Anomaly Detection using DBSCAN Clustering Technique for Traffic Video Surveillance

R. Ranjith, J. Joshan Athanesious, V. Vaidehi

Abstract— **Detecting anomalies such as rule violations, accidents, unusual driving and other suspicious action increase the need for automatic analysis in Traffic Video Surveillance (TVS). Most of the works in Traffic rule violation systems are based on probabilistic methods of classification for detecting the events as normal and abnormal. This paper proposes an un-supervised clustering technique namely Novel Anomaly Detection-Density Based Spatial Clustering of Applications with Noise (NAD-DBSCAN) which clusters the trajectories of moving objects of varying sizes and shapes. A trajectory is said to be abnormal if the event that never fit with the trained model. Epsilon (Eps) and Minimum Points (MinPts) are essential parameters for dynamically calculating the sum of clusters for a data point. The proposed system is validated using benchmark traffic dataset and found to perform accurately in detecting anomalies.**

Index Terms- Anomaly detection, NAD-DBSCAN, Density reachable, trajectory, Traffic Video Surveillance (TVS).

I. INTRODUCTION

An activity is said to be an anomaly if it identifies significant objects and events that violates the rules in a wide-range of realm. TVS is one such domain, where an advanced system generates enormous volume of spatio-temporal information of moving objects. The objective of TVS is to track, evaluate the activities of the target, detect the anomalies, predict the future behavior and predict the potential abnormal event before they occur. Factors like illumination, dynamic background and camera tampering make traffic video processing complex and challenging [1].

In addition to the above challenges, the accuracy of TVC gets reduced by human operator errors. This deliberation has strongly encouraged the systems to automatically define common behaviors and identify abnormal ones. The main idea is to understand the activity patterns, which represent the way objects move in a scene. In other words, the study of object trajectories enables us to understand the normal behavior of a scene. Irrespective of the objects closer or farther from CCTV camera, a vehicle trajectory provides better reliability. In this paper, vehicle trajectory along with clustering approach is used for finding common activity patterns.

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Cluster is defined as the group of data having same identify. The clustering approaches [2, 3, 7, 8] is based on the idea of grouping the similar activity patterns. Outliers present in the cluster correspond to anomaly events, which occur rarely in traffic video scenes. For example, a vehicle moving in contradiction direction of all moving vehicles denies the normal behavior. Those actions that fit the trained data are said to be normal, whereas actions that never fit within the cluster center are considered as anomalies.

Most of the existing work [9, 10, 11] in traffic anomaly detection has of two stages: (i) Scene modeling and (ii) Anomaly detection. In scene modeling, the moving objects are modeled to describe their activities in the scene. It can be performed in two methods: (i) object based modelling (ii) feature based modelling. Object based modelling is to detect, track and store the trajectory of moving object and feature based modelling, describes the motion using low level features. In Anomaly event detection, suspicious activities that had never occurred before are detected. In many cases, limited number of fixed clusters is assumed and small dataset are taken for analysis[10, 11].

Therefore, this paper proposes NAD-DBSCAN for detecting the anomalies in a well-organized traffic junction. The methodology uses Gaussian Mixture Model (GMM) for background modeling. Blobs are used for vehicle trajectory estimation, tracking and motion features extraction. DBSCAN clustering technique is used to identify the anomalies in the scene. In this method, there is no need to mention about the number of cluster initially. The proposed NAD-DBSCAN technique is validated using benchmark traffic datasets and is found to achieve good detection accuracy.

This paper is organized as follows. Section II deliberates about the related work being carried out in the area of clustering based anomaly detection in TVS. Section III illustrates the proposed NAD-DBSCAN methodology for detecting the anomalies in traffic scene. Section IV describes the experiments results and analysis. Section V concludes the paper.

II. RELATED WORK

Most of the anomalies in traffic video surveillance use various clustering based methodology to generate a learning pattern.

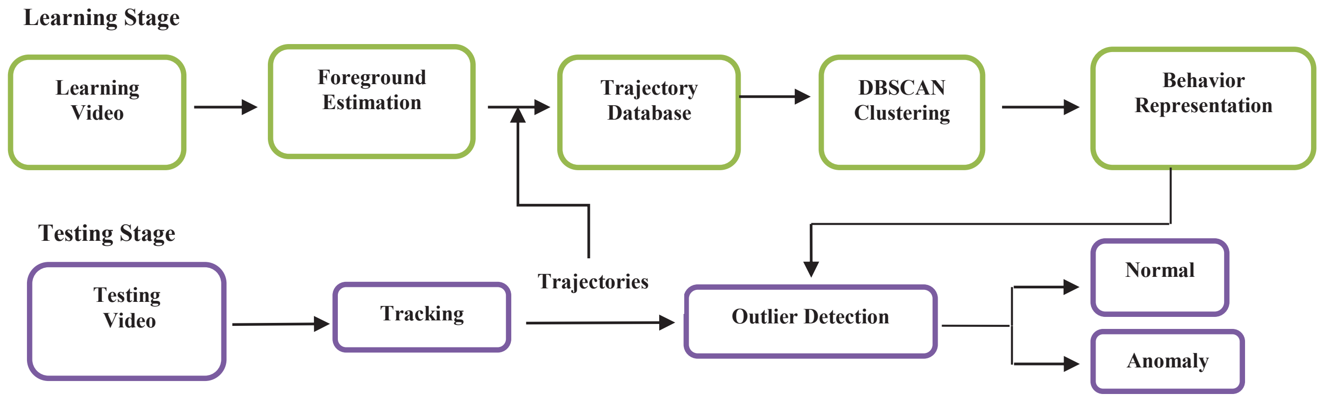

Fig. 1. Architecture of the proposed NAD-DBSCAN system

S. Kamijo et al, [2] have proposed a method for detecting anomaly by considering the activities of the objects along with its relation to other surroundings objects. Using the popular k-means clustering approach, trajectory vectors are grouped together. Z.Fu et al, [3] present a categorized structure to cluster the movements of vehicle. Spectral clustering technique is used for clustering related trajectories in a traffic junction. Wang et al, [4] proposed an unsupervised technique in which a scene is partitioning into regions. The movement of the objects is observed for a period and a scene model is built. In their approach, using a new trajectory similarity measures, activities of different kinds are separated into clusters and anomaly is detected by scene semantic models.

To represent each moving blob, Xiang et al, [6] used a 7-D vector. An event that never fit into the learnt model is considered as an anomaly. Morris et al, [7] proposed an unsupervised approach for modelling the path that learns the normal motion in the scene. Hidden Markov Model (HMM) [21] determines the spatial-temporal motion characteristics of the objects.

Jing et al, [8] proposed a 2-depth greedy search approach which includes dynamic hierarchical trajectory clustering. Ryan et al, [12] proposes a texture of optical flow to identify abnormal objects in traffic scene. Kwon et al, [13] proposed a collection of trajectories are grouped by K-means clustering. Yang et al, [14] proposed an unsupervised methodology to identify motion patterns in a video. Feature-based methodology extracts prominent features to analyse the traffic scene.

There are many object detection techniques which use Haar feature based Detector [24], SVM classifier [22], etc. Though they perform well, there are a few negative aspects such as a complex training process and the requirement of many labeling instance for a perfect training.

Though there are numerous techniques available in the literature for detecting anomalous events in traffic surveillance, a better method is needed to deal with number of clusters which varies dynamically. Therefore, this paper proposes a NAD-DBSCAN based anomaly detection to deal with clusters in the video data.

III. Proposed NAD-DBSCAN System

This paper assumes trajectory analysis system shown in Fig.1. The NAD-DBSCAN architecture contains learning stage and testing stage

In learning stage, feature information like x, y co-ordinates, area and direction of pixels are extracted and trajectories are grouped and activity model is generated. The learned set of data is utilized for analyzing the activities in the testing stage. The NAD-DBSCAN in TVS include following steps:

A. Object Detection and tracking:

The proposed system uses background subtraction technique. Efficient foreground detection is important, as the subsequent process like object tracking, feature extraction, etc. are dependent on the outcome of the foreground detection process. The background is modelled using GMM and foreground object is detected which is initiated using Expected Maximization (EM).

Modeling the pixel values by numerous distributions makes the system invariant to illumination changes. The likelihood of pixel has the value of Xt is assumed to be:

$$P(X_t) = \sum_{i=1}^{k} w_{i,j}\eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \quad (1)$$

where $w_{i,j}$- Weight, $\mu_{i,t}$- Mean and $\sum_{i,t}$ -Co-variance of the ith element [15]. Probability Density Function (PDF) [26] is defined as:

$$\eta(X,\mu,\Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} e^{-1/2(X-\mu)^T\Sigma^{-1}(X-\mu)} \quad (2)$$

B. Feature Extraction:

The features used in proposed work include area, centroid and angle. Once the foreground is detected, foreground object is tracked from frame to frame using blob tracking. Centroid of 2-dimentional region or area is calculated by the average of points in the bounding box. Even though occlusion take place between the vehicle the centroid can differentiate them effectively and continues the tracking successfully. Once the tracking is done, a set of points are saved as trajectories for moving vehicle. Trajectory vector are represented by:

$$Trajectory\ vector(T):\ [x_1 y_1, x_2 y_{2,} \ldots\ldots, x_n y_n] \quad (3)$$

$$Feature\ vector\ (f) = \{x_i,\ y_i, \Theta_i\} \quad (4)$$

$$Angle\ (\Theta_i) = arctan\left(\frac{y_i}{x_i}\right) \quad (5)$$

Where x_i, y_i and Θ_i represent the position and angle of moving vehicle in the ith frame respectively. The trajectory starts once the vehicle comes into the frame and ends when it leaves the frame. Fig. 2. Illustrates the method used to find the point in the bounding box at a given angle. Let a and b are the size of the bounding box, C be the centroid of the box (Xc, Yc). Fig. 2 shows the calculation of angle of the vehicle for a given point.

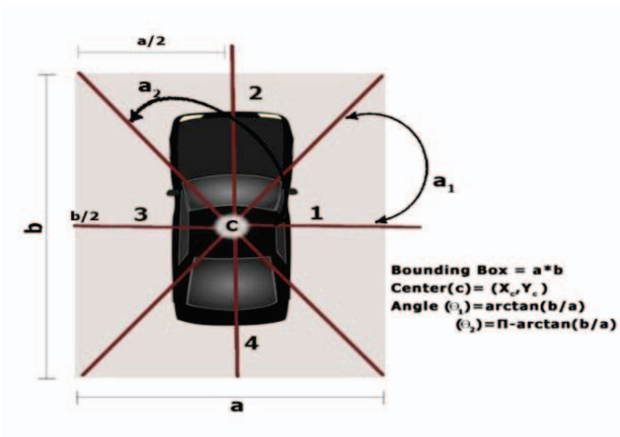

Fig. 2. Angle calculation for a given point.

C. Anomaly Detection:

Anomaly (or outlier) detection refers to identifying a point in the Dataset D that does not conform to be a normal point. In this case, outliers represent the rule violated vehicle in video surveillance. This paper uses an unsupervised DBSCAN clustering for anomaly detection. The main idea behind this work is to identify regular motion patterns that fall into cluster and irregular motion patterns which correspond to outliers.

DBSCAN [16] performs clustering based on the density of points, to separate high and low density regions. This algorithm handles clusters of different shapes and size in advance. The algorithm is also robust to noise and scalability. DBSCAN principally focus on density reachable with two essential parameters Eps (neighbors of point p) and MinPts (minimum no. of points).

$$Eps\ (p) = \{q \in\ D | distance\ (p, q) \leq Eps\ \} \quad (6)$$

$$p\ \in Eps\ (q) \quad (7)$$

$$|Eps\ (q)| \geq\ Minpts \quad (8)$$

A point p is said to be density reachable from q based on the equation (6) & (7). The parameters Eps (p) and MinPts are used for categorizing a point into anyone groups namely: border point, core point, noise point. A Core point is a point if sum of points is more than specified MinPts. A border point is lesser in number than MinPts, however they are neighbors of core point.

A point do not belong to any of the cluster is named as noise point or outlier point [19]. In Fig. 3, for a given dataset core point, border point, noise point is calculated for MinPts equal to 5 and Eps equal to 1 unit.

In this technique [20], clusters are created by a set of densely connected points. The process begins from selecting a rand point p and with reference to Eps and MinPts. Recover points that are density-reachable from p. If p is said to be border point then none of the neighbors are density-reachable from p, subsequently the algorithm moves to neighboring point in D. This process is to find a sequence of points (p1, p2, p3..., pn), which belong to high density region.

A cluster is a subgroup of D which satisfies the below constrain:

1) For all p and q: if p fit into a cluster and q is density reachable from p then q belongs to cluster.

If C1… Cn be the clusters of D and a point in D is named as noise which does not belong to any of the cluster. Table. 1 represents the DBSCAN Clustering algorithm.

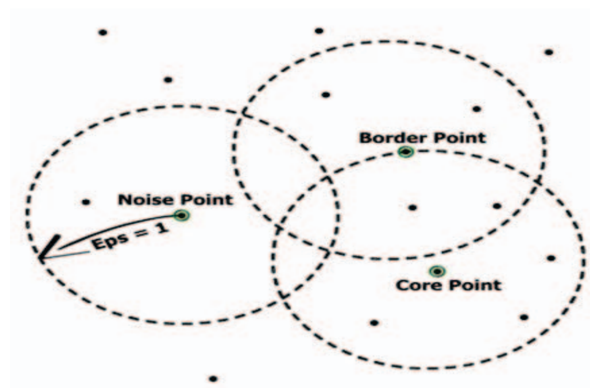

Fig. 3.DBSCAN with MinPts: 5 and Eps: 1 unit

Table 1: DBSCAN Clustering Algorithm

Algorithm:
Inputs: Dataset (D) Distance of Neighborhood (Eps) Minimum number of points (MinPts)
Output: Detect anomalies
Algorithm: **Step1:** Begin with random selection of p **Step2:** Calculate density reachable points from p $\mathrm{Eps(p)} = \{\mathrm{q} \in \mathrm{D} \mid \mathrm{distance(p,q)} \leq \mathrm{Eps}\}$ **Step3:** Form cluster, if $\mathrm{p} \in \mathrm{Eps(q)}$ $\lvert\mathrm{Eps(q)}\rvert \geq \mathrm{Minpts}$ **Step4:** Move to next point in D, if $\mathrm{p} \in \mathrm{Eps(q)}$ $\lvert\mathrm{Eps(q)}\rvert < \mathrm{Minpts}$ **Step5:**Goto Step 2, until all the points in D is visited

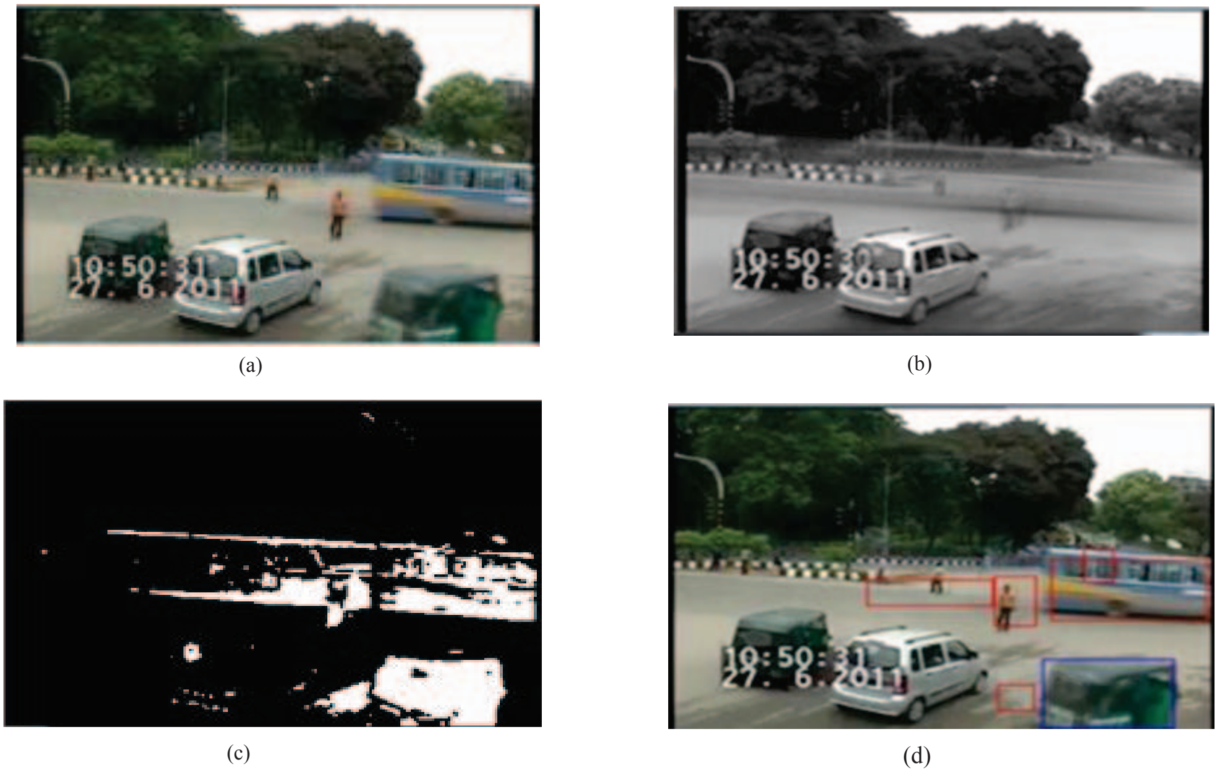

Fig. 4. Object Detection and Tracking scenario. 4(a). Input frame 4(b). Background modelling 4(c). Foreground estimation 4(d). Blob tracking

IV. Experimental Result And Analysis

The proposed anomaly detection methodology is tested using surveillance video of traffic junction. This structure is only intended for identifying anomalies depend on the moving vehicles trajectories. Various benchmark dataset is used as input to evaluate the proposed work.

A. Object Detection and Tracking:

The proposed work is implemented using C++ and OpenCV 2.4.9 libraries in Intel Core i7 processor and 20 GB RAM. In training phase, background is modeled for detecting the moving object in the traffic scene. Once foreground is estimated, blob based algorithm is used to track the vehicle in the upcoming frames. Figure 4 shows the background modelling, foreground estimation and blob tracking for an input frame.

B. Feature Extraction:

Once the vehicle is being tracked, by means of centroid of a bounding rectangle, features like position and angle of the moving vehicles are extracted. Fig. 4a shows the input frame, Fig. 4b presents the result of background subtraction modelling, Fig. 4c gives the foreground estimation and bounding rectangle in Fig.4.d shows the tracked vehicles for every consecutive frame. Centroid is calculated by average of all points in the bounding box.

Table 2 shows the values of position (x, y co-ordinates) and angle (Θ_i) of moving vehicles at time t.

Table 2: Features like position and angle of ith frame for time t.

$\mathbf{X}_i$	Y_i	$\Theta_\mathbf{i}$
21	53	0
31	53	90
40	51	45
48	54	0
55	53	45
63	51	75
69	54	90
86	53	0
102	53	0
109	56	90
118	54	90
129	54	45
186	52	75

C. Abnormality Detection:

Abnormalities in TVS are learnt using unsupervised learning techniques namely DBSCAN clustering technique. The goal of this technique is to identify the abnormal point in Dataset (D) that does not fit with the cluster. The perfect Eps parameter is calculated by setting the MinPts to 200 and experiments are performed with Eps of 10, 15, 19 units respectively. When Eps parameter increases, detection rate of anomalies decreases. To calculate the MinPts parameter, the Eps is set to 10 units

(a) (b)

Fig. 5(a-b). Example frames for single anomaly: Jaywalker crossing the road

(a) (b)

Fig. 6(a-b). Example frames of multiple anomalies: Accident in traffic junction.

(a) (b)

Fig. 7(a-b). Example frames of Narrow traffic dataset: A biker crossing the road violates the traffic rules.

and the experiments are performed with MinPts of 170, 200 and 225.

If the anomaly is made by single object, it is referred to as single anomaly. Fig. 5 shows the example for single object anomaly in consecutive frame. In Fig 5(a-b), a man crossing the road instead of walking on a pedestrian pathway. If an anomaly occurs with interaction of several objects then it is called as multiple anomalies. In Fig. 6 shows the example for multiple anomalies. In Fig. 6(a-b), a bus violates the traffic rule which leads to an accident. The proposed NAD-DBSCAN is also tested on Narrow traffic dataset [23]. In Fig. 7(a-b), a biker crossing the road violates the traffic rules. The performance of proposed work is evaluated by 'Jaccard' co-efficient which is used to calculate the abnormal accuracy.

The Jaccard co-efficient [18] is defined as

$$J = {}^{C_{TP}}\!/_{(C_{TP} + C_{FP} + C_{FN})} \tag{9}$$

where parameters are:
$\boldsymbol{C_{TP}}$:: Count of True positive which gives the correctly identified abnormalities. $\boldsymbol{C_{FP}}$: Count of False Positive which gives the incorrectly identified abnormalities. $\boldsymbol{C_{FN}}$: Count of False Negative which gives the missed abnormalities. Table 3 compares the performance analysis of proposed NAD-DBSCAN system with the existing methodology [25].

Table 3: Performance analysis of accuracy in TVS

Methodology	**Accuracy (%)**
Topic based anomaly localization[25]	63.15%
NAD-DBSCAN (proposed)	68.70%

V. Conclusion

This paper proposes a unique NAD-DBSCAN methodology for identifying anomalies in TVS. The proposed work detects anomalies based on the trajectories of moving vehicles. Irregular trajectory paths are detected based on the non-reachable property of DBSCAN technique. The experiments are validated on narrow traffic dataset and a detection accuracy of 68.70% is achieved. The work is under progress for enhancing the abnormal detecting accuracy by trajectory simplification methodologies.

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