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NIGHTTIME VEHICLE LAMP DETECTION AND TRACKING USING KALMAN FILTER

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ABSTRACT

Traffic surveillance is an important component in intelligent transportation systems. Traffic flow management and monitoring have become vital issues in these systems. Traffic flow shows the state of traffic in fixed time intervals. It helps to manage and control traffic when there is a jam.In this paper, Kalman filter is proposedfor automatic tracking of vehicle. Fog lamps are eliminated at preprocessing time for faster and effectively detectionof vehicles in nighttime situations. A preprocessing step is useful to extract vehicle lamps, to filter out reflections and to eliminate fog lamps.Vehicle candidates areclassified by checking symmetric and similaritydegree of light components.The proposed method counts the number of four wheelervehicles that can be used for various purposes such as emergency vehicle notification systems, automatic road enforcement, variable speed limits, collision avoidance systems etc. Using Kalman filter vehicles can be tracked and their speed can be estimated. Using these parameters vehicle's accident can be predicted in nighttime.The proposed method has considered various road environments in nighttime. Results show the detection rate of 91.80% in NORMAL_1, 87.85% in NORMAL_2, 66.32% in RAINING_1 and 85.55% in HIGHWAY scenario. The results of experiments shows that the proposed method is efficientas compared to contrast based method,Background-subtraction-based method, Pairing-light-based methodand Salvi method.

Index Terms: *Nighttime Surveillance, Vehicle tracking,Vehicle detection, Kalman Filter, Intelligent Transportation System(ITS).*

I.INTRODUCTION

Traffic surveillance systems provide useful information such asaverage traffic speed, traffic flow density, total vehiclesand length of queue in fixed time interval. There are efforts to createprocedures related to intelligent transportation systems (ITSs) by involving surveillance techniques for upgrading the adequacy of traffic management for increased load. ITSs consist of Vision-based vehicle detectionutilizing video cameras as the sensor due to cost effective compared withinductive loop sensor, radar and lidar. In traffic monitoring systems, during daytime, vehicles are detected and analyzed by using grayscale, color, and motion information. However, for the nighttime traffic conditions, the previous information becomes unacceptable

and the vehicle can be seen by its headlight and rear light. This paper concentrates on night time vehicle detection and Kalman filter is used for tracking the vehicle.

The paper is organized in the following sections. Section II details the literature review. Section III deals with the proposed framework which gives an overview of the problem with the work done in the research. Section IV describes the vehicle detection method and tracking using Kalman filter. Section Vdetails parameters considered and tentativeresults are reported. Finally, Section VI describes the conclusion and future scope of proposed work.

II.LITERATURE SURVEY

Previous studies have discussed traffic surveillance [1]–[2],autonomousvehicle guidance and driver assistance systems [3]–[6] and road traffic information systems [7].In daylight vehicle detection, template-based methods [13]–[14] use the trained patterns to match vehicle using correlation. Gabor filter, Histogram of oriented gradients (HOG),Haar-like features and Support Vector Machine (SVM) arewell used for the vehicle detection. Sivaraman and Trived[15] proposed to combine Adaboost classification, active learning and Haar-like features. Yuan et al. [16] proposed to combine SVM classification, HOG features and Orientation determined using multiplicative kernel learning. These methods (HOG, SVM, Haar like features) are computationally expensive and give quite less accuracy in caseof detectedobjects are of incomplete shape due to occlusion.Appearance based methods extracts textual information such ascolors [10]–[11], edges [9] and corners [12] for feature analysis.Traffic informationthrough moving vehicles can be obtained bychange detection, frame differencing [17]–[21] based techniques or other statistical models to segregate moving vehicles from motionless background sights.[17], [18] uses spatial and temporal difference features to take out moving vehicles. [19]–[21] utilizes background subtraction based techniques to segment moving vehicles.Jazayeri et al [22],utilized Optical flow and hidden Markov model classification. On the other hand, the backgroundmodel during nighttimeis neither adaptive nor fast for holding dramatic changes in luminance. In addition,due to trafficcongestion, when vehicle's movement is moderate or unmoving, the false detection rate may increase. These methods are mainly designed to work under the daytime conditions, where more and moredetailsand appearanceinformation of vehicles can be captured.

Under dark illuminated conditions, headlights and rear lights are the well-known featuresof moving vehicles. Huang *et al.* [31]proposed interframe change information based method andblock-based contrast analysis. Contrast-based method canefficiently detect objects, using a stationary camera, in a given surveillance area. Interframe change and contrast information results in incorrect vehicle detection as they are sensitive to the illumination effects of moving vehicle headlights.Zhou *et al.* [26] method'sis too specific and less adaptive as fixed block sizes are considered for extractingthe headlight blobs. As vehicle's detailed and appearance information can-not be capturedduringnighttime sonighttime vehicle detection ismore technically complex.

III. PROPOSED FRAMEWORK

3.1 Workflow

The proposed workflow is a fivefold method, as shown in figure 1.

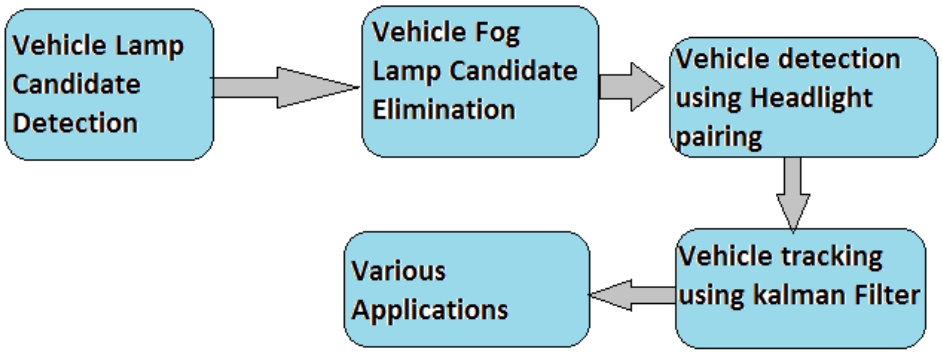


Figure 1. Basic procedure of the proposed method.

This work proposes vehicle detection and tracking scheme in nighttime using Kalman filter by analyzing the road images for traffic vehicle counting. A preprocessingstep is considered to filter out the reflections, fog lamps and for segmentation of the headlights. Next, lamps are pairedto detect a single vehicle using sizes and symmetric degreeof lamps. A tracking event using Kalman filter is triggered to track the pair when a vehicle is detected untilit leaves the area of interest. The proposed method uses two look up tables for detection and tracking of vehicle.

1) One sorted lookup table containing information about the lamp candidates that are used for quickaccess, and

2) Other Look up table stores the information of vehicle at various time intervals.

3.2 Data Set

Data set[33] used to validate the proposed work contains different videos of nighttime. Videosconsist of different scenarios likeon highway, on urban road, after raining, two and four wheeler vehicles. This proposed method is detecting and tracking only four wheelers out of them.

3.3 Vehicle Detection and Tracking: Algorithm

The following algorithm shows the proposed flow for vehicle detection and tracking in nighttime scenario. The detail discussion of these steps is done in further sections.

Algorithm:

Problem: Nighttime vehicle detection and tracking

Input: Nighttime Traffic Video, Output: Vehicle Count, Detection Rate.

1. Load the video.
2. Initialize 'vehicle_appear','vehicle_leaving' to zero and VL_list to NULL.
3. For every video frame repeat steps from 3 to 9 till the end of video.
4. Convert it into gray scale image.

5. Perform preprocessing steps: Select ROI, Morphological Operation, Thresholding, Filteration, Fog lamp Elimination.
6. Create LC list of extracted vehicle lamp candidates.
7. If VL_list is not empty go to step 8 .
8. Predict new location of each entry in VL_list using Kalman Filter and update status.
   a) if vehicle present on predicted position, update status to 'Tracked'.
   b) if vehicle is not found on predicted location for some time, update status to 'disappear'.
   c) if vehicle crosses the leaving line, update status to 'leaving' and vehicle_leaving=vehicle_leaving+1.
9. Detect new vehicle pair appeared on 'Detection Line'. Add their entry into VL_list.
   a) Make their status to 'Appear'.
   b) Vehicle_appear= Vehicle_appear+1.

3.4Preprocessing

Basic method of vehicle tracking includes mainly preprocessing, vehicle detection and vehicle trackingcomponents.In preprocessing, a region of interest (ROI) is taken as half of the frame shown in Figure 2(b) because blur occurs at the farthest part of the road as in Figure 2(a). Then, ROI is processed by multilevel thresholding (uses Otsu method introduced by Nobuyuki Otsu In 1979) toextract bright objects as shown in figure 2(c).Morphological opening and closing operations are applied to remove noise as shown in figure 2(d). Filtration methods are then applied to remove non-vehicle lamp candidates as shown in Figure 2(e).Fog lamp elimination method as shown in Figure 2(f) is then used to eliminate fog lamps from ROI for fast and effectively vehicle tracking.

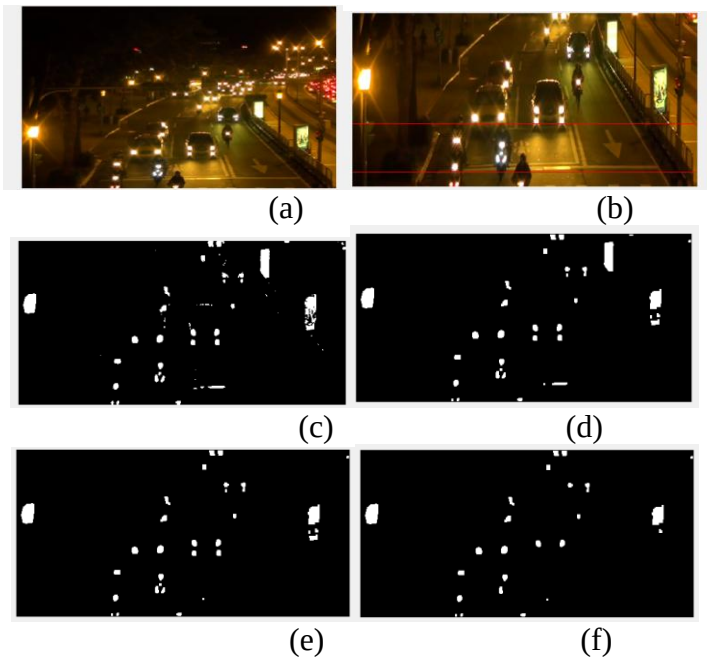


Figure 2. Preprocessing of the Frame (a)Original Image (b)Frame after the Selecting ROI (c)Frame after multilevel thresholding (d)Frame after applying the opening and closing Operation. (e)Frame after filtering out nonvehicle lamp candidates(f)Frame after Fog Lamp elimination.Filtered image after fog lamp elimination is labeled. A labeled list (LC) is used to record each filtered bright component. Each labeled lamp is denoted by

$$LC_i = \{\text{label value, state, x, y, height, width, area, centroid}\}$$

where 'label value'tells the labeled value in the frame after applying the connected component labeling method, state can be 0 or 1 thatdonates if a lamp candidate has already being tracked, (x,y) indicatesthe top left corner of a lampcandidate, and (width,height) indicates the width and height of a candidate.

Based on the observations, it is considered that vehicle lamp's ratio of height to width are constrained to a range. Non-vehicle lamp components are filtered out using this range, such as the street lights,reflections of lights etc. Ratio1 and Ratio2are empirically found to be 0.5 and 1.8, respectively during the elimination process of non-vehicle lamp candidates. The proposed method uses the height to width ratio from the LC_ilist asshown in equation 1:

$$Ratio1 < \frac{LC_i.\text{height}}{LC_i.\text{width}} < Ratio2 \qquad (1)$$

3.5 Fog Lamp Elimination: The last step of preprocessing is fog lamp elimination. For all lamp candidates in LC list, try to find such lamp candidates that are approximately below the vehicle lamp candidate. If the detected lamp candidates are within some range distance then it is examined for fog lamps.The search area of vehicle lamp candidate LC_i and fog lamp candidate $LC_j$is empirically found to be as follows:

$$LC_i.y + LC_i.\text{width} - LC_j.y <= 8 \;\&\&\; LC_i.x - LC_j.x <= 4 \qquad (2)$$

If both search criteria fulfills then fog lamp candidate (LC_j) is detected and eliminated.

IV.NIGHTTIMEVEHICLE DETECTION AND TRACKING

In the middle of the frame a horizontal detection line is set and a leaving line is positioned to 15 pixels above from the bottom of the image. Now the vehicle that passes through the detection line is set to status 'Appear' anda tracking event using Kalman filter is triggered to track until it reaches the leaving line. In this paper, a vehicle tracking list (VL_list) is used to record the detection and tracking of vehicles. The vehicle information is stored in the VL_listwhen a pair of lamp componentsappear on the detection line. The main function of this list is to store the track information of all the vehicle candidatesthat enters in the ROI and to update the status of each pair. The information of each vehicle appeared in ROI is shown as followsat time 't' :

VL_list={'l ','ly ','lx ','lw ','lh', 'r', 'ry', 'rx ','rw', 'rh', 't', 'status'}

Where the letterl and rare used for the left and right lamp candidate information respectively. Herein (l,r) stores the label value of left and right lamp candidate, (lw,lh,rw,rh)records the width and height of left and right lamps, (lx,ly,rx,ry) records the upper left pointcoordinate of left and right lamp candidate. 't'records the time of last update. Status of vehicle can be concluded by comparing 't' with current time.'Status'representsa number of states that are described as follows:

1) Appeared- When a lamp pair enters the ROIthat is not already in VL_list, it is considered as a new vehicle candidate pair. A new entry is introduced in VL_list and its status is set to 'Appeared'.
2) Tracked- Check the already existing VL_list for every incoming frame and predict location of vehicle candidate present in VL_list using Kalman filter. If a vehicle is present in the predicted location *Status* is updated to '*Tracked'* and new co-ordinates are updated in VL_list.

3) Disappeared- During the updation ofVL_list process,fi the predicted coordinates of a vehicle pair using kalman filter cannot be matched with the new incoming frame vehicle coordinates, status of that vehicle will be updated to'Disappeared' state. Vehicle's entry will be deleted from VL_list if 'Disappeared' status crosses the threshold time period.
4) Leaving- When an already tracking vehicle crosses the leaving line, its stateis changed to 'Leaving'. Vehicle is counted and the entry of vehicle from VL_listis deleted.

The detail working procedure of VL_list is in the following Figure 3.

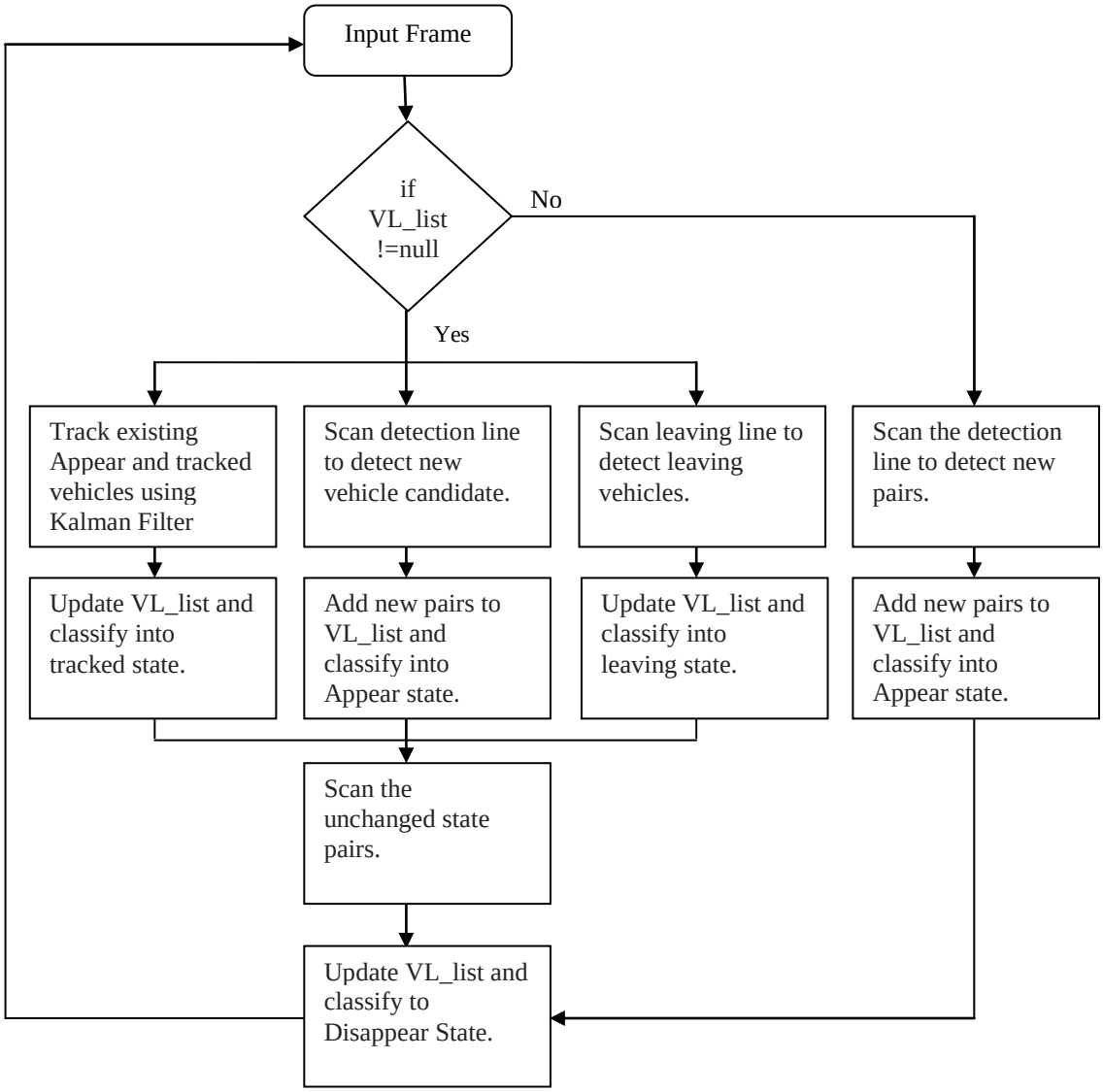


Figure 3: Vehicle Detection and Tracking

4.1 Detection of Vehicle

4.1.1Scanning Of Detection Line

Detection line is scanned from the left to the right position using a cursor (Cr). When a bright element is detected on detection line, the element'sentry is searched fromLC (Lamp Candidate) list by examination of the labeled value.If LC_m.state entry is 0 (which signifies that theLC_mhas already being matchedin the labeled image), then the obtained $LC_m$is a left vehicle lamp candidate and if not, then the Cr will go on with the scanning of detection line.Cr will then move to theCr +3×LC_m.size(width) position after the detection of a left candidate and go on to detect theright vehicle lamp candidate (LC_n) within distance range defined asfollow in equation 3:

$$\mathrm{Cr} + 3 \times \mathrm{LC_m.size\ (width)} < \mathrm{Range} < \mathrm{Cr} + 8 \times \mathrm{LC_m.size\ (width)} \qquad (3)$$

Since the distance of the observation camera is not known normally so the search distance is takenby considering the width of lamps. The distance between the lamps are experimentally observed to be 3 and 8 basedon the considered vehicledata videos. If rightvehicle lamp candidate $LC_n$is also found, the next step is to verifythat if $LC_m$and LC_ncandidates belong tothe same vehicle or they are false detections.

4.1.2 Vehicle Verification Mechanism

At the point when a candidate pair of vehicle lamps (LC_m,LC_n) is recognized from the past stage, verification along these lines is required to maintain a strategic distance from the matching of reflections, bike lights, or other non-vehicle light sources.

Checking on degree of similarity

Rule based classification method is used to check if both candidates belong to same vehicle.

a) They have comparable heights for a period of time.
b) They have similar width for a period of time.
c) They have almost same area.
d) They are running on same horizontal axis.

Checking degree of symmetry

By calculating normalized cross correlation (NCC), the degree of symmetry between two lamp candidates is checked. The NCC valuelies between −1 and 1, where 1 indicates the highest degree of similarity and the value closer to -1 indicates the vice versabetween two lamp candidates. If the correlation value is above a threshold value, left candidate and right candidateare considered highlysimilar. Threshold value is empirically found to be 0.75. Higher or lower value of threshold lowers the detection rate.

4.2 Vehicle Tracking

4.2.1 Updating 'VL_list': The point of updating the VL_list is to store the information of newsize and positionof detected vehicles, plus updating their position when aincomingimage is obtained. Whenever a new arriving frame is available, each pair of vehicle lamp in VL_list is updated. After preprocessing, for each entry in VL_list, vehicle coordinates are matched with current frame's LC list using enlarged region on the current frameP_{pos} and P_{size}. The area forSearch Box (SrchBox) is taken as follows:

$$P_{pos}.x - P_{size}.\mathrm{width} < \mathrm{SrchBox.width} < P_{pos}.x + P_{size}.\mathrm{width} \qquad (4)$$

$$P_{pos}.y - P_{size}.\text{height} < \text{SrchBox.height} < P_{pos}.y + P_{size}.\text{height} \quad (5)$$

If LC_i matches, measured location is passed to Kalman filter to correctly predict the location of vehicle. Otherwise, previous VL_list values are passed to Kalman filter. This VL_list will act as a measurement model in Kalman filter that is used for vehicle tracking.

4.2.2Kalman Filter:Itis an Iterative Mathematical process that usesconsecutive data inputs and a set of equations.Kalman filter[34] can be used where there is uncertaininformation about some dynamic system.Itrapidly estimates the true value,velocity, position, etc. of an object, when the measured values contain random error. Using Kalman filter, awell-informedguess can be madeabout what the system is going to do next. If something interrupts with the clean motion of object, the Kalman filter will often figure out what actually happened. Kalman filter has the advantage that it is very fast and it is light on memory. Itonly needs to store previous state forpredicting future state from all of history states.Kalman filter is well suited for embedded systems and real time problems.Its algorithm includes two stages: prediction stage and measurement stage.

Measurement Model: Updated Vehicle Tracking List (VL_list) act as a measurement model for Kalman filter in the proposed work. Section 4.1 explains how the VL_list is updated. The best estimate that can be made for location of the vehicle is provided by adding our knowledge from the measurement model and previous location value of the vehicle.

Prediction Stage: Kalman filter assume thatthe state of a system at a time tcan be predictedfrom its prior state at time‘t-1’by using equations (6) and (7)**.**

$$x_t = F_t x_{t-1} + B_t u_t \quad (6)$$

$$P_t = F_t P_{t-1} F^T{}_t + Q_t \quad (7)$$

x_t vector has state information containing terms of interest (position, velocity).

$F_t$indicates state transition matrix.

$B_t$indicates control input matrix.

$u_t$indicates controlvector contains known external influences like steering angle, braking force etc.

P_t denotes the covariance matrix.

$Q_t$denotes the covariance.

The new estimate state (x_t) is a prediction made from its previous estimate (x_{t-1}) state, plus a correction for known external influences (u_t).

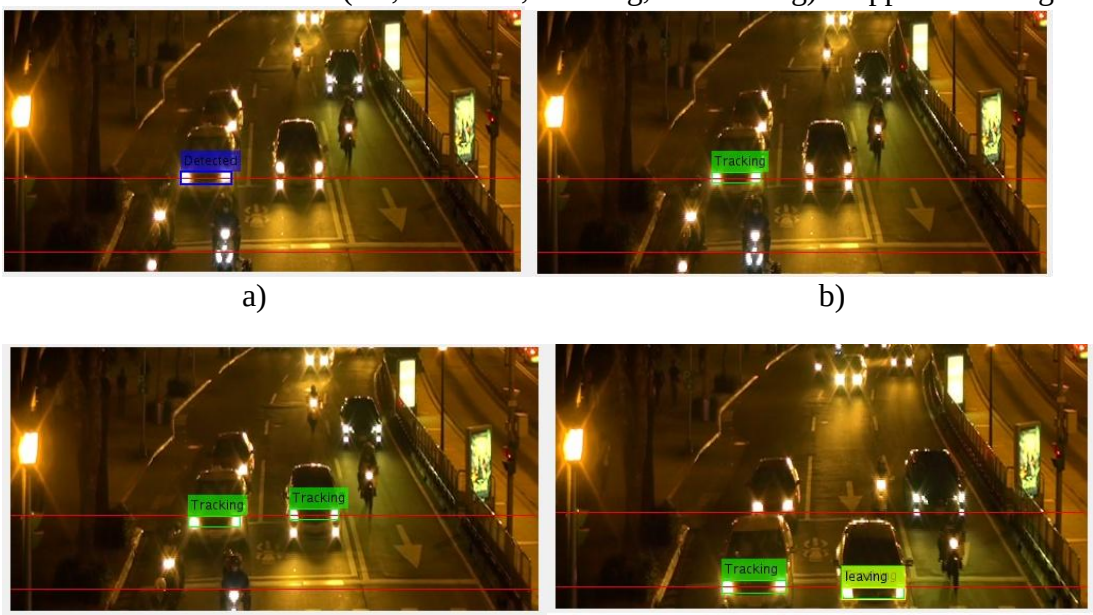
The old uncertainty (P_{t-1}) value is used to predictnew uncertainty (P_t) with some additional environment uncertainty (Q_t).

To configure a kalman filter, it needs these five ((MotionModel, InitialLocation, InitialEstimateError, MotionNoise, MeasurementNoise) parametric values to start predicting new values of vehicle location. Constant acceleration model has been taken as motion model. InitialLocationvalues of vehicle are taken from VL_list values. InitialEstimateError is uncertainty variance i.e empirically taken as [[1 1 1]*1e5]. Motion noise is initialized to expected deviation of selected and actual model values and experimentally it is taken as [25, 10, 10]. Measurement noise is variance inaccuracy of detected location and empirically taken as 25.

If vehicle is found at the estimated position, VL_list_i.Status is altered to the 'Tracked'and original co-ordinates are updated in VL_list. Otherwise, status is updated to the 'Disappear'state.

V.EXPERIMENTAL RESULTS AND ANALYSIS

On main roads and on highway roads mostly four wheeler vehicles are seen. So, proposed method focuses on four wheeler vehicles only. In spite of the fact that there are distinctive illumination conditions but our attention is on "nighttime" soconsidering video during the night only. A blue rectangle denotes the vehicle has entered the ROI, a green rectangle demonstrates that the vehicle is being tracked and the yellow rectangle denotes that the vehicle has left the ROI. A case for each case (i.e., Detected, tracking, and leaving) is appeared in Figure 4.



a) b)

c) d)

Figure4:Exampleof the detection(blue), tracking(green) and leaving(yellow)states.

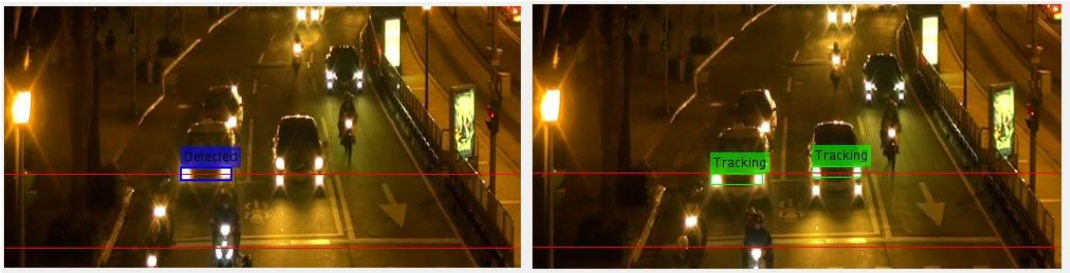
5.1 Parameters considered

5.1.1 Total Vehicles Detected is the count of number of vehicles that are detected by the proposed method.

5.1.2 Detection Rateis computed by using the true positive T_p, false negative F_n and false positive F_p.$T_p$represents the count of accurately detected vehicles, F_p is the count of wronglydetected vehicles and $F_n$denotes the countof vehicles that are missed. The detection rate is calculated as follows:

$$\text{DetectionRate} = \frac{Tp}{Tp+Fp+Fn} \qquad (8)$$

The frame rate of videos considered is 30 true-color FPS.Thecalculation needed to process one input frame depends on thecomplexity of traffic-scene. Few identification blunders happenedwhen some vehicles with broken headlights are misclassified as non-vehicle. Figure 5,6,7,8 shows the detection and tracking of vehicles on different videos of data set.



(a) **(b)**

Figure5: Detection process in test video NORMAL _1.

Figure 6: Detection process intest video NORMAL_2.

Figure 7: Detection process in test video RAINING_1.

Figure 8: Detection process in test video HIGHWAY.

5.2Results: Table 1 details the results of proposed method on different video sequences NORMAL_1, RAINING_1,NORMAL_2 and HIGHWAY. Table includes the video sequence length, video resolution, Number of total vehicles in the video, total number of detected vehicles and detection rate. Results show the detection rate of 91.80% in NORMAL_1, 87.85% in

NORMAL_2, 66.32% in RAINING_1 and 85.55% in HIGHWAY scenario. Proposed method does not work well in raining case.

EXPERIMENTAL DATA AND RESULTS

Table 1

Video Name	Sequence Length	Resolution	Number of Vehicles	Number of Detected Vehicles	Detection Rate %
NORMAL_1	3"09'	720*480	61	56	91.80%
NORMAL_2	3"45'	720*480	48	42	87.75%
RAINING_1	6"01'	720*480	98	65	66.32%
HIGHWAY	50"00'	320*240	4499	3849	85.55%

5.3 Comparative Results

Results are compared with that ofSalvi[29], Guo[30], BGS method[22], Wang et al[5] and Chen et al[27] using the NORMAL_1, RAINING_1,NORMAL_2and HIGHWAY scene sequence and the results are shown in Table 2. The experimental outcomes demonstrates that the proposed technique is compelling when contrasted with contrast based strategy, Background-subtraction-based strategy, Pairing-light-based strategy and Salvi [29] strategy. Proposed method focuses on both detetection and tracking on vehicle while other methods focus only on detection of vehicle. Figure 9 shows the relative results of vehicle detection on test video sequence HIGHWAY.

Table 2 : Comparison of performance among the Proposed Method and Former Schemes

Video Name	Proposed Work	Guo et al [30]	Salvi[29]	Contrast Based Method[28]	Background-subtraction-based method[32]	Wang *et al.*[5]method
NORMAL_1	91.80%	96.70%	91.67%	----	----	----
NORMAL_2	87.75%	93.75%	76.53%	----	----	----
RAINING_1	66.32%	85.71%	----	----	----	----
HIGHWAY	85.55%	98.46%	----	56.70%	Less than 30%	59.88%

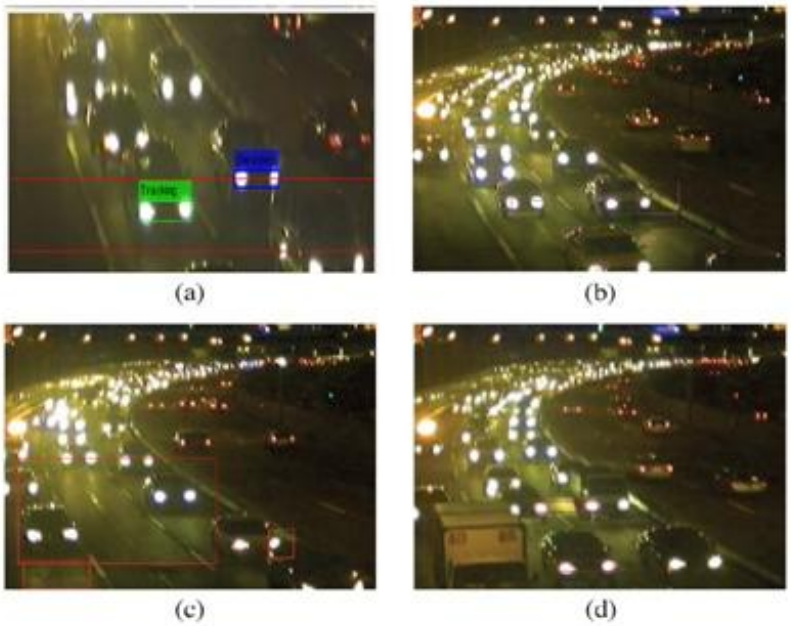


Figure9: Vehicle detection comparative results on test video sequenceHIGHWAY.
(a) Proposed method (b) Contrast-based method[28] (c) Background-subtraction-based method[32] (d) Wang *et al.*[5] method

VI. CONCLUSION AND FUTURE WORK

In this paper, Kalman filter for vehicle tracking has been proposedfor fast and effectively track vehicles in the nighttime scenario. Fog lamp is eliminated at preprocessing time for reducing the complexity of vehicle detection.With the help of two lookup tables, this strategy accomplishes high-exactness execution at low computational cost. Examining outcomes check the feasibility of the proposed technique as far as handling throughput and precision.Using Kalman filter, vehicles can be tracked and their speed can be estimated. Using these parameters vehicle's accident can be predicted in nighttime by analyzing track of the vehicles. Vehicle speed limits can be changed at different hours by analyzing traffic congestion. This strategycan be used for different applications, for example, emergency vehicle notification systems, automatic road enforcement, variable speed limits, collision avoidance systems etc.

For future work, the classification of vehicle type function can be further enhanced. Itcan beintegrated with some sophisticated deep learning techniques, to further upgrade the characterization ability. Utilizing improved characterization ability, more detailed vehicle types, for example, transports, trucks, buses and light and large motorbikes can be identified.

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