

Automatic Abnormal Behaviour Detection from videos

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Abstract: This paper address the detection of anomalies in real time video surveillance applications such as ATM attacks, accidents, crime, etc. A new technique is proposed to detect anomalies using Joint Kernel Sparsity Model (JKSM) with Multi-Channel Kernel Fuzzy Correlogram (MKFC). Moving objects are segmented by using MKFC in the situations like occlusion, newly appearing or disappearing objects and JKSM is used to detect the anomalies involving in multiple objects. It extracts the features of normal/anomalous events, assign the label to features, and model the prelabeled features as linear combination in a training dictionary. The proposed technique is implemented on two different data sets and the result shows improved precision and recall over the existing technique.

Keywords-Video Anomaly, Joint Kernel Sparsity Model, Multi-Channel Kernel Fuzzy Correlogram.

1. INTRODUCTION

Anomaly detection in videos gains more popularity in the research field very recently. Anomaly detection in the videos is helpful to identify attacks, violations, crimes and other unwanted activities. For identifying the Anomalies we have to detect the objects, in object detection area lot of research work has been done.

For detecting the objects several methods are available. Optical flow [1] method is intensity based method, which involves in measuring the optical flow field of image and doing the clustering process according to optical flow distribution characteristics this method detect the moving objects from the Background with 85% accuracy, this method faces some problem regards huge amount of calculations, sensitivity to noise, poor anti-noise performance, these conditions makes it is not suitable for real time object detection. Frame differencing [2] uses the motion detection method and it is consider the pixel-based differences to detect the moving objects can be identified in the frame by measuring the difference between two consecutive images. This method is suitable for dynamic environment but problems happened at obtaining complete outline of moving object. Temporal Differencing [3] method extract moving regions from the background by using the pixel-wise differences between two or three consecutive frames in a video imagery. It is depends

on the dynamic scene changes although it cannot always extract all relevant pixels of a foreground object mostly when the object moves slowly or has uniform texture When a foreground object stops moving, temporal differencing method cannot detect a change between consecutive frames and results in loss of the object. Point detector [4] is another method in object detection; these are used in identifying useful points in images, useful point's means which have an expressive texture in their respective localities. A useful interest point is one which is invariant to changes in illumination and camera viewpoint. Some commonly used interest point detectors include Moravec's detector, Harris detector, KLT detector, SIFT detector. Another traditional and most commonly used object detection technique is background subtraction technique [5]. This method attempts to detect the moving objects from the difference between the current frame and background frame and finding deviations for each incoming frame in the video imagery. Any significant change in an image region from the background model is noted down as a moving object. Background subtraction method has different approaches to detect the anomalies. An object in motion needs to be classified accurately for recognizing as a human being. To do these three types of classification methods are used. Shape based approach first describe the shape information of moving regions such as points, boxes, blobs. It is commonly considered as a standard template matching technique but we cannot detect humans accurately from other moving regions. Texture-based such as histogram of oriented gradients (HOG). It uses high dimension features based on edges and use support vector machines to detect the human regions. Motion-based method, it is based on the idea that object motion characteristics and pattern are unique enough to distinguish between objects.

After identification of objects, there is a need to classify the activities of object for detecting the anomalies Motion trajectories gives the rich Spatio temporal information about object activities. Spatio temporal information can be obtained by robust and compact representation of trajectory data. HMM [6] based classifiers are used for representing the motion trajectories. In this object trajectories can be segmented into atomic units which are known as sub trajectories and we can represent these sub trajectories

into principal component analysis (PCA) Subspace to learn statistical model for each class of object motion. Hierarchical Bayesian model [7] written in multiple levels that estimates the parameters of posterior distribution. In this videos can be sub divided into number of documents and events are subsequently encoded as quantized features. Ratio Histogram Approach [8] histogram is calculated from all of the pixels in the image and peaks and valleys in the histogram are used to locate the clusters in image. It is used to represent object features and suspicious objects [9]. Motion label representation [10] is used to encode the events by labelling the motions, these are called class labels the comparison of new motions against the class labels. A deviation from all the classes indicates anomaly. Recently trajectory based a sparse reconstruction technique employed in video anomaly detection. The fundamental working of this model is to extract the features of normal/anomalous events, It assigns the labels to features model the pre-labeled features as linear combination in training dictionary. Sparse reconstruction technique [11] [12] works well in the situations like high noise, occlusions but the problem is to identifying the anomalies involving in multiple objects. To avoid such problems joint sparsity model is used.

Sparse Reconstruction technique is worked based on trajectories. Trajectories have long been popular in video analysis and anomaly detection .A common characteristic of trajectory-based anomaly detection [13] approaches is the derivation of nominal classes of object trajectories in a training phase, and the comparison of new test trajectories against the nominal classes in an evaluation phase.

A statistically significant deviation from all classes indicates an anomaly. Trajectory based approaches have some advantages

- 1) Interactions between multiple objects are quite naturally captured in trajectory representations.
- 2) Recent advances in object tracking ensure that trajectory extraction is both fast and reliable. Nevertheless, in theory, any event representation can be used with our model.
- 3) Finally, sparse structure conveys information about normal/anomalous event classes—in the absence of training data for anomalous events we can develop and use outlier rejection measures that can develop the anomalous event classes and enables the unsupervised anomaly detection with high accuracy rate.

II. Related Work

For detecting Anomalies, one of the previous approach is Gaussian Mixture technique (GMM) [14] along with sparse reconstruction technique. Whereas GMM is used to detecting the objects and sparse reconstruction techniques is used to identify the anomalies. GMM works well in the situation like indoors and with static background. The GMM works in the following manner, It is a background model used to detect the moving objects. In this we compare each input pixels to the mean of the associated components. If the value of a pixel is near to a chosen component's mean, then that component is taken as the matched component. In order to be a matched component, the difference between the pixels and mean must be less than compared to the component's standard deviation. Update the weight of Gaussian, mean and Standard deviation (variance) to reflect the new obtained pixel value. In relation to non-matched components the weights, decreases whereas the mean and standard deviation stay the same. It is dependent upon the learning component in relation to how fast they change. Here we identify which components are parts of the background model. To do this a threshold value is applied to the component weights'. Finally foreground pixels are identified. But the GMM performs poor at the situations like occlusion, outdoors, dynamic background changes. These problems are avoided by using a new technique Multi-Channel Kernel Fuzzy Correlogram based background subtraction.

MKFC technique is used along with Joint Kernel Sparsity Model which extracts the features of normal/anomalous events, assign the label to features model the pre-labeled features as linear combination in a training dictionary. There are some problems while detecting the multiple anomalies. To solve those problem joint sparsity model has been employed to detect the anomalies involving in multiple objects.

III. ANOMALY DETECTION USING JOINT KERNEL SPARSITY MODEL WITH MKFC

This proposed technique uses JKSM with MKFC based background detection approach. Here Multi-Channel Kernel Fuzzy Correlogram based approach is used to detect the objects. MKFC is region based background modelling technique which considers the regions around the pixels. Correlogram is the new concept towards object detection, correlogram is effective for dynamic backgrounds because it captures the inter pixel relations of a two pixels at specified distance, thereby include the spatial information along with feature information. Whereas, Multi-Channel Correlogram is calculated using inter and intra channel

Correlograms defined in [16]. Inter-channel correlogram excludes the inter-pixel relation within the same colour plane but it captures the colour information as well as dependency across the colour plane. In Multi-Channel correlogram inter-pixel relations also captured which is the combination of inter and intra channel Correlogram. Multi-channel Correlogram obtain the colour information without ignoring the colour dependencies, inter-pixel relations across and within the same colour plane but Correlogram used in that captures only inter-pixel relations on a single colour plane.

To reduce the computational concept fuzzy membership matrix. The Correlogram are mapped into new space of reduced dimensionality by applying a transformation using fuzzy membership matrix and the mapped Correlogram are referred as a Fuzzy Correlogram. Membership values in intra channel fuzzy Correlogram are calculated using traditional fuzzy C-means algorithm [15] and it uses the Euclidean distance measure to calculate the distance between the clusters and data points, and is restricted to spherical clusters. With this method faces problems at outliers and it is restricted to spherical clusters only to avoid such problems kernel fuzzy c-means algorithm applied. It will be termed as Multi-Channel Kernel Fuzzy Correlogram because membership values are applied over multi-channel correlogram. It uses the kernel induced metric instead of Euclidean for calculating the distance between clusters and data points by using this method computational complexity is reduced in distance calculations.

Multi-Channel Kernel Fuzzy Correlogram [16] based method is region based technique, it performs well in dynamic backgrounds without any noticeable loss in the shape of the moving objects. It does not require explicit training frames for background model initialization and can be initialized with moving objects also. The multi-channel correlogram can be achieved using inter and intra channel Correlogram.

In this technique initially correlogram was computed for input frames and then quantization is applied and it is followed by MKFC computation, fuzzy similarity evaluation and finally foreground/background is classified and model initialization is done by using first frame and in all subsequent frames models are initialized.

MKFC approach works in following manner

If (input frame at time 0 that is first frame) calculate the quantized intensity of the pixel in frame on colour channel. That is measure the colour components R, G, B and correlogram computation and then perform the current MKFC computation after this

measure the similarities between current and background models. It assigns labels to the pixels finally update the backgrounds. In this paper multi-channel kernel fuzzy correlogram technique is implemented along with JKSM which helps to detect the anomalies based on the trajectories.

Sparsity based anomaly detection technique

Sparse reconstruction analysis of trajectory is very recent and useful approach to detect the abnormal behaviours in the field of video anomaly detection. This approach works based on the trajectory information. We can check the test image by using number of training samples from all classes. Any new trajectory can be approximately be modelled as a linear combination of each trajectories.

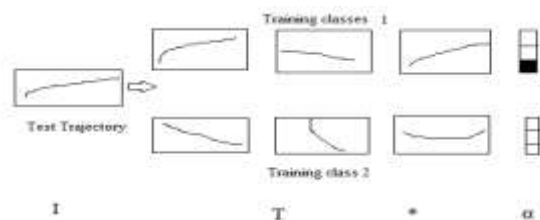


FIG 5: trajectory classification

The above figure shows the trajectory classification using sparse reconstruction model here the training dictionary consist of two classes, each class contains three trajectories and test trajectories can be well represented by 1 and 3 from class 1. I is the test image, T is training samples and α is sparse indeed.

Sparsity based reconstruction technique is the very effective one, where the situation like occlusion, noise etc. it can maintain the information about both the normal/anomalous classes and it can develop the outlier rejection methods for the anomalous event in the absence of training data. Trajectory extraction is both fast and reliable. It captures the interaction between the multiple objects quite naturally and effectively. Challenges remain in the sparsity model are 1) to detect the anomalies involving in the multiple objects 2) ability to allow for class separation. These challenges can be overcome by using new approach joint-sparsity model for Trajectory Based Video Anomaly detection.

For example: in real world some events like ATM attacks, accidents, thefts are happened based on the joint object behaviour not only with the individual objects. Joint sparsity model is used to detect such kind of attacks [17]. Sparsity model is used for object trajectory algorithm [17]. This algorithm is depended on structure of trajectory data if the data is not linearly separable enough, the trajectory based sparsity model

may not detect the anomalies may not sufficient accurately.

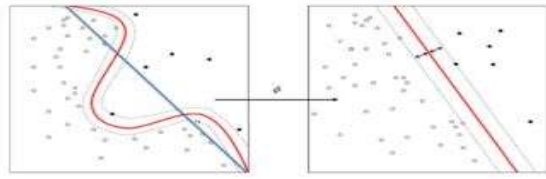


FIG 6: Kernel function is used to project non-linear data into linear data [17].

To convert the nonlinear data into linear data kernalization can be applied to the sparsity model for object trajectory and named it as kernel sparsity model for object trajectory [17].This kernalization technique applied to Joint Sparsity Model and named it as Joint Kernel Sparsity Model (JKSM).

Algorithm Joint Kernel Sparsity Model with MKFC:

- Step1: Take the input video.
- Step2: convert video into frames
- Step3: Apply MKFC based background subtraction
Algorithm for object detection [16]
- Step4: Then use Joint Sparsity Model to detect Anomalies involved in multiple objects [17].
- Step5: Apply kernalization to joint sparsity model to detect anomalies even if the data is Non-linear separable.
- Step6: Anomaly detection.

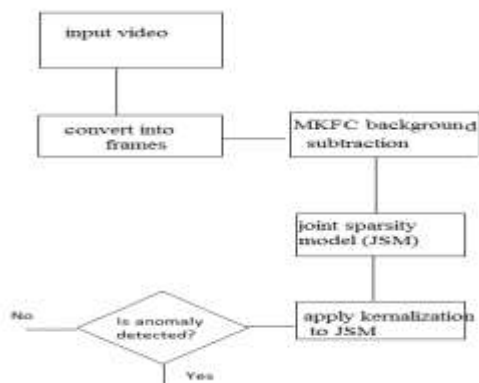


FIG 7: Block diagram of proposed Approach

IV. PERFORMANCE EVALUATION

JKSM with MKFC technique works better than other approaches in video anomaly detection. JKSM with MKFC and JKSM with GMM techniques applied on two different datasets. In dataset1 video is captured from the office and dataset2 was taken from the web, it contains the video data related to ATM attack in Bangalore. JKSM with MKFC approach gives better precision and recall values than JKSM with GMM. The following figure gives better understanding about this approach.



FIG 8: JKSM with GMM (data set1: person is attacked by other person in office)

Figure 8 represent JKSM with GMM technique is applied on data set1, this technique detects the anomalies but it contain the noise it is showed in the figures 8.It takes every moving thing as an object that leads to failure in some situations and this noise can be reduced by using JKSM with MKFC technique. It can be well suited in the situations like occlusion and missing trajectories. This technique will be applied on the two different data sets and it shows good results.

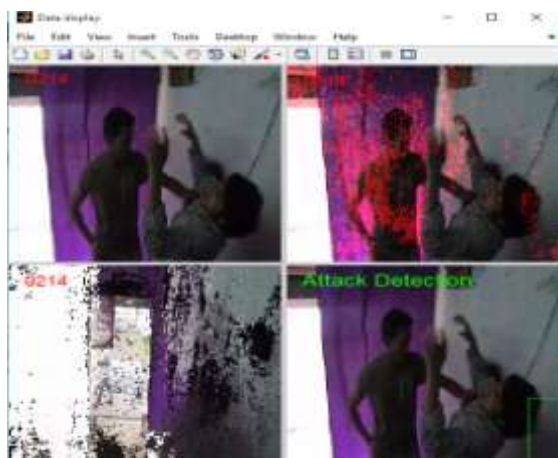


FIG 9: JKSM with MKFC (data set1: person is attacked by other person in office)

These two techniques are applied on dataset2 also again JKSM with GMM fails to detect the anomalies in high noisy video as shown in figure 10. In figure 11, JKSM with MKFC technique is applied on the same data set . The results shows the anomalies are detected effectively in the noisy video.



FIG 10: JKSM with GMM (data set2: person is attacked by other person in ATM center)

JKSM with MKFC approach detect anomalies more accurately than JKSM with GMM technique.

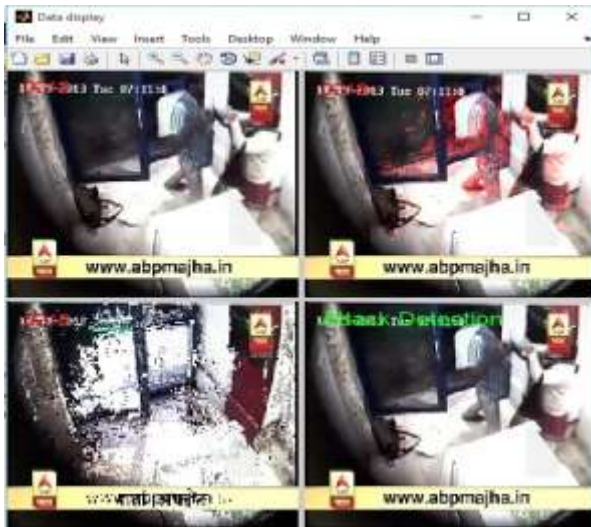


FIG 11: JKSM with MKFC (data set2: person is attacked by other person in office)

Table I
Precision and recall values on dataset1

DATA SET1	Precision	Recall
JKSM with GMM	95.34	96.89
JKSM with MKFC	98.36	98.46

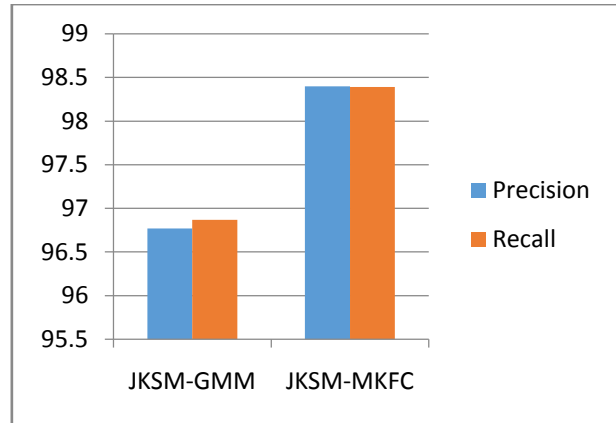


Fig 12: performance analysis for precision and recall value of JKSM with GMM and JKSM with MKFC on dataset1

Table II
Precision and recall values on dataset2

DATA SET2	Precision	Recall
JKSM with GMM	96.77	96.87
JKSM with MKFC	98.40	98.39

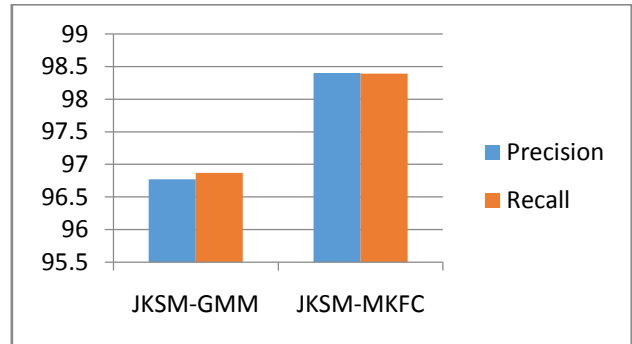


Fig 13: histograms for precision and recall value of JKSM with GMM and JKSM with MKFC on dataset2

In the above table JKSM with MKFC technique gives better precision and recall values than JKSM with GMM technique.

Precision and recall values can be calculated using following formulas.

Confusion matrix:

		Detected	
		Positive	Negative
Actual	Positive	True Positive	False Negative
	Negative	False positive	True Negative

Recall or Sensitivity is the proportion of positive cases that were correctly identified, as calculated using equation

$$\text{Recall} = \frac{\text{Truepositive}}{\text{Truepositive} + \text{Trueneegative}}$$

Precision (P) is the proportion of the predicted positive cases that were correct, as calculated using the equation:

$$\text{Precision} = \frac{\text{Truepositive}}{\text{Truepositive} + \text{falsepositive}}$$

Effectiveness of the proposed approach is demonstrated numerically and pictorially by comparing with JKSM with GMM approach for two different video sequences, having various situations like ATM, room. The parameter precision and recall are used to identify the effectiveness of the approaches. In case of precision the JKSM with MKFC improved its detection rate more than 2% when compared with JKSM with GMM. When considering recall the JKSM with MKFC improved its performance more than 2% when compared with JKSM with GMM in both the data sets.

V.CONCLUSION

These papers propose a technique for anomaly detection in a video by using JKSM with MKFC. MKFC detects moving objects in various scenarios like occlusion, dynamic background changes, and slow moving objects. JKSM is used to detect the joint anomalies in videos. When JKSM combined with MKFC led to improved anomaly detection rate when compared with the existing approaches. This technique helps in detecting the anomalies more efficiently and effectively in different scenarios.

VI.REFERENCES

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