# A Review on Vehicle Detection Techniques in Digital Image Processing for Intelligent Transportation Systems and Emergency Healthcare Mobility Applications

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## ABSTRACT

The Video Based investigation for traffic surveillance has been a vital part of ITS (Intelligent Transportation System) .The traffic surveillance in urban environment have become more challenging compared to the highways due to various factors like camera placement, cluttered background, pose variation, object occlusion and illumination changes. This paper provides review on video based vehicle surveillance for detection, tracking and behavior analysis with systematic description. We need to classify the dynamic attributes of vehicle with respect to vehicle motion and appearance characteristics, including velocity, direction of movement, vehicle trajectories on a single camera. The common existing surveillance system collects traffic flow information that mainly includes traffic parameters and traffic incident detection. The system developed is able to capture vehicles visual appearance and extract more information about them through vehicle detection, tracking, recognition and behavior analysis.

**KEYWORDS**: Vehicle Counting **,** Vehicle Tracking ,Vehicle Detection, Traffic Analysis, Video image Processing.

## 1. INTRODUCTION

The escalation of vehicle in urban areas made traffic surveillance a greater challenge in the medium and large sized cities. The advancements in computer vision, computing and camera technologies have raised the interest in video based traffic surveillance applications, which has become the key part of intelligent transportation systems (ITS). The existing surveillance system collects traffic flow information that mainly includes traffic parameters and traffic incident detection . The system developed is able to capture vehicles visual appearance and extract more information about them through vehicle detection, tracking, recognition and behavior analysis. To improve video based traffic surveillance systems many efforts have been devoted by various researchers, but they still face many challenges and issues in real traffic scenes for an ITS application. The typical scenes include vehicle occlusion, pose variations, all day surveillance and behavior understanding of a vehicle on a single camera network. The variability in vehicle types, size color and pose limits vehicle tracking to specific scenes . An investigation on vehicle detection, tracking and on road behavior analysis can be found in . A review on various techniques used in video based traffic surveillance is discussed from a computer vision perspective. These techniques include vehicle detection, tracking and behavior understanding on single camera. This paper also includes improvements, modifications, highlight the advantages and disadvantages.

## 2. MATERIALS AND METHODS

**2.1 VEHICLE DETECTION :** The localization of an image and robust vehicle detection is the first step in video processing. The efficiency & accuracy of vehicle detection is of importance for vehicle tracking, vehicle movement expression, and behavior understanding and is the basis for video processing .The vehicle detection process was then divided into appearance based and motion based techniques . The appearance based techniques mainly uses the appearance features like shape, color & texture of the vehicle to detect the vehicle or separate it from the background, whereas the motion based techniques uses mostly the moving characteristic to distinguish vehicles from the stationary background image.

**2.1.1 Motion-Based Features :** Motion detection is a very important task in computer vision. In traffic scenes, the most common characteristic of interest is that whether a vehicle is “moving” since it is typically only the moving vehicles that are of interest (traffic counts, safety, etc.).Motion detection aims to separate the moving foreground objects from the static background in the image. The motion cues are used to distinguish moving the vehicles from stationary background and it can be classified as : temporal frame differencing [28] that depends on the last two or three consecutive frames, background subtraction , which require frame history to build background model and finally optical flow [24] is based on in stantaneous pixel speed on image surface.

*Table 1 Representative Work In Vision Based Vehicle Detection*

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| Techniques | Methods | References |
|---|---|---|
| Motion-Based Features | Frame Differencing | [28] [11] [25] |
| | Background Subtraction | [33] [30] |
| | 1.Median Filter 2. Kalman Filter | [29] [34] |
| | Single Gaussian pixel distribution | [4] [16] |
| | Gaussian Mixture Model | [35] [36] [5] |
| | Optical Flow | [24] [12] |
| Appearance-Based Features | Feature Based Technique | [37] [14] |
| | 1.SIFT 2.HOG 3.Haar-like | [15][38] [6] [21] |
| | Part-Based model | [32] [15] [8] |

**2.1.2 Frame Differencing :**The pixel wise difference is computed between two consecutive frames in temporal frame differencing method. The moving foreground regions are determined by using a threshold value . Street parking vehicles were detected using frame differencing in with noise suppression. The use of three consecutive frames improves detection as in where dual inter frame subtraction are calculated and followed by a bitwise AND to extract the moving target region.

**2.2 BACKGROUND SUBTRACTION:** Background subtraction methods are the most widely used approach for motion detection. Foreground objects are extracted by calculating the difference by pixel between the current image and a background image . In the simplest common case, the background image is constructed by specific known background images, e.g., background averaging method, in which a period of image sequences, are averaged to obtain a background model [30]. However, in real traffic scenes, the background are usually changing; therefore, this kind of methods are not suitable for dynamic traffic scenes. Thus, the background is constructed without any known background image, which make the following assumptions.

1) Background is always the most frequently observed in the image sequence.
2) The background pixel has the maximum appearance time at a steady state.

Using provided threshold, the static parts of sequential video frames must be cleaned. The main challenge here is that the performance of image analysis algorithms suffers from darkness, glare, long shadows or bad illumination at night,that is which may cause strong noises. Therefore, the grayscale image might be unspecified in such situations and make the detection task a bit more complex. Edges essentially separates the two various regions which are static region (the roadway) and dynamic region (moving vehicles). The static background is then deleted to the locate moving objects in each frame. The result zone leaves only vehicles and some of the details as moving objects in sequential images which are changing frame to frame. A combination of forward and backward image differencing method and also Sobel edge detector has been used in this work. According to this method, the three sequential frames are chosen and the middle one should be compared to its previous and the next frames. Consequently, extracted edges of each of the frame detected by Canny edge detection achieved from previous section are used here. Then the differences of the frames can be obtained just by subtracting each two sequential pair of generated binary images, as in equation 1:

**BinaryImage** (Canny (Fn-1) ∩ Canny (Fn)) – **BinaryImage** (Canny (Fn) ∩ Canny (Fn+1)) …………..(1)
Where Fn-1 is previous frame, Fn is current frame and Fn+1 is the next frame. This process continues to the last three sequential video frames.

**2.2.1 Median Filter:** In non-recursive median filtering the background is estimated by finding the median value for each pixel from a set of frames stored in a buffer. This technique is based on the assumption such that the background pixels will not vary dramatically over a time period. This technique estimate the median through a simple recursive filter that increases or decreases by one if the input pixel is greater or less than the estimate respectively and it is not changed if it equals. In addition to the high computational complexity of non recursive median filtering, its memory requirement is high. In contrast the major strengths of the approximate median filter are its computational efficiency, robustness to noise, and simplicity.

**2.2.2 Kalman Filter:** The Kalman filter is a mathematical power tool that plays an important role in computer graphics. It is also known as linear quadratic estimation. The kalman filter make use of series of measurements observed over time, containing noise and other inaccuracies, and produces estimates of unknown variables that tend to be more precise and than those based on a single measurement alone. The Kalman filter can make full use of the historical information and reduce the whole search range of the image, to significantly improve system processing speed. The Kalman filter increases the tracking accuracy and stability

**2.2.3 Single Gaussian Pixel Distribution Temporal single Gaussian is used to model back:** It improve robustness and reduce memory requirement. To achieve more adaptive background model pixels variance was additionally calculated [4]. The model is computed recursively in the form of cumulative running average and standard deviation [16]. Based on the pixel position, each pixel is classified either a background or a foreground pixel. Thus single Gaussian model can be considered as the statistical equivalent of dynamic threshold [16].

**2.3 VIDEO PROCESSING:** Video processing is a subclass of Digital Signal Processing techniques where the input and output signals are video streams. In computers, one of the best important ways to reach video analysis goals is using image processing methods in each video frame. Here motions are simply realized by comparing sequential frames. Video processing includes prefiltering, which can cause contrast changes and noise elimination along with video frames pixel size conversions and Highlights particular areas of videos, deleting unsuitable lighting effects, just eliminating camera motions and removing edge artifacts are performable using video processing methods. Open Cv library of python is equipped with many functions that helps us to manipulate videos and images. Open CV Python makes use of Numpy technique, which is a library for numerical operations with a MATLAB style syntax. All the Open CV array structures are converted from one to another Numpy arrays.

**2.4 RGB TO GRAYSCALE CONVERSION:**
The sequence of captured video frames should be transformed from RGB color mode to a 0 to 255 gray levels. When converting an RGB image to a grayscale mode, the RGB values for each pixel must be taken, and a single value reflecting the brightness percentage of that pixel should be prepared as an output data.

**2.5 DETECTION ZONE:** As an observation (detection) zone, a region must be defined to display moving vehicle's edges in a bounding box at the time that the vehicle enters it. This zone is in middle of the screen and covers about 1/3 of its height and 3/5 of its width (considering minimum and maximum available size of detectable passing vehicles in pixels). This area which contains the most traffic can embed both small and long vehicles and the main goal of defining it is to avoid perspective challenges and thewrong type counts. Based on the proposed method in background subtraction level, a vehicle is detected in three sequential frames. When a moving vehicle is detected, the bounding box whelming vehicle borders in binary image is drawn.

**2.6 OPTICAL FLOW:** Optical flow is the instantaneous speed of pixels on the image surface, which corresponds to moving objects in 3-D space. The main idea behind optical flow is to match pixels between image frames using temporal and gradient information. The dense optical flow was used to separate merged blobs of vehicles., optical flow was used with 3-D wireframes for vehicle segmentation. The iterative nature of optical flow calculations provides accurate subpixel motion vectors at the expense of added computational time. Yet, the optical flow methods are still popular for vehicle detection since these techniques are less susceptible to occlusion issues.

**2.7 APPEARANCE-BASED FEATURES:** The visual information of an object can be categorized into: color, texture, and shape. Prior informations are usually employed for modeling when using methods based on these features. The feature extraction method is used to compare the extracted 2-D image features with the true 3-D features in the real world environment. In contrast to motion based methods, appearance based methods can detect and recognize stationary objects.

**2.7.1 Feature-Based Techniques:** The visual appearances of the vehicles are characterized using the coded representative feature descriptions. A variety of features have been used in vehicle detection such as the local symmetry edge operators. It is sensitive to size and illumination variations. These simple features evolve into more general and robust features that allow direct detection and classification of vehicles. Scale Invariant Feature Transformation (SIFT) , Histogram of Oriented Gradient (HOG) and Haar like features are extensively used in vehicle detection literature.

**2.7.2 Scale Invariant Feature Transformation:** In Scale Invariant Feature Transformation (SIFT) [18]the features are detected through a staged filtering approach, which identifies local edge orientation around stable key points in scale space. The generated features are invariant to image scaling, translation, rotation and also it is partially invariant to illumination changes and affine or 3D projection. In addition to the feature vector, the characteristics scale and orientation of every key point is calculated. It can be used to find the correspondence of object points in different frames.

**2.7.3 Histogram of Oriented Gradient:** The Histogram of Oriented Gradient (HOG) [19] computes the image gradient directional histogram, which is an integrated presentation of gradient and edge information. It was originally proposed to detect pedestrian, then in [20], it was introduced for vehicle detection by using 3-D model surface instead of 2-Dgrid of cell to generate 3-D histogram of oriented gradient (3-DHOG). A combination of a latent support vector machine (LSVM) and HOG was used in [9] to combines both local and global features of the vehicle as a deformable object model. Illumination and geometric invariance together with the high computational efficiency are the main advantages of this feature.

**1.7.4 Haar-Like Features:** Haar like features [26] are formed of sum and differences of rectangles over an image patch to describe the grey level distribution of adjacent regions. The filters used to extract the features consist of two, three or four that can be at any position and scale. The output of the filter is calculated by adding the pixel values for the grey region and white region separately, and then the difference between the two sums is normalized. A Haar feature was used in [37] to detect vehicles and it was employed to train a cascaded Adaboost classifier. The advantage of this feature are it is sensitive to vertical, horizontal and symmetric structure, which make them well suited for real time application. The disadvantage is that it has a high computational efficiency.

**2.8. VEHICLE TRACKING:** Vehicle tracking is used to predict vehicle positions in subsequent frames, match vehicles between adjacent frames, and ultimately obtain the trajectory and location for each frame in the camera FOV of the vehicle. Tracking method gets hold of vehicle trajectory through identifying motion dynamic attributes and characteristics to locate its position in every frame [1].Vehicles tracking can be merged with the detection process or performed separately. The detected vehicles and its correspondence are jointly estimated by updating location iteratively using information obtained from previous frames. In the latter case, vehicle detection is performed in every frame, and data association is used to provide correspondence between vehicles in consecutive frames [32].Current trends in vehicle tracking can be classified into: region based (shape or contour), and feature-based tracking.

**2.8.1 Region-Based Tracking:** Tracking based on region detects vehicles is as connected regions within rectangular, oval or any simple geometric shape, which can be characterized by area, coordinates, centroids, edges, contour or intensity histogram etc. Data association between region characteristics within consecutive frame is used to perform tracking. In [21] shape based tracking with Kalman filtering were used to match simple region. In [10] graph based region tracking was used for highway vehicles by finding the maximal weight graph. The disadvantages of this technique are computational complexity and its failure in crowded situation. The length and height of the convex hull were used to track vehicle. In the contour of two vehicles was used to resolve occlusion. Vehicle contour tracking method was used in [8] to handle visual clutter and partial occlusions.

**2.8.2 Feature-Based Tracking:** The feature based approach is suitable for tracking those targets with small area in the image by compactly representing parts of a vehicle or local areas. The various vehicle features detected are used to perform matching with consecutive frames. The corners and edges were used to represent vehicles in earlier techniques. The combination of corners, edges or interest points with feature descriptors like SIFT , HOG and Haar are proposed in several techniques for vehicle tracking. Other techniques perform tracking based on color histogram, which is more robust to noise and invariant to vehicle rotation and translation [27].But the main challenge in this technique is to choose the appropriate set of features which can effectively represent the moving object (i.e. vehicle).

***Table 2 Representative Work In Vehicle Tracking Categories***

| Techniques | Methods | References |
|---|---|---|
| Region-Based Tracking | Shape-Based | Mandellos, et al., [21]<br>Lai, et al., [10] |
| | Contour-Based | Zhang, et al., [38]<br>Meier, et al., [8] |
| Feature-Based Tracking | Buch, et al., [22]<br>Bouttefroy, et al., [27] | |

**2.8.3 Tracking Algorithms** All tracking techniques require prediction and data association process that can be performed using tracking algorithms that include Kalman filter and Particle filter.

a) **Kalman Filter Tracking** Kalman filtering is used to estimate the object position in the new frame assuming that the dynamics of the moving object can be modeled and that the noise effect is stationary with zero mean. The Kalman filter is estimated recursively using the previously estimated states and current measurements to obtain a new state. Projective Kalman filter was combined with mean shift algorithm in [22] to perform vehicle tracking. To provide accurate estimation of vehicle position, a non linear projection of the vehicle trajectory is integrated in its observation function. Variable sample rate Kalman filter proposed in [23] track 3D model vehicle on the ground plane. Kalman filter was used in [47] to predict the possible location of the vehicle, and then accurate estimation was achieved by predicted point matching using Gabor wavelet features.

b) **Particle-Filter Tracking** The particle filter is a generalization of the Kalman filter. The basic idea of particle filter is to use a set of random samples with associated weights and estimation based on these samples inorder to represent the posterior probability density. According to Monte Carlo theory, when the number of particles is big enough, then the group of particles with associated weight can completely describe a posteriori probability distribution. At this point, the Bayesian estimation of particle filter is optimal [17] is used, which overcomes the constraint of a single Gaussian distribution of Kalman filters. Vehicle contour tracking in [8] is based on particle filter condensation algorithm. Color histogram and edge-based shape features were combined in , to improve the efficiency, even with significant color variations, poor lighting, and/or background clutter edges.

**2.9 COUNTING AND CLASSIFICATION FUNCTIONS:** Vehicle counters are used in computing capacity, establishing structural design criteria and computing expected roadway user revenue [10]. Typically in the proposed technique vehicles are classified as four common types:

- Type1: bicycles, motorcycles
- Type2: motorcars
- Type3: pickups, minibuses
- Type4: buses, trucks, trailers

It is necessary to have the width and length of each vehicle's bounding boxes in pixels range to diagnose that the passing vehicles belongs to which of the mentioned types. The area of each bounding boxes shows which type should be allocated for the vehicle. Each vehicle type can be shown by a special type of rectangle color. Type 1 has been represented by red, and Type2, Type 3 and Type 4 have been characterized by green, blue and yellow rectangles, respectively.

In counting step, four isolated counters used for each vehicle type and also a total counter is needed to store the sum value of them. All counters should count just the vehicles which are passing in specific direction. So if a vehicle stops, turns or moves in wrong direction in the detection zone such that it should not be counted. In this technique, counting is according to the total number of moving vehicles detected in the detection zone and classified in one of mentioned groups.

Total passed vehicles, which will be shown in yellow, help us to analyze traffic flow in a period of time. Also by then calculating the bounding boxes height and width in pixels, vehicle types can be distinguished and counted by related counters. Furthermore, in both counted vehicles, edges will be covered with green rectangles, which shows that they belong to Type 2 (even the green numbers inside bounding boxes confirm this result).

## 3. CONCLUSION

In this paper, we have provided an extensive review of the state of the art literature addressing computer vision techniques used in video based traffic surveillance and monitoring systems. These systems perform three major operations that are vehicle detection, tracking and behavior understanding. Vehicle detection was divided into two main categories based on the vehicle representation, namely, techniques based on motion cues and techniques that employ appearance features. Both techniques can be used to isolate vehicles from background scene with different computational complexity and detection accuracy. Vehicle tracking was categorized into region and feature based tracking with a discussion on motion and parameter estimation schemes employed like Kalman and Particle filtering. We also provide a detailed summarize on vehicle behavior understanding on a single camera using trajectory information. We believe that, this paper provides a rich bibliography content regarding vehicles surveillance systems, which can provide valuable in sight into this important research area and encourage new research. Python is very good library like numpy, matplotlib, scipy, which can help to count traffic, classify the traffic and save the time of engineer.

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