idea is applied for the block candidate background. In order to select the block background, the probability of each block in the matrix which is the sum of pdfs for each pixel is computed the probability of block at time t.

E. Background Subtraction

The technique used in the image processing fields and in the computer, vision is called as Background subtraction. This can be also known as detection of foreground. It is method wherein foreground of an image is extracted and processed further. The regions of an image which is interest are objects (humans, cars, etc.) and are foregrounded. It is a widely used technique for detecting objects moving in videos captured from static cameras. The process of subtracting and separation of the foreground object from the background image in the sequence of frames of video is called as background subtraction. The background is estimated by differencing the previous frame from the current frame. The background subtraction equation then becomes:

$$B(a,b,t) = I(a,b,t-1)$$

$$\Downarrow$$

$$| I(a,b,t) - I(a,b,t-1) / > th$$

Where th = threshold

Frame difference:

$$| frame_s - frame_{s-1} | > th$$

The background frame which is estimated is just a subtraction previous frame from the current frame and is evidently worked on only on its certain conditions of speed of an object and rate of frame. It is very sensitive to the threshold condition.

F. Foreground Detection

In the background subtraction approaches, when the background image is generated the difference between the current image in the sequence and the background image is calculated. Then, a threshold operation is applied to decide if a pixel belongs to the background or to the moving object.

The selection of the best threshold can be difficult. The most algorithms select it by testing a set of threshold values and then choose the one which is given the best results. In this paper we use the threshold proposed by the following equation:

$$th(x, y) = 1 - exp(t\ (x, y))$$

Where I is the current image and B denotes the background image. The value of the threshold th(x, y) has to be in range 0,1. When the absolute difference is small, the threshold goes to 0, and if the absolute difference value is significant, th(x, y) converges to 1. the moving object can be represented by a binary image. The elaboration of this binary image will be realized by the computation of the binary motion detection mask D (x, y). The pixel belongs to the moving object when the result of the absolute difference is significant, therefore the threshold value is close to 1, otherwise is belong to the background. The binary image which represents the moving objects at time t of the sequence is computed.

G. Gaussian Mixture Model Algorithm

The GMM is a mixture of K Gaussian distributions representing the distribution of pixel intensities in current frame. It means that the probability of intensity within frame at time t is modeled as:

$$P(x_t) = \sum_{k=1}^{K} w_{k,t} \times N(x_t, \mu_{k,t}, \Sigma_{k,t}) \qquad (1)$$

$$w_{k,t}, \mu_{k,t}, \Sigma_{k,t}$$

Where, are weight estimation, mean, and covariance matrix of Gaussian kth, respectively. In this paper, we assume the color R, G, B that are independent. Thus, the covariance matrix of Gaussian kth is referred from standard deviation as (2):

$$\Sigma_{k,t} = \sigma_{k,t} \times I \,. \qquad (2)$$

The new pixel intensity t x is estimated with respect to each Gaussian component to find the nearest distribution where it should belong to. Then, the new parameters,
wk t k t k t μ Σ are updated. By using the Gaussian Mixture Model, the set of background pixels are characterized adaptively follow temporal domain. Therefore, it is useful to use GMM to eliminate all of possible background pixels. In another word, GMM based background subtraction is robust against such illumination changing.

IV. RESULTS

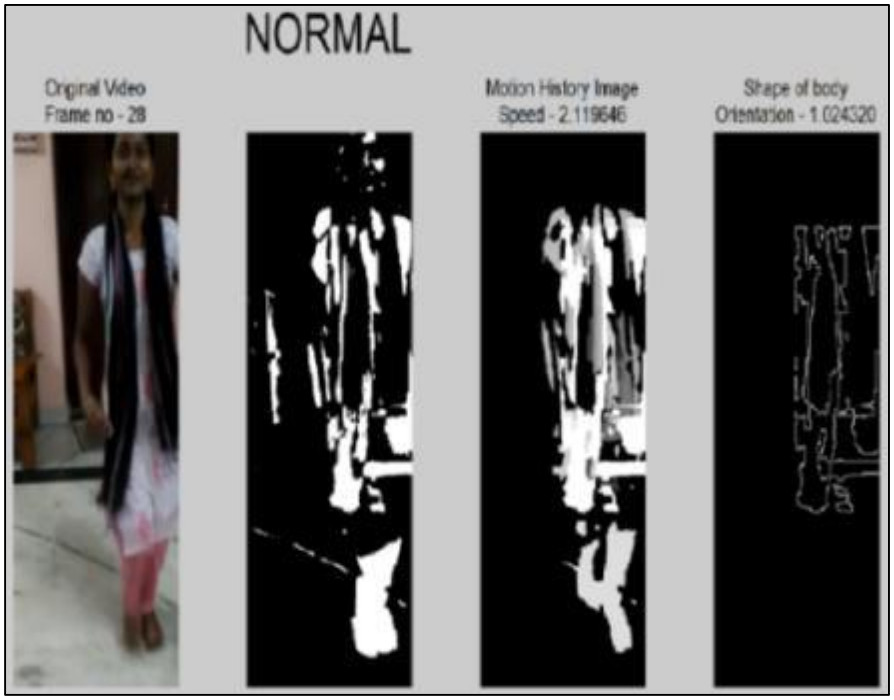

Fig. 2:

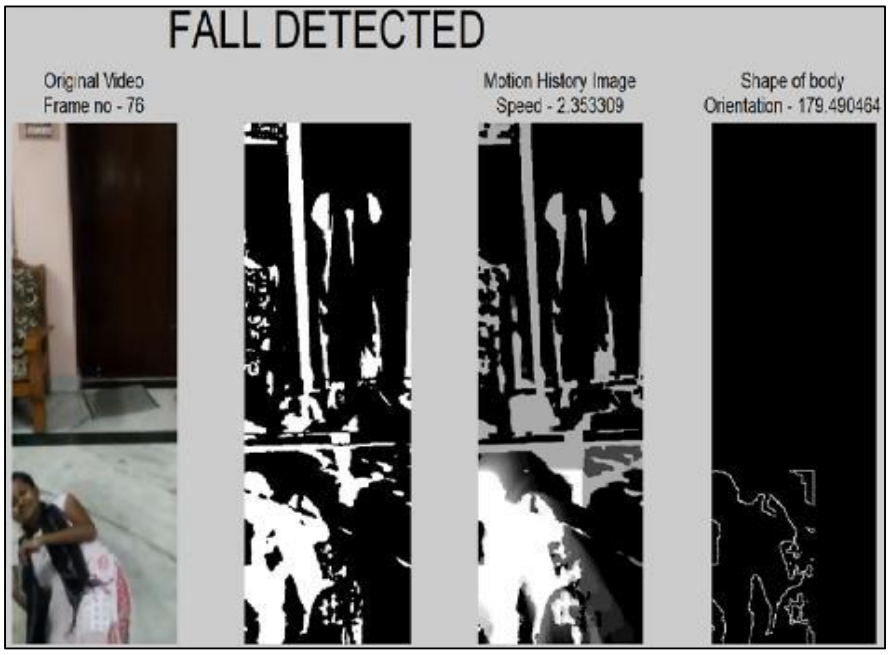

Fig. 3:

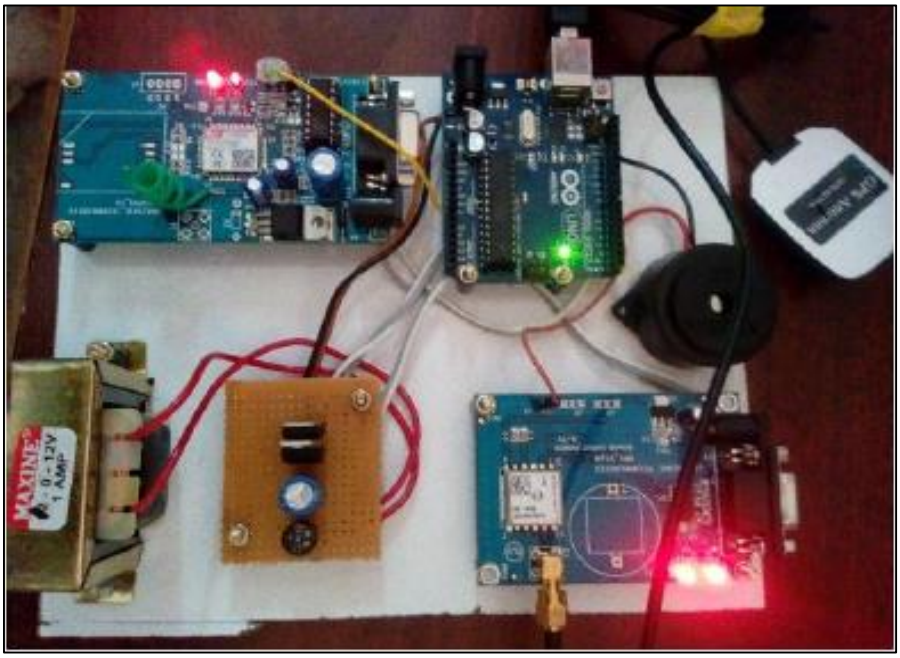

Fig. 4:

V. CONCLUSION

This paper presents a framework for abnormal event detection and group behavior analysis in video surveillance. We propose fully unsupervised method that uses not only basic trajectory features (such as speed and duration), but also fine motion features to represent body movements. Therefore, compared to the existing trajectory-based and pixel-based approaches, our method detects different types of abnormality, from basic to complex events. Indeed, to the best of our knowledge, our work is the first one that, based on dense tracklets, is able to detect abnormal behaviors on both individuals and groups moving in the scene. This is possible thanks tothe trajectory extraction step that provides the bounding box of each individual and each group in the scene. We have tested our approach with three datasets that include different types of abnormality. Experimental results show that our approach is able to detect all kinds of abnormal events, including wrong direction, loitering, and stopping, no payment in metro/subway videos, fighting and car moving in parking lot videos. Although there are some missed events, our approach is able to detect all types of abnormal events with very low number of false alarms when compared to existing approaches. Since our approach is based on unsupervised learning, an interesting direction for future work is the performance analysis of our approach in an online setting, learning “on -the-fly" and running in real-time.

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