A Highly Robust Vehicle Detection, Tracking and Speed Measurement Model for Intelligent Transport Systems

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Abstract
The high pace rise in vehicle counts, traffic density, and security concerns, a potential system for traffic surveillance, vehicle monitoring and control has become an inevitable need to facilitate intelligent transportation system (ITS). Although, numerous approaches have been proposed for moving vehicle detection and tracking, still the optimization needs can’t be ignored. In this paper, a robust image processing based vehicle detection, tracking and speed measurement model has been developed. The proposed model implements enhanced pre-processing, background subtraction, morphological operation as well as feature mapping processes for moving vehicle detection, tracking and speed estimation. To achieve optimal performance, a multi-directional filtering scheme has been develop for moving vehicle detection, which considers intensity, moving pixel orientation etc. for efficient candidate vehicle detection in traffic video. To enhance background subtraction, a novel multi-directional intensity strokes estimation approach has been introduced that plays significant role for distinguishing vehicle region from other background contents. In addition, the enhanced thinning and dilation based morphological process has been introduced that exhibits more precise and accurate vehicle detection. A novel feature clustering scheme with heuristic filtering based blob analysis and adaptive bounding box generation makes our proposed model more efficient for vehicle detection and tracking. Furthermore, a novel moving vehicle speed estimation approach has been developed that can be significant for efficient ITS systems.

Keywords: Vehicle detection and tracking, background subtraction, vehicle speed, intelligent transport system, directional filtering.

Introduction
The high pace emergence of communication system and associated technologies such as image processing has given a new dimension for Intelligent transportation systems (ITS), which has attracted attention of major researchers from industries as well as academics. The economic and easily availability of hardware have motivated researchers to develop more efficient solution for computer vision based applications. Image processing based computer vision has become a promising technology for real time supervision, monitoring, and control, that serves major areas, ranging from civil applications, industries till defence utilities. Especially considering significance of ITSs, the vision based supervision has the significant contribution, as it can facilitate real time monitoring, vehicle tracking and identification. In addition, other parametric identification such as vehicle speed, vehicle density, vehicle classification etc. has been demanded for efficient traffic monitoring and control. The provisioning for these requirements can enable optimal ITS solution in present day scenarios.

The exponential rise in vehicles on road has alarmed researchers to develop certain robust and efficient traffic monitoring system that could provide significant information about varied traffic related parameters such as vehicle count, traffic congestion and vehicle density, speed of vehicles etc. The fact or matter is that road accident caused deaths has increased with alarming rate globally. Interestingly majority of such accidents takes place due to uncontrolled the speed of the vehicle. Thus, an efficient vision based supervision framework for vehicle tracking and its speed measurement can be of great significance. A number of approaches have been proposed on the basis of video sequences processing and analysis. Some researchers have made efforts towards developing solution for moving vehicle/object tracking, traffic surveillance, traffic density estimation, trajectory estimation and vehicle speed measurement and most of the researches have used video processing and vision based concept [1-5] to achieve these objectives. However, majority of researches have either focused on vehicle or object tracking or its classification. On contrary, the irony is that there is an inevitable need for such systems which could provide optimal vehicle segmentation in all circumstances (environmental conditions, illuminations, background scenarios, noise etc.), without compromising with the accuracy of detection and classification. To ensure it, the algorithms require optimization at every level of video processing. In this paper, we intend to introduce novelty and optimization at each functional phase of image processing, segmentation, detection and tracking. There are numerous constraints such as conventional segmentation and background extraction, generic morphology approaches, light and brightness dependencies etc. In addition,
some other factors such as brightness, complexities in background, and speed of the moving vehicle etc are the predominant factors that cause intricacies in efficient detection and tracking. Specially, the consistent image brightness assumption between different sequential frames is one of the mostly used constraints. In order to optimize the vehicle detection accuracy and stability, some other constraints such as motion smoothness constraint has been suggested. However, the existing approaches could not solve the issues caused due to noise in ambience, disturbances, and occlusion. In real time scenarios, the background might spatiotemporally vary due to the natural complexity like non-uniform background texture, variation in background illumination, wind-driven motion etc. Furthermore, vehicle itself can exhibit a number of characteristics such as rigidity, elasticity or fluidity, which have an important impact on accuracy of detection and prediction. Hence, considering these existing intricacies and drawbacks of the existing approaches, in this paper, a video processing and vision based highly robust vehicle detection, tracking and speed estimation system has been developed. In order to enhance the efficiency of the proposed system, a number of optimization approaches have been implemented for efficient moving object or candidate (vehicle) detection, enhanced morphological approaches for precise detection, efficient blob analysis for noise reduction etc. that intends to enhance each components of the moving vehicle detection and speed estimation scheme. The other content of this paper is divided into five sections. In Section 2, the related works are presented, which has been followed by a brief of our contribution in Section 3. In Section 4, the proposed methodologies and its efficient implementation has been discussed. Section 5 discusses the conclusion of the proposed system. The references used in this paper are given at the last of the presented manuscript.

Related Works
In this section, some of the predominant literatures discussing vehicle detection techniques etc are discussed.

Motion Vehicle Detection and Segmentation
The detection of moving objects in the same image sequence, captured at different intervals is considered to be one of the interesting research fields in computer vision. There are a number of applications which consider detection of change as the event to perform various tasks such as surveillance system, computer aided diagnosis (CAD) and treatment, sensing system and monitoring and control for civil, industrial as well as military applications [6]. Traffic video surveillance deals with the analysis of the traffic images which contain moving vehicle detection and its accurate segmentation. A number of approaches have been proposed based on background substrations, frame differentiation and motion based algorithms for video processing [7, 8] but still these approaches can be found confined in dealing with vehicle detection and tracking, especially in case of dynamic scenarios. In general, this approach comprises three predominant mechanisms for vehicle segmentation. These are:

1. Background Subtraction approach.
2. Feature Based approach.
3. Frame Differentiation and Motion Based approaches.

In this paper, a hybrid model using background subtraction and feature extraction has been developed for vehicle detection, tracking and speed estimation. A brief discussion of the background subtraction scheme is given in following section.

Background Subtraction Methods
Background subtraction technique deals with extracting the moving foreground objects from background image. This approach has established itself as one of the extensively employed methods for change detection and can be used for vehicle regions detection. Still this approach suffers due to variations in lighting conditions and the climate situations [9]. Therefore, a number of researches have been performed to resolve these existing limitations of background subtraction methods. Researchers in [10, 11] proposed a statistical and parametric paradigm for background subtraction where they used the Gaussian probability distribution model for individual pixel in the image. In this approach, researchers have updated the pixel values using Gaussian probability distribution model iteratively from new image in a series to detect moving object. It has been followed by the categorization of the individual pixel \((x, y)\) in the image where the pixels are categorized either be a part of the foreground or background. In [12], an enhanced approach was proposed for background subtraction where it was intended to segment moving vehicle from intricate and complex road conditions. They used a filtering approach on the basis of a histogram that gathers significant information from frame sequences with scatter background. Such background subtraction approach exhibited better in various conditions such as orientation, illumination, overcrowding situations etc [12].

Researchers in [13] developed an example-based scheme for vehicle traffic detection. In the first step, they implemented an adaptive background approximation approach which was followed by division of frame into multiple non-overlapped sections to identify the candidate vehicles. In second step, researchers applied Principal Component Analysis (PCA) to estimate the two histograms for individual candidate, which was further used by support vector machine (SVM) for vehicle classification. Ultimately, the classified parts of the vehicle region were shaped and connected as a parallelogram so as to obtain the vehicle final shape. In fact, this approach is computationally highly complex. Later, in [14] shadowing based vehicle detection was proposed, where the size features of vehicles were extracted. Researchers estimated the size as the distance between ends of front and rear tires for beneath vehicle’s shadow so as to differentiate the existence of vehicles on the lanes. A similar filtering based approach was proposed in [15], where researchers used two filters for eliminating swinging trees and raindrops. The proposed swinging trees algorithm has been used to reduce the computational complexity in vehicle tracking. Additionally, shade removal algorithm has been combined with a robust background deletion scheme to subtract moving vehicles from the background images. In [16], researchers developed a vehicle tracking algorithm by considering key features such as location, color dissemination, volume, speed of the group of the forefront entity and background based on Gaussian Mixture Model. Researchers used the concept to categorise individual pixel as noisy or forefront (background) so as to detect vehicle.
**Feature Based Methods**

In numerous researches, various structural features of vehicle such as, edges and corners have been used to segment it from background image [17, 18]. On the basis of these features they identified moving and static background for vehicle detection. In addition, researchers in [17] proposed a model to deal with occlusion problem between the overlapping vehicles, where they used the concept of background subtraction [17]. A background discrimination approach was developed using various image features and a trainable object detection approach was proposed in [18]. Initially, they used HAAR wavelet transform for feature extraction, which was then followed by learning based classification. They have used learning scheme that takes a set of labelled training data so as to perform labelling of the extracted objects features, as input. To perform classification, they used SVM classifier.

In [19], a sub region detection and analysis approach was used for feature extraction of the partially occluded vehicles. In addition, the used a multiscale transformation that posses the frame elements which are indexed by features such as orientation, position, measure and significant time-frequency localization characteristics, which have been retrieved through curvelet transform. The curvelet transform based feature extraction for vehicle detection algorithm was developed in [20]. In order to classify the vehicles, they used KNN and SVM classifiers. In [21], researchers developed a new traffic criterion detection paradigm where they used Epi-polar Plane Image (EPI). They used an enhanced Sobel operator based approach to deal with noise sensitivity and rough edge of the vehicles. In addition, to enhance performance, researchers used the Gabor operator texture edge detection scheme for feature extraction. In [22] a vehicle detection algorithm was developed, where they used the edges of the vehicle body, edge of windshield. The extracted features were processed for structural shaping using Bayesian network.

**Frame Differencing and Motion Based Methods**

This approach deals with distinguishing two subsequent frames so as to segment the moving object from the background image. In addition, this approach employs process to isolate moving blobs based on orientation and speed of the blob movement for detection optimization [23, 24]. Researchers suggested inter or intra-frame tracking levels to recognize and manipulate the occlusion vehicles. Researchers in [25] suggested for inter-frame and intra-frame manipulation for efficient vehicle detection and tracking [25]. A multimodal temporal panorama (MTP) approach was proposed in [26], where a remote multimodal (audio/video) monitoring system was developed to extract and reconstruct vehicles under moving conditions. Some other approaches have been proposed [27] which performs visual-based dimensional approximation for extracting motion vehicles. In addition, a shadow removal approach has been proposed to vehicle detection and classification [27]. In [24] a versatile movement histogram approach has been used to detect the moving vehicles. In their approach, a novel background variation model was used to enable lighting adaptation for vehicle detection in video data. In addition, researchers have used an adaptable movement histogram technique for vehicle detection.

**Our Contribution**

Detecting Moving vehicle from video accurately is challenging task. To detect moving object there are various approaches such as temporal differencing method, optical flow algorithm, background subtraction algorithm. Temporal differencing method uses two adjacent frames only to get background image. This method has one disadvantage that it cannot detect slow changes accurately. The approach of optical flow algorithm can detect object independently using camera motion, but unfortunately it is computationally complex and not suitable for real time application. In background subtraction absolute difference between background model and each instantaneous frame is taken to detect moving object. Background model is an image with no moving object. In our proposed model, a novel and enhanced background subtraction algorithm has been developed for moving vehicle detection. Our proposed model considers background subtraction concept for moving vehicle detection but unlike conventional approaches, we have introduced numerous algorithmic optimization approaches such as multi-directional filtering and fusion based background subtraction, thresholding, directional filtering and morphological operations for moving vehicle detection. The proposed system employs a directional filtering scheme for detecting moving vehicles, while considering its intensity and orientation variance as detection parameter. In addition, the multi-directional intensity strokes estimation approach has been applied that plays significant role for distinguishing vehicle region from other background contents. The implementation of the robust morphological scheme including thinning and dilation parameter with well calibrated content region identification makes our proposed system more robust and efficient. The feature clustering scheme with heuristic filtering based blob analysis makes our proposed model more efficient and precise for accurate moving vehicle detection. To enable better visualization of traffic monitoring, a bounding box generation scheme has been incorporated. In addition to the efficient vehicle detection system, in this paper a speed estimation mechanism has been developed, which measures the speed of vehicle in real time movement.

The overall discussion of the proposed system is given in the following section.

![Functional Architecture of the proposed vehicle detection and surveillance system](image-url)
Proposed System
In this section of the presented manuscript, the proposed algorithms and its efficient implementation is discussed.

Video Data Acquisition
In this paper, in order to examine the performance of the proposed vehicle detection and speed estimation system for efficient traffic surveillance, the real-time video data and some standard vehicle traffic data have been used. The real-time video data has been recorded using camera with pixels adjustment facilities. The input video data are in RGB form, which are further converted into gray color format for processing.

Image Pre-Processing
To develop efficient vehicle detection and speed estimation scheme, the appropriateness of the input data and its quality is of great significance. In this phase, the pre-processing of the video has been done where the input RGB video has been converted into the frames that has been followed by the extraction of various parameters such as number of frames, frame rate, colour format, frame size etc. Unlike majority of existing systems, where the initial declaration of the total number of frames is must, in our proposed model, an automatic frame and dimensional extraction approach has been incorporated that makes our proposed system capable to process any kind of videos having different features and dimensional characteristics. Once retrieving the frames of the input videos, the RGB images (Figure 1) have been converted into gray color image (Figure 2), which is then followed by filtering and vehicle segmentation process.

Moving Vehicle Region Detection
Unlike conventional approaches, in this paper, it is intended to construct a feature map using multiple significant characteristic of the moving vehicle such as, vehicle edge strength, density, variance of orientations along with background subtraction scheme, as discussed in the previous section. Unlike majority of existing systems, where only the background extraction has been used as the foundation to detect vehicle, in our proposed vehicle detection approach a novel multilevel optimization approach has been introduced that ensures efficient video analysis and feature mapping for final video tracking purposes. In our model, the resultant feature map is a gray-scale image having the same size of the input image, where the pixel intensity signifies the probability of Vehicle. The overall process of moving vehicle detection is discussed as follows:

Background Extraction
This is the matter of fact that the core of Background Subtraction approach is to retrieve the background of the moving video. In traffic surveillance system, while recording video on highway; it becomes highly intricate to get the image without any moving vehicle. In order to retrieve such image we have implemented background subtraction model. In this work, average of all frames pixel values, have taken into consideration. Thus, retrieving the background image, the region of interest extraction has been performed. In our proposed work, vehicle moving towards camera has been are tracked so that only one lane of road is considered as ROI. Each frame has been multiplied with extracted region of interest. In the proposed model, before processing for multiplication, the RGB frames have been converted into Gray level. Before processing for background subtraction, a motion integer background extraction has been done, where the background objects such as tree or other non-vehicle objects are eliminated to retain intact detection of moving vehicle (Figure 3).

In addition, a multi-directional filtering and fusion scheme has also been introduced in the proposed model, that along with above discussed background subtraction, assures optimal performance for precise background extraction and moving candidate region (vehicle) detection. The multi-directional filtering and fusion is discussed in next section. The proposed approach enables avoidance of any irrelevant movement such
as waving trees, or any other unwanted movement etc. It is required to do to get accuracy in vehicle detection. The absolute difference of each instantaneous frame and background model after multiplying both with extracted ROI has taken to detect only moving vehicles. The background subtracted frame is given in Figure 4.

**Figure 4: Background subtracted**

**Threshold Estimation**

Our proposed system employs a thresholding based segmentation scheme that converts grey scale image to binary image. This is the fact that the selection of an optimal threshold plays a vital role in assuring optimal image segmentation, especially in thresholding based segmentation. Therefore, in this paper, to distinguish foreground moving vehicle from the static background, thresholding scheme has been used. The considered conditional thresholding mechanism is given in the following equation (1).

\[
T(x, y) = \begin{cases} 
0 & \text{for } f(x, y) < S_{th} \\
1 & \text{for } f(x, y) \geq S_{th} 
\end{cases}
\]

where \(T(x, y)\) represents the threshold video frame, \(S_{th}\) depicts the selected threshold value and \(f(x, y)\) represents the instantaneous frame.

**Directional filtering**

In order to achieve optimal performance, the magnitude of the second derivative of intensity has been used as a measurement of edge strength, because it facilitates optimal detection of intensity peaks that usually characterize vehicle in the current video frame. We have estimated the edge density of the moving vehicle on the basis of the average edge strength within a frame, which has already been converted from RGB video to the gray scale image. To enhance the vehicle detection efficiency, in this paper a novel multidirectional filtering has been proposed that retrieves multi-directional edge intensity \((E_{\theta=0\text{or}180,45,90,135})\) estimation of the moving vehicle frames. These all directional intensity vectors comprise all the characteristic of the edges of the frame including moving vehicle that enables effective vehicle detection and seed estimation.

**Edge selection**

This is the fact that vertical and horizontal edges can form the most significant strokes of the object (here moving vehicle) in an image and its lengths can also represent the dimensional characteristics of the corresponding vehicle, which can be significantly used to classify vehicles based on it geometry. Extracting and grouping these strokes, the vehicle region with different heights or dimensions can be located precisely. In practical scenarios, there can be both strong vertical as well as horizontal edges, reflecting the shape of vehicle. In addition, the horizontal and vertical edges generated by such moving objects can have large dimension, especially the length. Hence, performing classification of these edges into long and short edges can be significant to eliminate extreme large (vertical or horizontal) edges and the short edges can be considered for further processing for vehicle detection. Because of non-uniform background, color, intensity or illumination, long vertical edges generated by non-vehicle objects can have a large intensity and feature variance, such as pixel uniformity, color variations etc. Performing the thresholding process, such long vertical edges might turn out to be distorted short edges that as a result can cause false alarms. Similarly, non-uniform surfaces of the vehicle from various lighting, shadows and other features of the vehicle shape itself too cause broken vertical edges. To remove these false grouping caused due to those broken edges, in this paper, we have incorporated a two-stage edge generation approach. In the first approach the strong vertical edges are obtained as given in equation (1).

\[
Edge_{\text{Vertical}}^{\text{strong}} = |E_{90}|_2
\]

where \(E_{90}\) represents the 90° intensity edge image which is nothing else but the 2D convolution result of the original image having 90° kernel, \(\cdot|_2\) represents a thresholding operator which is used to achieve a binary result of the vertical edges. As this approach intends to extract the strong edges, it can’t be stated to be sensitive to the threshold value. In the second approach, it is intended to retrieve the weak vertical as depicted through following equations (2-4):

\[
dilated = \text{Dilation}(Edge_{\text{Verticalbw}}^{\text{strong}})_{1\times3}
\]

\[
closed = \text{Closing}(\text{dilated})_{m\times1}
\]
In this process, the morphological dilation has been introduced that plays significant role in eliminating the impacts of slightly slanted edges and a vertical linear structuring element $m \times 1$ which has been followed by the implementation of a closing operator so as to force the strong vertical edges clogged. There can be the trade-off on selecting the value of the size of structuring elements. Here, in this paper, we have assumed that the small value can be computationally efficient and consumes less time at the expense of false positives while a large value can significantly increase the precise detection but at the cost of elevated computational cost.

In our proposed model, considering the requirement of an effective and efficient system, $m$ has been assigned as $m = (1/25) \times \text{width}_{\text{frame}}$, which enables optimal vehicle detection results with an acceptable computation cost for a real time vehicle surveillance system. The ultimate edges formed are the combination of strong as well as weak edges, which has been retrieved using equation (5).

$$
\text{Edge}_{\text{Verticalbw}} = \text{Edge}_{\text{Strong verticalbw}} + \text{Edge}_{\text{Weak verticalbw}}
$$

In our proposed model, a morphological thinning operator has been implemented which is followed by a connected component labelling algorithms. These functions are:

$$
\text{thinned} = \text{Thinning} (\text{Edge}_{\text{Verticalbw}})
$$

$$
\text{labeled} = \text{BWlabel} (\text{thinned}, A)
$$

In our proposed vehicle detection and surveillance system, the morphological thinning operator makes the widths of the resultant edges one pixel thick and the connected component labelling operator performs labelling of the thinned vertical edges. In our proposed model, we have used 8 and 4-pixel connectivity for labelling. Performing labelling of the connected components, the individual edge has been uniquely labelled as a single connected component having its unique component number. Thus, the labelled edge frame has been processed by a length labelling process that intends to let the intensity of edge pixels represent their respective dimensions (lengths). Consequently, all the pixels belonging to the same edge have been labelled with the same number which is proportional to its dimensional length. Since, the high value in the length labelled vehicle video frame represents a long edge, in this paper a thresholding scheme has been employed to distinguish short edges ($\text{short}_{\text{verticalbw}}$). This is also the matter of fact that achieving 100% automatic precise vehicle detection in moving space in highly intricate task, in this paper, the efforts have been made to reduce the false negatives of missed detection. Here, we have used a low threshold value along with edge density and variance of orientation to optimize vehicle detection and precise speed estimation for efficient traffic surveillance system.

The outputs of the directional filters (vertical and horizontal) are given in Figure 6 and Figure 7. The combined vehicle detected is given in Figure 8.

**Feature Mapping**

In our proposed model, the practical facts that the regions with moving vehicle would have significantly higher edge density value, strength as well as variance of orientations as compared to the non-vehicle background regions. In our proposed model, these key characteristics have been exploited so as to enhance the vehicle region detection by means of generating a feature map values that significantly decreases the false regions and optimizes true candidate (moving vehicle) region detection. The overall process is illustrated through equation (8-10).

$$
\text{Candidate}_{\text{Vehicle}} = \text{Dilation}(\text{short}_{\text{Verticalbw}}, m \times m)
$$

$$
\text{Refined}_{\text{Vehicle}} = \text{Candidate}_{\text{Vehicle}} \times \sum_{\theta=90,180} E_{\theta}
$$

$$
\text{f}_{\text{map}}(i,j) = N \sum_{m=c}^{c} \sum_{n=-c}^{c} \text{Refined}_{\text{Vehicle}}(i+m, j+n) \times \text{weight}(i,j)
$$

In this approach, the morphological dilation operator having a $m \times m$ structuring element has been applied for selecting the short vertical edge image so as to get precise vehicle region detection. In our proposed vehicle detection system, multidimensional or multi-orientation edge information ($E_{\theta=90,180}$) have been used to refine (performing fusion of $E_{\theta=90}$ and $E_{\theta=180}$) the potential candidate moving vehicle detection. In equation (10), $f_{\text{map}}$ represents the resulting feature map, and $N$ gives a normalization operation that normalizes intensity (feature mapped values) in the range of $[0, 255]$. In our proposed model, a weight function weight($i,j$) has been employed that estimates the weight of pixel ($i,j$) on the basis of the number of orientations of edges within a video frame. Using the weight function, our proposed model distinguishes the candidate vehicle regions from background regions. The vertical ($E_{\theta=90}$) and horizontal scanning ($E_{\theta=180}$) outputs are given in Figure 6 and 7 respectively.

*Figure 6: Vertical Scanning*
The combined output is given in Figure 8.

Now, combining vertical and horizontal detected vehicles, we get the combined vehicle output, given in Figure 10.

Feature clustering
The moving vehicles and its associated dimensional features can be clustered to localize the moving vehicle on the road. In fact, the characteristics of the components connected with moving vehicle are different from the static background. In practical scenarios, the characteristics such as the intensity of the feature map depicts the probability of vehicle in the current frame, certain simple thresholding can be applied to distinguish regions with higher vehicle possibility. Thus, employing certain morphological dilation operator the close regions can be connected together while ignoring or isolating those regions located far away. In our implemented vehicle detection model, a morphological dilation operator having square structuring element has been used that joints vehicle regions in the retrieved binary regions.
Detecting a bounding box while crossing the defined track, the simultaneous horizontal and vertical search and match scheme. From input traffic video data. Unlike conventional approaches extracted have been tracked over sequential frames retrieved the height of the boundary box have been padded by a small pixels existing near or outside of the initial boundary, width and the vehicle. Thus, the proposed system can efficiently remove algorithm based on Mahalanobis distance, in our proposed approach more accurate and efficient for better moving detection and tracking. The boundary boxes generated for each detected vehicle has been saved that makes tracking more efficient. The combined vehicle detected and its speed presentation is given in Figure 11.

**Boundary Boxes Generation**
Retaining the blobs reflecting vehicle in the running frame, it has been enclosed inside boundary boxes. We have estimated four pairs of the boundary box coordinates using the maximum and minimum coordinates of the top, bottom, left and right points of the subsequent blobs reflecting vehicle in the running frame. To avoid any probable missing of the vehicle related pixels existing near or outside of the initial boundary, width and height of the boundary box have been padded by a small amount. To make detection more precise, visible and road condition adaptive, in our proposed model, the large boxes such as borders, highway dividers etc. have been ignored and an additional adaptive padding has been introduced that makes our approach more accurate and efficient for better moving detection and tracking. The boundary boxes generated for each detected vehicle has been saved that makes tracking more efficient. The combined vehicle detected and its speed presentation is given in Figure 11.

**Vehicle Tracking**
In this paper, the proposed vehicle tracking system has been made on the basis of feature tracking concept. The features extracted have been tracked over sequential frames retrieved from input traffic video data. Unlike conventional approaches of tracking where researchers have used object matching algorithm based on Mahalanobis distance, in our proposed model, track identification and replica matching based tracking system has been developed. Here, initially the feature mapping for all frames has been estimated and a track graph has been prepared. To eliminate the probability of any error, few initial frames have been ignored. In this approach, a track has been deployed that traces the presence or passing of bounding boxes and thus indicating number of vehicles crossing the track. A search scheme has been used that searches bounding boxes in each frame and marks it for tracking status. The implemented function enables swift bounding box detection by means of a simultaneous horizontal and vertical search and match scheme. Detecting a bounding box while crossing the defined track, the vehicle has been counted and a template marking has been done that indicates the status of passing vehicle. Our proposed system represents an object matching scheme that estimates distance between vehicle features or the object features in the previous frame, which has been stored in track graph metrics and instantaneous frame. In addition, an additional marking template for vehicle ID presentation and speed estimation has been used that makes system better realizable and perceptible.

**Speed Estimation Scheme**
In this paper, the detected moving vehicle possessing its matching ID has been tracked over frames of the video data. In order to calculate the total number of frames having same object, has been estimated following using equation:

\[
\text{TotalFramesCovered} = \text{frame}_\text{Last}_n - \text{frame}_\text{First}_0
\]  
(11)

Where \(\text{frame}_\text{First}_0\) represents the first video frame when vehicle enters into the region of interest (ROI) and \(\text{frame}_\text{Last}_n\) represents the frame when detected vehicle passed away from defined ROI. In addition, the real world distance has also been mapped on the image. Ultimately, the total frame count has been multiplied with the duration of a frame, which has been measured from the frame rate of video. In our proposed speed estimation model, with the fixed distance, the total time taken by vehicle to traverse it has been estimated in real world, which has been mapped into image.

The mathematical expression for speed measurement is given as follows:

\[
\text{Speed} = \frac{\text{Distance}}{(\text{FF} - \text{Framerate})}
\]  
(12)

As depicted in Figure 11, the speeds of the vehicles obtained are 15km/s, 16km/s and 11km/s.

**Conclusion**
The moving vehicle detection, tracking and its speed measurement system is of great significance for present day intelligent transport system. Considering limitations of the existing systems, such as conventional background subtraction, noise and illumination sensitivity, etc., in this paper a novel multi-directional filtering and fusion based background subtraction model has been developed that considers intensity.
moving pixel orientation etc. for moving vehicle detection. The proposed multi-directional intensity strokes estimation scheme has enabled better performance for precise moving vehicle candidate detection and tracking so as to distinguish moving vehicle region from other background images. Further, the enhanced thinning and dilation based morphological process has made proposed system more robust and accurate. Performing moving vehicle detection, feature mapping has been done where feature clustering and heuristic filtering approach has been incorporated, which has made blob analysis more efficient to detect precise candidate vehicle region. Later, the boundary box generation has facilitated precise vehicle tracking. In addition, to the efficient moving vehicle detection and tracking, in this paper, an efficient vehicle speed estimation scheme has been developed that enables real time vehicle tracking and its speed measurement. Predominantly, this paper focussed on vehicle detection and tracking on single lane road that in future can be developed for multi-lane system. In addition, in future density estimation and vehicle classification can also be done.

Reference