

# Identifying Abnormality in Traffic Videos

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**ABSTRACT:** Abnormal vehicle detection in traffic videos using video surveillance systems are attracting more extensive interest due to public security in traffic signals to avoid accident. Lot of techniques is evolved but, there is no specific study involved in anomalous vehicle behaviors based on traffic rules. Basic steps in abnormal vehicle detection are object detection, object tracking and object classification. In this paper, abnormal vehicle detection techniques are discussed for object detection, tracking and classification. The events are detected using mining semantic information. The application of this concept is used in different traffic scenes for public security.

## **Keywords**

Object detection, object tracking, abnormal event detection, object classification, video surveillance.

## **1. INTRODUCTION**

Automated surveillance systems aim to integrate real-time and efficient computer vision algorithms in order to assist human operation. This is an ambitious goal which has attracted an increasing amount of researchers to solve surveillance problems of object detection, object classification, object tracking, abnormality detection and counting vehicles in traffic scenes using interesting algorithms. In video surveillance system, object detection and tracking are the main issue of the central importance for any of the modern video surveillance [10] and behavioral analysis system. The abnormal event detection techniques are shown in Fig. 1. Automated video surveillance systems consist of video sensors, which are used for observing people as well as other moving objects in a traffic scene for identifying normal/abnormal activities of objects, interesting events and other specific events.

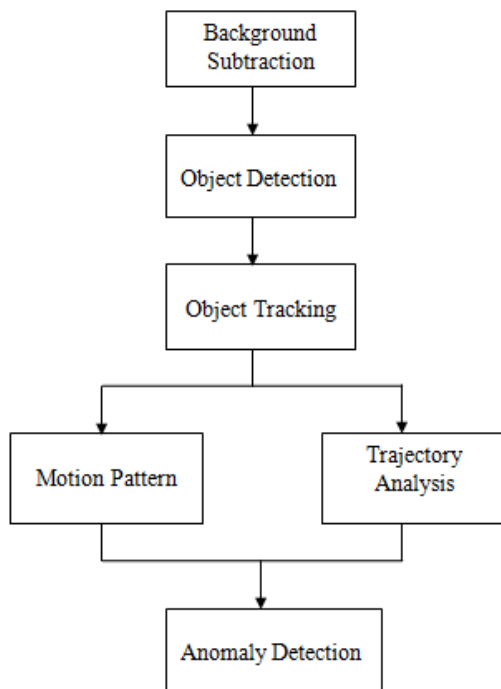
Surveillance cameras [3] are video cameras that are used for the purpose of observing abnormal activities in banking, airport, traffic scene, parking slot, colleges. In foreign countries surveillance cameras are used in traffic scenes to detect the abnormal activities of that are breaking the traffic rules. They are often connected or continuously monitor through a recording device and may also be watched by a security guard.

Cameras and recording equipment used for detecting abnormal activities are relatively expensive. It also requires humans to monitor camera videos and frames, but analysis of frames has been made easier by automated software/algorithms that organizes digital video frames into a trainable database, and by video analysis software. The amounts of video cameras are also drastically reduced by motion sensors; it only records data when motion is detected. The

surveillance cameras are very simple and inexpensive enough to be used in home security systems, and for everyday surveillance. It is very useful to governments and law enforcement application to maintain social activities, recognize and monitor threats, and prevent criminal activity in common environment.

The basic operation in video surveillance system is object detection. It is commonly used to detect the objects in crowded scenes, moving videos using background and foreground subtraction [1]. If there are few objects in a scene, each object is connected to the foreground object usually corresponds to a background object; these kind of object is denoted as single-object. It is common that several objects form one big object, which is called multi-object. The single and multi object are merged because of the angle of the camera, shadow of other objects, and moving objects near each other. Multi-object is detected as one foreground; it is difficult to obtain the appearance feature of each single object. It is difficult to track [5] and classify the particular object in a scene. For this kind of problem numerous algorithms are proposed.

Object classification is used to classify moving objects into semantically meaningful categories. This recognition task is difficult, due to object with diverse visual appearances, which results in large intra-class variations. Objects are classified only after the object detection. The object shapes in videos may change randomly under different camera views and angles. In addition, the detected shapes may be noised by shadow or other factors. Another important feature is the appearance-based method to achieve robust object classification in diverse camera viewing angles. However, due to low resolution, shadow, and different viewing angles, classifying objects with only one of these features is not sufficient in video surveillance.



**Fig. 1. Abnormal vehicle detection techniques**

Abnormal event detection [4] and object tracking are other important task in video surveillance. The scene models are learned by using the observations of tracks over a long period of time. Based on the learned information, abnormal events are detected, improve the performance of object tracking, and help vehicles to travel in correct path. Automated video surveillance systems consist of video sensors observing people as well as other moving and interacting objects in a given surroundings for observing normal/abnormal activities, interesting events, and other domain-specific goals. Based on signal detection and estimation theory, these metrics are extended for correct application towards performance evaluation of video surveillance systems. These metrics are evaluated after establishing correspondences between ground truth and tracker result objects.

## **2. RELATED WORK**

In recent years, some approaches are used to improve the performance of object detection. Detecting foreground objects by subtracting background [9] objects. It is a simple approach to detect moving objects in video. The basic step is to subtract the current image from a background image and to classify each pixel as foreground or background by comparing the difference with a threshold. Morphological operations followed by a connected component analysis are used to compute all active regions in the image.

Chen [6] *et al* proposed a novel background subtraction method, called hierarchical background model (HBM). It first segments the image in the training sets by mean shift segmentation. By using the gray histograms as features, then build the MoGs with a different number of distributions for each region. The number of distributions can be set manually or computed by an unsupervised cluster algorithm. These MoG models are used as the first level detector to decide which region contains the foreground objects. The histograms of oriented gradients of pixels are employed to describe regions.

Object classification methods are used to extract suitable features of image data representation. Common features for classifying objects after motion-based detection include size, compactness, aspect ratio and simple descriptors of shape or motion. Bose and Grimson describe a scene-invariant classification system that uses the learning of scene context information for a new viewpoint. Brown presented an object classification system for distinguishing humans from vehicles for an arbitrary scene. Many other features are also used. These methods need camera calibration to reduce the parameters to be estimated and can hardly achieve real time performance due to high computation complexity.

Han Li [2] *et al* proposed a novel algorithm to detect traffic abnormal events refer to the abnormal traffic flow in highway caused by occurrence of highway events. Because of the random and unpredictable properties of abnormal traffic events, video-based traffic abnormal detection has become a popular problem in the research field of traffic safety. The major difficulties of traffic anomaly detection include two aspects: motion modeling of abnormal traffic events and vehicle behavior classification. Hidden Markov Model (HMM) and 3D model are widely used for motion modeling. Multiple observations of HMM are adopted it into the description of object movement, but the model depends upon the quality and quantity of observational data, the accuracy of events characteristics are associated.

Weiming Hu [7] *et al.* use the 3D model for vehicle motion tracking and modeling, but it is difficult to obtain the accuracy from the video. In behavior classification approach, neural network and clustering method are widely used. Hu employ the self-organizing fuzzy neural network to learn the motion patterns of vehicle trajectory for anomaly identification and calculation. But a lot of abnormal event videos are required to ensure the accuracy of this method. Patino classify the vehicle trajectories based on hierarchical clustering method, the classification results may be affected due to the errors caused by decomposition or combination in certain clustering level.

Lixin [8] *et al* proposed large amounts of methods for traffic analysis are proposed based on vehicle tracking in traffic. Vehicle tracking can yield traditional traffic information, such as lane changes and vehicle behaviors. Calculating the trajectory levels over space and time, the traditional traffic parameters are more stable than corresponding measurements from point detectors

which can only average over time. Traffic parameters are often calculated based on the numbers and instantaneous speeds of tracked vehicles.

The survey of different techniques used in different papers is shown in Table 1 and their applications are explained.

Table 1. Comparison of different methods

S.no	Method	Advantage	Disadvantage	Application
1	Object classification using Multi-block Local Binary pattern	Real time and robust	Not applicable for background images	Image segmentation
2	Principal component analysis for labeled and unlabeled data	Unlabeled data are used	More complicated	Normal distribution function
3	Multiple instance learning for object tracking	Real time	Only for supervised methods	Training dataset
4	Bayesian network for trajectory analysis	Space complexity is less	Time is increased	Traffic application
5	Mean shift and k-means clustering	Time complexity is less	Only for neighboring points	Traffic application

### 3. PROPOSED SYSTEM

The proposed system includes the concept of mining semantic context information to detect abnormal vehicles. Methods are: object detection, object classification, object tracking, event

detection are shown in Fig. 2. These are implemented by calculating the probability density function for trajectories using Gaussian distribution. Additional features like speed and direction are included. Trajectory cases are already mentioned, vehicles crossing the trajectories they are detected as abnormal.

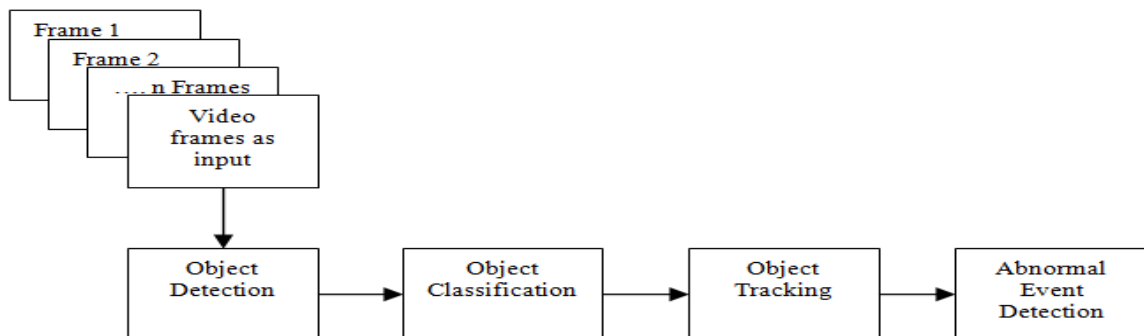


Fig. 1 Overview of the framework

#### 3.1 Object Detection

The initial step of object detection is background subtraction. If there are few objects in the traffic scene, each one is a connected component of the foreground usually corresponds to an object; this kind of blob is denoted as single-object. It is common that several objects form one big object, which is called multi-object [5]. The single and

multi object are merged because of the angle of the camera, shadow of other objects, and moving objects near to each other. Because the multiple objects are detected as one foreground, it is difficult to obtain the emergence element of each single object.

$$p(MV/x_i)$$

$$L = \frac{1}{p(SV/x_i)}$$

### 3.2 Object Tracking

The learned information is used to detect abnormal event, improve object tracking, and also guide vehicles to avoid accidents. Recently, many approaches have been proposed to learn motion patterns using moving videos. Some of them are based on the trajectory analysis in traffic scenes. Tracking detected objects frame by frame in video is a significant and intricate charge. It is a crucial part of smart surveillance systems since without object tracking. The organized systems are not extracting from the time information about objects and higher level behavior analysis steps would not be possible.

### 3.3 Object Classification

Moving regions detected in video may correspond to different objects in real-world such as pedestrians, vehicles, clutter, bags, etc. It is very important to recognize the type of a detected object, as the results here are further analyzed to detect abnormal events. Currently, there are two major approaches towards moving object classification which are shape-based and motion-based methods. The object classification is used to classify the vehicles from pedestrians. Common features used in shape-based classification schemes are the bounding rectangle, area, silhouette and gradient of detected object regions. Some of the methods in the literature use only temporal motion features of objects in order to recognize their classes.

## 4. EXPERIMENTAL SETUP AND PERFORMANCE ANALYSIS

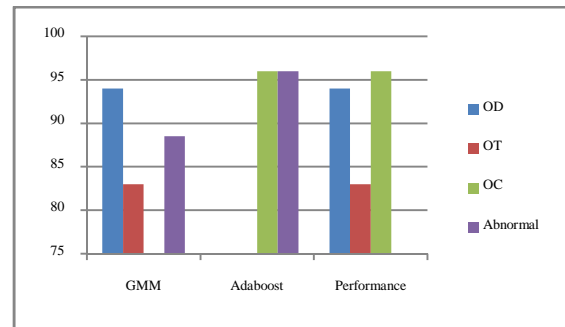
The abnormal event detection algorithms are implemented using the windows operating system, intel core processor with 2.93 GHz processor, 2.0 GB RAM and visual studio 2010 using c#.net for developing. The input video dataset are taken from free source. Input videos are of different format like avi, JPEG, MPEG. Based on tragedies in traffic videos abnormal vehicles are detected. The results are analyzed as follows.

The performance analysis of different algorithms used for object detection, tracking, classification and speed estimation are calculated as follows:

Input	OD	OT	OC	Abnormal
GMM	94	83	-	88.5
Adaboost	-	-	96	96
Performance	94	83	96	92.5

**Table 2 Performance of algorithms**

The abnormal vehicle detection algorithms performances are shown in table 2. It consists of techniques and algorithms explained in rows and columns. Overall abnormal percentage is 92.5.



**Fig. 3. Performance analysis**

The graph consists of abnormality percentage compare to different techniques shown in fig. 3.

## 5. CONCLUSION

The detection of anomalous vehicle behaviors techniques are studied and a novel method is proposed to detect the vehicle abnormality in traffic scenes based on mining semantic context information. It will be used in traffic application. Mining scene specific context information by using object specific context information. By trajectory analysis; vehicle movement can be continuously monitored based on direction and speed of the vehicle. Using semantic context information object detection, object tracking, vehicle abnormality detection can be efficiently improved.

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