International Journal of Computer Science and Information Security (IJCSIS),
Vol. 18, No. 12, December 2020

Nighttime Vehicle Detection Methods based on Brake Light/Taillight Features: A Review

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Abstract— **At night, the vehicle's whole body is not visible due to poor illumination which probably is the principal cause of road accidents that happens at night. Due to the same reason, detecting and tracking vehicles at night is very difficult. Moreover, the visual appearance of vehicles is altered owing to numerous issues like the color of the vehicle, the amount of light that vehicles reflect, and the ambient light. It is apparent that, at night, driving necessitates more attention than the day. Hence, the increase in visibility is important for the sake of the safety of the road users at night. In dark conditions, taillights and brake lights make the rear of the vehicle perceptible. The main aim of this review paper is to survey, present and summarize the various proposed techniques, and future directions so that new methods of vehicle detection can be developed to circumvent nighttime accidents.**

Keywords- vehicle detection; vehicle recognition; taillight; taillamp; brake light; nighttime

I. INTRODUCTION

Vehicle detection performs a very significant part in surveillance applications, traffic regulation, and autonomous driving. However, at night detection of vehicle is more difficult than detection at day because of poor contrast and inadequate luminosity [17]. In current years, vehicles on the road are growing exponentially in numbers and therefore, road accidents are escalating day by day [1] [13]. Road accidents are occurring because the appearance of vehicles during night time is hugely different from its daytime [2] [10]. To ensure safety and avoid accidents, vehicle detection has become a significant topic for research. Detection of vehicles is the most challenging, ongoing and active area of exploration and research in the advanced driver assistance system (ADAS), automated driving system (ADS) , and intelligent transportation system (ITS) [3] [18]. ADAS received significant attention in recent years because many accidents are caused primarily by drivers' lack of awareness of fatigue. At night, vehicles are observed from back, and only red colored rear-facing brake lights are seen. Henceforth, the diverse sizes, forms, and types of these rear-facing taillamps aid us to assess the type of the vehicles at night [2] [8] [10].

For vehicle detection and tracking, there are various techniques available. Most of the nighttime vehicle detection system used features such as headlight (HL), taillight (TL), and brake light. The main problem is to nighttime detection of vehicles. For efficient nighttime detection of the vehicle some factors need to be considered e.g., diverse traffic conditions, different environmental circumstances, various road symbols, precision in vehicle detection, effective real-time operations, etc. [3].

To decrease accidents at night, detection of vehicles is essential. Vehicle detection and tracking have always been a challenging and a difficult problem at nighttime because of the poor illumination conditions [11] [16]. Keeping this in mind, many researchers have worked to identify vehicles at night and are still working in this field. They have assumed several image processing techniques and presented some of their development strategies for vehicle detection during the night based on vehicle headlight and taillight. In dark environments, vehicles are observable by their brake lights/taillights and headlights. Therefore, headlight, brake light/taillight are extremely dependable features for detection of vehicles at night [1] [3].

In this review paper, we have summarized as much research as possible on the detection of nighttime vehicles based on the brake/taillight. Many nighttime vehicle detection approaches have been discussed in this paper. Most of them concentrate on the procedures and technologies used to detect vehicles. We have categorized the studies of nighttime vehicle detection into three sections: (1) Nighttime vehicle detection approaches based on taillight (2) Nighttime vehicle detection approaches based on brake light (3) Nighttime vehicle detection approaches based on both taillight and brake light.

The residual of the paper is arranged as follows. A common approach in detecting vehicles at night is illustrated in section 2. In section 3 the basic difference between taillights and brake lights is discussed. In section 4 nighttime vehicle detection approaches based on taillight is illustrated. The nighttime vehicle detection techniques based on brake light is presented in section 5. In section 6 nighttime vehicle detection approaches based on both brake light and taillight is illustrated. Finally, section 7 states the conclusions.

II. COMMON NIGHTTIME VEHICLE DETECTION APPROACH

There are several techniques and algorithms in existence to detect vehicles based on taillight and brake light at nighttime. Taillight and Brake light are among the main features in the process of detecting vehicles. The common work flow for the

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detection of vehicles during night is displayed in Fig. 1 that involves seven stages.

As shown in Fig. 1 the vehicle detection system captures an input image using camera and then further image processing algorithms are applied on this image. ROI (Region of Interest) processing is then applied for selecting the particular area of the image. Then the collected color image is converted to a monochrome (i.e. binary) image. Next the binary image undergoes morphological processes for denoising and subsequently the edges in the input image are determined by the approximation of the gradient magnitude of the converted image. Finally, image-based object detection procedure is applied for detection of vehicle with brake/taillight. In [3] authors have discussed some use of vehicle detection as follows:

- ✓ Assessment of vehicular concentration for traffic shaping
- ✓ Airborne investigation of the vehicular stuffs
- ✓ Automatic system for parking to determine vehicle types
- ✓ Tracking of vehicles

III. Basic Difference Between Taillights And Brake Lights

Fig. 2 shows the location of the taillights and brake lights [20-21]. In most of the vehicles, the taillamps and the brake lights are placed on the same sphere. Taillights and brake lights are a vital safety feature of vehicles. They are situated in the hindmost and face to the rear to indicate other vehicles where the vehicle is situated on the road. Some features of the taillights and brake lights are shown below [22-23]:

- ➢ Taillight Features
  - ✓ Color: Red
  - ✓ Location: Rear end of the vehicle
  - ✓ Types: LED lights, Halogen lights, Xenon lights
- ➢ Brake light Features
  - ✓ Color: Luminous red
  - ✓ Location: Near the taillight

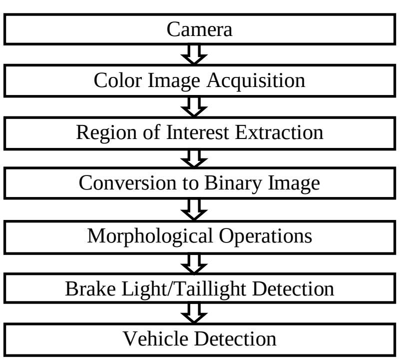

Fig. 1. Common methodology for nighttime vehicle detection based on brake light/taillight.

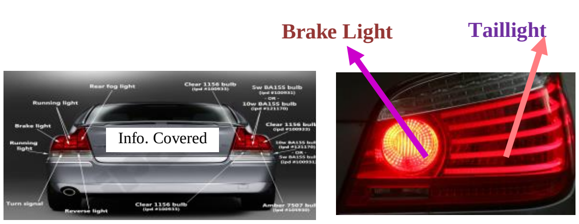

Fig. 2. Location of the taillight and brake light [20-21].

Red colored taillights are activated when the front headlights are turned on, while the brake lights will turn on automatically as soon as pressure is applied to the brake paddle and indicates speed reduction. Taillights shine less luminously than brake lights because it is only designed to be active in hazy situations, such as nighttime, heavy rain or fog.

IV. Nighttime Vehicle Detection Approaches Based on Taillight

Nighttime vehicle detection is a challenging task that aids in regulating accidents at night as well as at dark settings that vary from the daytime in environmental circumstances, vehicle illumination, etc. [9-10]. This is the reason for which researchers are still working on it to develop methods to detect vehicles at night. The taillight is one of the most important features at nighttime. Many methods are available out there for detection and recognition of vehicles at night based on taillights. In this review paper we have presented as many as possible major advanced researches on nighttime vehicle detection based on taillamps.

Ronan O'Malley et al. [4] introduced a procedure for detecting nighttime vehicles employing a camera that searches for taillights. Information of hue, extent, symmetry, location and symmetry of rear-facing lamps of the vehicle, taken from relevant legislation is used to detect vehicles located at diverse distances and in diverse weather and illumination situations. It was suggested in the future work that High Dynamic Range (HDR) technique can be used to attain various views of rear lamps in the dark and the procedure can be adapted for detecting brake lights at daytime. Fig. 3 shows the detection procedure.

The method has exhibited that it performs fine in both light city zones and dark countryside areas and it also performs efficiently in wet situations where the reflection of hindmost lights off the road takes place. They have claimed that the front (or target) vehicle is detected with success and the detection

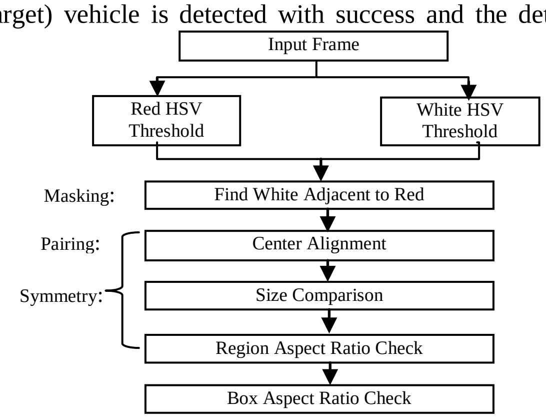

Fig. 3. Detection Procedure [4].

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rate is 95.3%. Fig. 4 depicts an instance of detection of their taillight at different distances.

Jianqiang Wang et al. [5] introduced a vehicle detection scheme based on region tracking that uses the image processing techniques that takes the brightness of the taillights as the distinctive feature at nighttime and thereafter, they have applied the available comprehensive detection method for the detection and pairing of the taillamps. A model (namely, time-series analysis) is proposed to guess vehicle's locations and the possible region (PR) in the subsequent frame. In this research, the main aim is to decrease the time of detection and evade the incorrect pairing that exists between the brilliant spots in the PR and out of the PR. They also have given a method with adaptive threshold. The three important steps of their projected approach are given below:

(a) Set the time series arrays of the positions of traced vehicles

(b) Predict the PRs

(c) Detect, in the predicted PRs, the vehicles within.

The vehicle detection procedure of their suggested method is presented in Fig. 5. Fig. 6 displays the outcomes of their projected technique that can decrease the false detection percentage. The current global detection procedure causes false-negative detection as revealed in Fig. 6 (a) and their proposed method attains the correct results as revealed in Fig. 6 (b). They have claimed that overall detection percentage of their projected method attains 97.472%.

Fig. 4. Successful tail light detection at different distances [4].

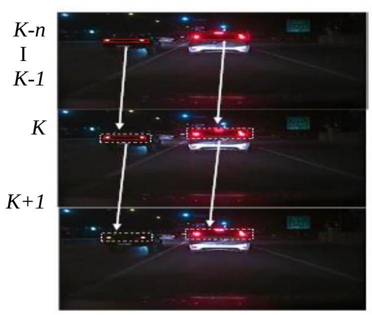

Fig. 5. Illustrates the tracking-based algorithm [5] for vehicle detection.

(a) (b)

Fig. 6. (a) Performance of the global detection process; (b) Outcome of the proposed method [5].

Hemanth Kumar B K et al. [6] presented a camera-based method for the detection of nighttime vehicles by searching for taillights. The researchers also developed an image-based processing system that was capable of competently spotting vehicles at various distances and in varying weather situations and lighting settings. Fig. 7 shows their projected method. Summary of their architecture is discussed below:

A. *Preprocessing*

Preprocessing is done using list of steps below,

– Binarization.

– Noise removal.

B. *Lamp Edge Detection*

The researchers have used the canny edge detector that determines edges in the input image by searching for the local maxima of the input image's gradient calculated using the derivative of the Gaussian filter. The Canny edge detector [24] uses double thresholding to gradients, a high threshold for low edge sensitivity and a low threshold for high edge sensitivity.

C. *Lamp Pairing*

Lamp pairing is done using the size, and intensity of the light objects, symmetry check, and the aspect ratios comparisons of the lamp candidates.

Fig. 8 shows the detected image. They have claimed that the detection rate of their proposed system is 98% and false positive rate is 1.8%. The researchers suggest that it also works in wet conditions.

Duan-Yu Chen et al. [7] proposed a visual-based method for the detection of turn signals during night using Nakagami-m distribution [25-26] and the color regulations by scattering modelling of taillights. Generally, in order to recognize turn signals' direction, the reflectance is disintegrated from the original image. The researchers have focused on finding the invariant features such as the position, size, and symmetry of the rear-facing vehicle to model the scattering of turn signals by Nakagami imaging hence, accomplished the detection procedure. They have claimed that their suggested system is capable of detecting vehicles under diverse illumination and traffic surroundings, and can identify the direction of turn signals with the accuracy of 82%. Fig. 9 shows a summary of their suggested method for turn signal detection.

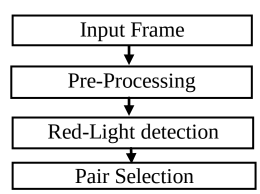

Fig. 7. Architecture of Proposed Work [6].

Fig. 8. Bounding Box of Detected Image [6].

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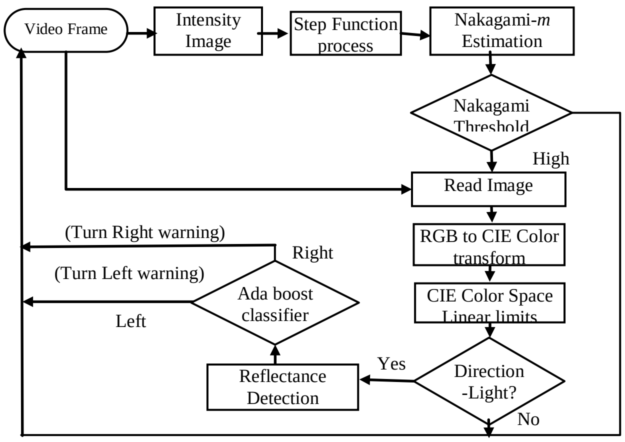

Fig. 9. Overview of the suggested approach for turn signal detection [7].

Their introduced method incorporates AdaBoost approach [27] [55] and is aimed at giving real-time performance. In their approach AdaBoost algorithm is employed to train the classifiers of turn signals of left and right directions. The AdaBoost algorithm is presented in Algorithm 1.

Algorithm 1 AdaBoost Algorithm

Inputs: (1) n_+ reflectance images and n_- non-reflectance images. The image label y_i is '1' for positives or '0' for negatives as follows: $\{(s_1, x_1), (s_2, x_2), \dots, (s_i, x_i)\}$ (2) X= $\{s_1, s_2, \dots, s_i\}$ is the set of images having i dimension feature vectors.

(3) **Initialization:**

The weight of training examples $D_1(i) = 1/m, i = 1, \dots, m$.

(4) For weak classifiers $t = 1, \dots, T$.

1. Find the weak classifier φ_t that minimizes the $D_1(i)$ weighted error

2. $\varphi_t = argmin_{h_j \epsilon H^{\epsilon} j}$, where εj = $\sum_{i=1}^{m} D_t(i)$ (for $y_i \neq \varphi_j(x_i)$)

3. Set the φ_t voting weight $a_t = 0.5 \times \log[\frac{1-\varepsilon t}{\varepsilon t}]$

4. Update the weight:

$D_{t+1}(i) = [D_t(i) \exp(-a_t y_t \varphi_t(x_i))]/Z_t$, where Z_t normalizes the equation over all data points.

Output: $P(x) = \sum_{t=1}^{T} a_t \varphi_t(x)$.

Bhavinkumar M. Rohit [8] studied many techniques about nighttime vehicle detection. In front, the vehicles are mostly perceptible by their taillamps and brake lamps. The taillights are vital since they indicate deceleration in distance from rear-end vehicle and to avoid a potential collision. The researchers have focused on the taillamps detection on the basis of the taillights' symmetry and its color characteristic. As future work they have proposed to detect brake light and distance for making the collision avoidance warning for driver assistance. Fig. 10 shows their proposed system flow for taillight detection.

The proposed system has been performed with four different types of road conditions. These are the urban traffic situations, unwanted light sources such as various traffic signboards and street lights are came into the frame, where in the case of rural traffic as the vehicles are very less compared to urban traffic the detection is more reliable and the accuracy for rural traffic is 85.01%, for urban traffic is 88.29%, for two way traffic is 76.13% and finally, for the highway traffic is 60.64%. Fig. 11 and 12 shows the result.

Swathy S Pillai et al [9] studied many techniques about vehicle detection. The Advanced Driver Assistance System (ADAS) is one of the strategies to evade traffic accidents. This research focused on detection of vehicles at night vehicle by taillights applying several processes on the image. Their suggested system begins with the methods for acquisition of an image, extracts the red-light area applying HSV thresholding, removes the noises employing the rudimentary morphological processes, finds the edges of the acquired image, and employs further tools for image processing. Their proposed system can success rate is up to 80%. Fig. 13 shows their proposed approach.

In Fig. 14, the captured image is not of the identical car and consequently the output was gotten up to the bounding box. The taillights are compared by means of the region of the bounding box found about the blobs employing the aspect ratio, and by gauging the remoteness between the blobs.

Swathy S Pillai *et al.* [10] elucidated many tactics to detect and recognize the taillights of vehicles at night. At night, front vehicles are mostly perceived by their taillights. The researchers have presented a car recognition system by means of identification and segmentation of taillights in road environment at night. Fig. 15 shows their vehicle detection steps.

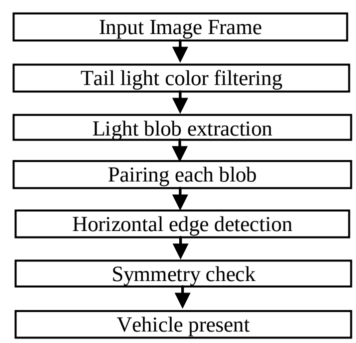

Fig. 10. System flow for tail light detection and verification of the same vehicle [8].

(a) (b) (c)

Fig. 11. (a) Urban Traffic frames (b) Binary converted frames (c) Detected taillights [8].

(a) (b) (c)

Fig. 12. (a) Two way Traffic frames (b) Binary converted frames (c) Detected taillights [8].

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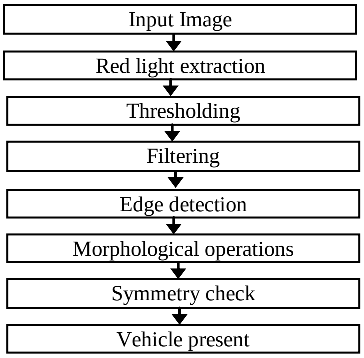

Fig. 13. Proposed System [9].

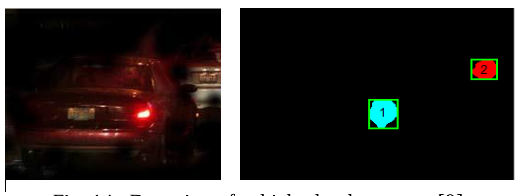

Fig. 14. Detection of vehicles by the system [9].

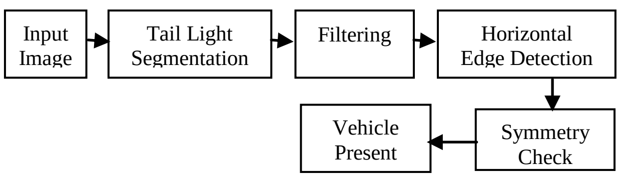

Fig. 15. Vehicle Detection Steps [10].

Fei Gao *et al.* [11] Introduced a technique to detect vehicles in the multi-lane intersection on the basis of detection of saliency for the system that performs traffic surveillance. At first, a frame difference technique is used in order to detect the objects that moving, and the rear lamps of vehicles are pulled out on the basis of color information together with saliency map. Then detection of vehicles is done by pairing off all the lights, which comprise steps like rechecking taillight pairs by using earlier knowledge, removing repaired taillights on the identical vehicle and eliminating the matching lamps between two lanes. Additionally, a verifying method for virtual taillight is examined for the detection of the vehicles that only have a sole valid taillight. At last, their suggested method is proved to be more dependable and quicker in detecting vehicle at night by comparing it with other available detection approaches. Fig. 16 shows their proposed workflows to detect vehicles at nighttime. Precision rate, recall rate and F-measure of their method are presented in Table 1. Fig. 17 displays the result of their suggested method together with the comparison with the other approaches.

Gizem MUSLU et al. [12] introduced an algorithm to detect vehicle taillight at night by combining cascaded Haar classifier and rule-based processing of an image. Haar [28] is often used for detecting vehicles in literature using taillamps or rear view of vehicles. The researchers also present a procedure and empirical outcomes for combination of Haar cascade classifier [29-30] and rule-based processing [56] of images for the purpose of vehicle taillight detection at night. Their

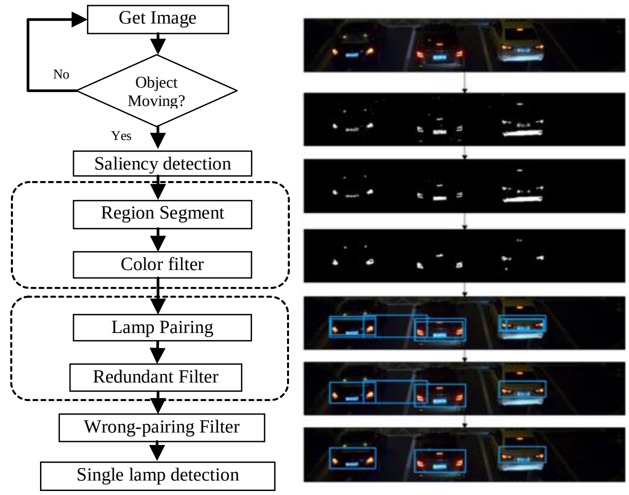

Fig. 16. Flowchart of nighttime vehicle detection [11]

TABLE I. ACCURACY RATE, RECALL RATE AND F-MEASURE OF NIGHTTIME VEHICLE DETCTION BY GAO ET AL. [11]

	Situations	
	Sunny night	Rainy night
real number	3132	123
night number	3100	121
miss number	32	2
error number	21	2
precision rate, %	99.33	98.37
recall rate, %	98.98	98.37
F-measure, %	99.14	98.37

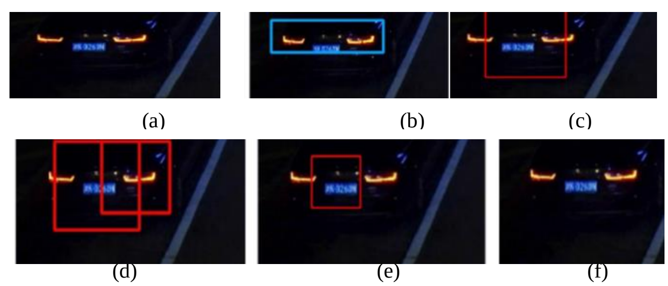

Fig. 17. Comparison of the suggested method and other approaches (a) Original image (b) Proposed technique (c) HOG (d) LBP (e) Haar (f) DPM [11]

experimental outcomes reveal that the suggested technique detects with higher precision than majority of the vehicle taillight detection procedures using only one classifier.

The proposed algorithms, accuracy, and future directions obtained from different researchers for vehicle detection at night using taillights are presented in the form of a summary in Table 2.

V. NIGHTTIME VEHICLE DETECTION APPROACHES BASED ON BRAKE LIGHT

The brake light is another one of the most important features at nighttime. There are many existing methods to

TABLE II. OVERVIEW OF THE NIGHTTIME VEHICLE DETECTION STUDIES BASED ON TAILLIGHTS

First Author, Year	Algorithms	Reported Accuracy	Future Directions
O'Malley et al. (2008)	Feature extraction algorithm, pairing algorithm	95.3%	High Dynamic Range (HDR) technology can be used to achieve different views of rear lights in the darkness.
Wng et al. (2013)	Image processing techniques, existing global detection method, pairing algorithm	97.472%	False detection rates can be reduced, HDR sensor can be used further.
Kumar et al. (2014)	Feature extraction algorithm, pairing algorithm	98%	---
Chen et al. (2014)	AdaBoost algorithm, Nakagami-m distribution	82%	More accuracy can be achieved in this research.
Rohit and Patel (2015)	Feature extraction algorithm, pairing algorithm	Rural: 85.01% Urban: 88.29% Two way: 76.13% Highway: 60.64%	To detect brake light and distance can be measure. To attain more accuracy.
Pillai et al (2016)	Image processing techniques,	Before tracking: 91.57% After tracking: 95.72%	---
Pillai and Radhakrishnan (2016)	Segmentation technique, feature extraction algorithm	---	To extend this work using classification techniques. Computer vision can be added.
Gao et al. (2018)	Feature extraction algorithm, pairing algorithm	Up to 80%	Distance between two taillights can be improved. Detection can be increased in complex traffic scene.
Muslu and Bolat (2019)	Haar cascade classifier and rule-based image processing	Higher accuracy	---

detect and recognize vehicles during night based on brake lights. In this part, we have presented as a review the works that have been done on nighttime vehicle detection based on brake lights.

Duan-Yu Chen et al. [13] introduced an innovative method that is able spot brake lamps at night employing a camera by performing the analysis of the signal in both frequency and spatial domains. They mainly concentrated on discovering the features like invariance in size, symmetry, and location of rear-facing brake lamps in the frequency domain, and then it could perform the detection procedure in a part by part. They claimed that their introduced system can detect brake lamps effectively under diverse illumination and traffic situations and the overall detection percentage is about 73.7%. Their proposed method contains of two main stages as displayed in Fig. 18. First stage performs detection of candidate areas in the spatial domain on the basis of color feature and the next stage transforms it to the frequency domain for verification based on First Fourier Transform (FFT) [31]. Two major phases of their approach are candidate regions detection and frequency domain analysis of taillight regions which are discussed here:

A. *Candidate Regions Detection*

DoG (Difference of Gaussian) [32] was first applied for band pass filtering to reduce noises and stress in the salient candidate areas of brake lamps. DoG filter was used for the detection of edges because it closely and competently works very similar to the Laplacian of Gaussian (LoG) filter [33]. The DoG has also been used for saliency detection [34-35].

B. *Frequency Domain Analysis of Taillight Regions*

In frequency domain the most important part of signals can be exposed that can decrease the computation complication to make it viable for real-time applications by using FFT. Vital attributes of separability, translation and rotation invariance, are used for investigating taillights.

Duan-Yu Chen et al. [14] introduced an innovative visual-based method for detecting brake lights during night by examining the taillights depending on the Nakagami-m distribution. In this research, they have used experiential features like position, size, and symmetry of the rear-facing vehicle. They have primarily concentrated on discovering the invariant features that models the brake lamps scattering by Nakagami imaging and it performs the detection procedure part by part. Here, a brake event is detected through a peak in the value rank curve as shown in Fig. 19. Their method contains four main stages as displayed in Fig. 20 and are discussed below in brief:

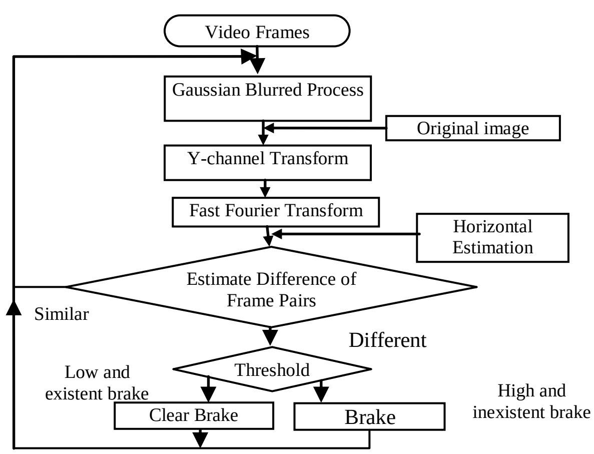

Fig. 18. Overview of the proposed approach [13].

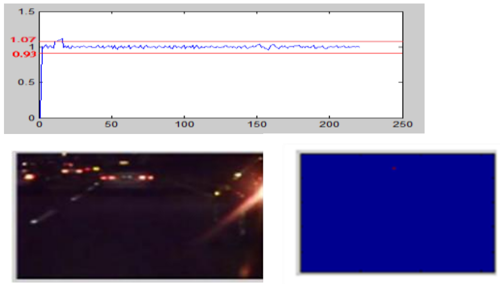

Fig. 19. Curve of the value Rank. A peak revealed in the curve denote a braking has happened [14].

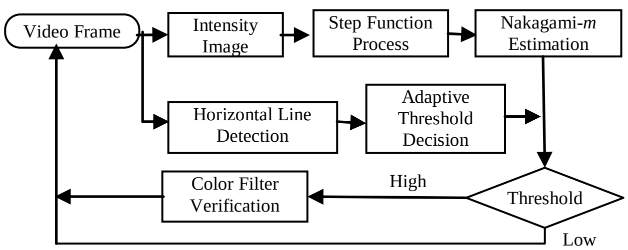

Fig. 20. Overview of the suggested approach for brake light detection [14].

A. *Preprocessing - Contrast Enhancement*

In this section, the original RGB video frame is transformed to an intensity image, then a step function is used to enhance the contrast. It is difficult to distinguish due to high degree of similarity that exists between the brake lights and taillights.

B. *Modelling Taillights by Nakagami Distribution*

In this section, the brake lights are detected robustly and the traits of the taillamp areas are modelled using Nakagami distribution.

C. *Adaptive Decision Making for Brake Light Detection*

In this part, they have applied adaptive threshold decision to detect brake light.

D. *Brake Light Verification Based on Color Filter*

In this section, the brake lights are detected and confirmed with a color filter.

Fig. 21 shows that the vehicles are successfully detected based on brake lights under the conditions. Many non-brake lights are totally and precisely filtered out around the vehicle in the center. They claimed that their suggested system can detect brake lights of vehicles effectively under diverse illumination and traffic situations with a rate of detection of about 87% in highway and, on an average, 79% in both city areas and highway.

Orcan Alpar [15] introduced a segmentation technique that is based on a single camera for detecting the brake lights while traveling at night and distinguishing them from the other lights i.e. turn lights and taillamps. They have proposed an innovative scheme that is put forward for separating brake lights which are

Fig. 21. Extensive data set captured under diverse road and traffic situations. (a) Urban area. (b) Heavy-traffic highway. (c) Normal-traffic highway (d) Wet road after shower. (e)–(f) Wet road during shower [14].

initialized with taking the image frames of the taillights of front vehicle using a mounted camera. They also applied image enhancement procedures on image frames to whiten the red corona and to darken the remaining part that contains the light sources center. Fig. 22 presents the main workflow of their proposed approach.

Nighttime vehicle detection study based on brake lights, the proposed algorithms, accuracy, and future directions obtained from different researchers are shown in the form of a summary in Table 3.

VI. NIGHTTIME VEHICLE DETECTION APPROACHES BASED ON BOTH BRAKE LIGHT AND TAILLIGHT

Thathupara S. K. et al. [1] proposed a technique for the detection of vehicles at night based on color feature of brake light/taillight from the input color image. They have considered brake lamps/ taillamps because these are the key traits for detection of front vehicles at night. They have claimed that their suggested method can easily evade the accidents occurred because of unexpected failure and also very supportive for the detection of vehicles for a smooth drive during night. In future, the range of segmentation can be enhanced and can be applied to the video also. Fig. 23 displays the flowchart of their suggested technique. Fig. 24 presents step-by-step demonstration of their detection approach.

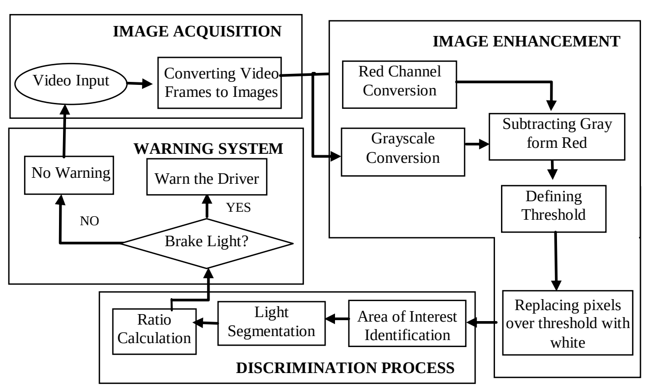

Fig. 22. Workflow of proposed approach [15].

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TABLE III. OVERVIEW OF THE NIGHTTIME VEHICLE DETECTION STUDIES BASED ON BRAKE LIGHTS

First Author, year	Algorithms	Reported Accuracy	Future Directions
Chen and Lin (2010)	First Fourier transform algorithm and image processing techniques.	73.7%	To attain more accuracy.
Chen et al. (2012)	Nakagami-m distribution, feature extraction algorithm.	highway: 87% highway and urban: 79%	Detection rate can be improved.
Alpar (2016)	Corona segmentation and image enhancement	-----------	Tracking can be improved and edge detection algorithm can be added.

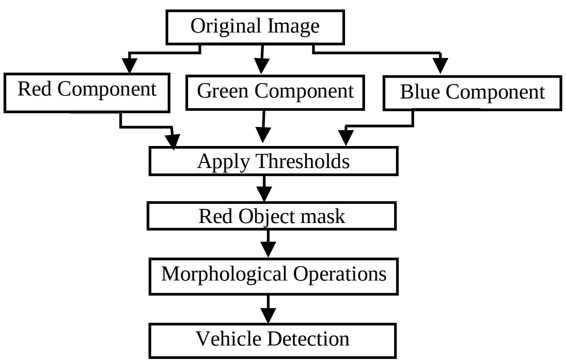

Fig. 23. Flow chart of the detection procedure [1].

(a) (b) (c)

Fig. 24. (a) Original input image (b) After morphological operation (c) Vehicle detection. The correct and error outcme in whole frame [1].

Their proposed technique has the following steps: At first, they have separated the color channels of input color image. Once all the color bands are separated, they have applied two thresholds, namely a lower and an upper value, to each component. Thereafter, to achieve precise and clear detection, they have filtered out the small regions and have used morphological operations for smoothing the border. Finally, the proposed system detects vehicles from a colored image.

Qing Tian et al. [16] introduced a technique for nighttime vehicle detection and tracking in video surveillance. In this process, they have extracted and used Histograms of Oriented Gradients (HOG) [36-38] features, and Support Vector Machine (SVM) [38-40] to recognize the object. They have also used Kalman filter [41-42] for tracking objects. They have claimed that their proposed system can precisely detect and track running vehicles in video frame sequences at nighttime and the detection rate is 97.07%.

In vehicle detection, there are two vital components, these are taking out the HOG features and training SVM classifier. HOG feature is a type of local descriptor and it collects object features by calculating histogram of gradient direction of the local region. SVM is a classifier that has been extensively employed in recognizing images and specifically achieved great success in detecting objects. For training the linear SVM classifier, it uses the feature vectors from HOG features. Fig. 25 displays the outcomes of detection and tracking of vehicles.

Hulin Kuang et al. [17] introduced a vehicle detection method during night that combines an innovative region of interest (ROI) extraction method deepening on detection of vehicle light and object proposals. This approach uses an improved multi-scale retinex (MSR) [43-44] to select precise ROIs and boosted images for correct detection of nighttime vehicle. Their empirical results demonstrated that the suggested technique for enhancement of nighttime images, score-level fusion of multifeature, and the process for extracting ROI are all operative and competent for detection of vehicles at night. Fig. 26 shows their proposed framework.

Their vehicle detection method has three vital parts:

- ✓ Nighttime enhancement of images depending on the extraction of ROI that combines detection of vehicle lamp with an object proposal method,
- ✓ MSR, and
- ✓ Fusion of score-level multifeature.

In Fig. 27, their proposed technique [17] detects nighttime

Fig. 25. Outcome of vehicle detection and tracking at night [16].

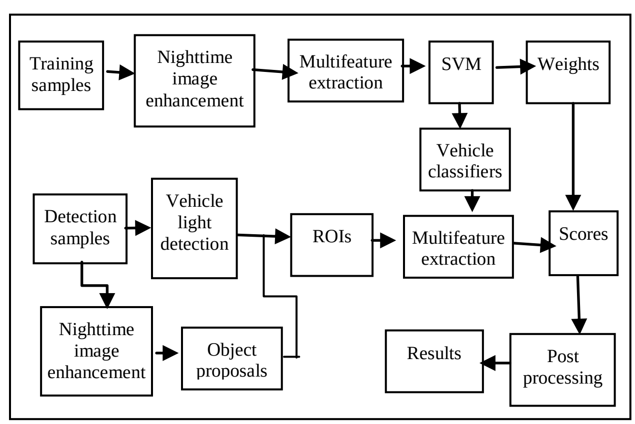

Fig. 26. Proposed framework [17].

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Fig. 27. Detection results [17].

vehicles that vary in size, background, number, and location. They have claimed that their introduced system is capable of efficiently detecting the obstructed and blurred vehicles and the accuracy of their proposed MSR method is 94.71%.

Hulin Kuang et al. [18] introduced a system that detects vehicles during night uses the combination of an innovative bio-inspired enhancement technique for an image and a weighted feature fusion method [45-49]. Similar to the mechanism in the retina [50] in natural human vision system, they have developed an image enhancement process that works at night. Their modelling includes the adaptive feedback that comes from horizontal cells and the bipolar cells' center-surround antagonistic receptive fields. At detection, they also generated accurate regions of interest by uniting vehicle taillamp detection and object proposals. Their suggested approach is also effective in dealing with various scenes that contains vehicles of diverse categories and sizes including occluded vehicles and in vehicles in blurred zones. Moreover, it can detect vehicles at different locations and many vehicles at a time. Therefore, they have claimed that their vehicle detection method is successful in the detection and the detection rate is 95.95% and false positives are 0.0575 per image. Fig. 28 shows the framework of their suggested method for detecting vehicles at night.

In this research, the researchers have employed the speedup framework using Fast R-CNN [51] to decrease the recognition time. Detection outcomes, in some intricate scenes, are displayed in Fig. 29, where all the automobiles with taillamps on in front of the driver are detected.

Yaoyang Mo *et al.* [19] proposed a framework that detects vehicle at night using vehicle to highlight information. At first, they have designed a precise vehicle highlight detector and produce a hierarchy for the vehicles label [52-53] to widen the inter-class difference and decrease the intra-class gap. They have also proposed a feature combining method that combines multi-scale highlight features with MSCNN mechanism [54] and the vehicle's visual aspects to get hints of the position of vehicle highlights for extra advantage. Furthermore, the method has gained enhancements when shifting their process to typical frameworks, demonstrating that their method is both operative and wide-ranging. Fig. 30 shows their proposed architecture.

Two vital steps are as follows:

- ✓ The initial cluster creating phase for obtaining initial subclasses and
- ✓ The improvement phase for revising the subclusters

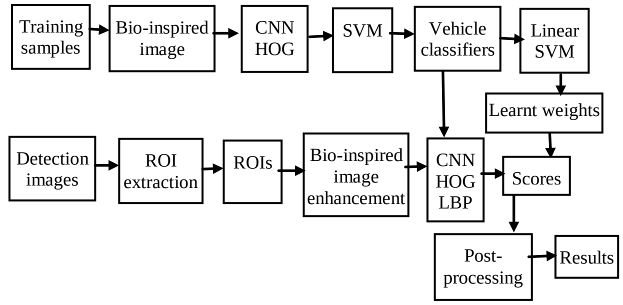

Fig. 28. Framework of the suggested at night vehicle detection technique [18].

Fig. 29. Detection results of the vehicles [18].

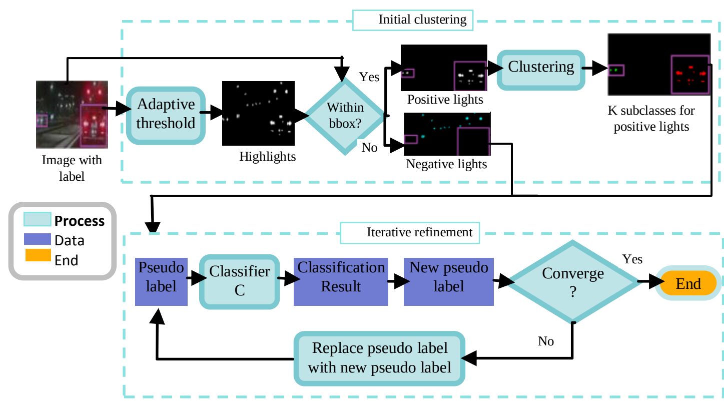

Fig. 30. Training pipeline of the vehicle highlight detection [19].

with better visual uniformity.

For improved visualization, red color is used to denote "preceding vehicle highlight" and "oncoming vehicle highlight" denoted using green color.

In Fig. 31, the network takes the whole image together with the highlight mask of corresponding vehicle as the input and outputs the detection result [19]. Fig. 32 presents their output compared with MSCNN [54]. In Fig. 33, the feature maps of various stages for the input are extracted and then combined with the vehicle highlight mask. The region proposal system then yields a sequence of proposals. The network uses the feature map that includes highlight information to perform the task. The proposals denote a bounding box possibly containing an object. In ROI pooling, for each proposal the features can be mined over the trait maps that are concatenated with the vehicles' highlight mask. Finally, the category and the location are projected by the classifier and the regressor.

In the nighttime, vehicle detection study based on brake light and taillight, the proposed algorithms, accuracy, and

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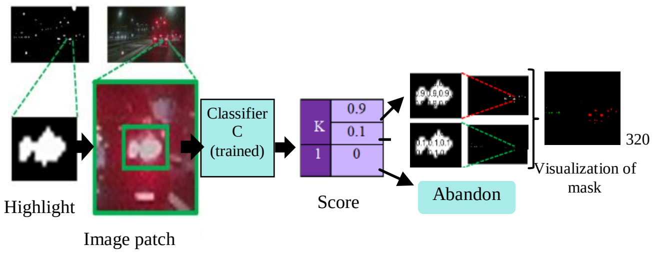

Fig. 31. The generation of the vehicle highlight mask [19.]

Fig. 32. Visualization ouputs. Cyan color: Proposed method and Red color: MSCNN [19].

future directions obtained from different researchers are shown in the form of a summary in Table 4.

VII. CONCLUSION

This review paper surveys diverse methods used for the recognition of taillights and brake lights of vehicles at night. Several vehicle detection approaches are elucidated that uses image segmentation methods. In this review work, various image processing procedures such as image segmentation, image neighborhood processing, and image enhancement are briefly elucidated. Different combination of the mentioned algorithms is used for the detection of taillights and brake lights that helps in reducing the accidents during the night to some extent. Above cited nighttime vehicle detection procedures are not applied for heavy vehicles because the height of taillights and brake lights is different from that of the common vehicles and motorcycles. The computer vision, machine learning and deep learning techniques can be used to solve this task but it requires high cost. Therefore, more in-depth analysis and researches are essential in this field for efficiently and accurately detect of all of vehicles in a scene.

TABLE IV. OVERVIEW OF THE NIGHTTIME VEHICLE DETECTION STUDIES BASED ON BOTH BRAKE LIGHT AND TAIL LIGHT

First Author, year	Algorithms	Reported Accuracy	Future Directions
Kavya et al. (2018)	Feature extraction and image processing techniques.	----------	The segmentation range can be improved and it can be applied to the video sequences
Tian et al. (2013)	Histogram of oriented gradients (HOG) and support vector machine (SVM)	97%	-------------
Kuang et al. (2016)	Multi-scale retinex (MSR), feature extraction algorithm and image enhancement techniques	94.71%.	ROI extraction and deep learning can be used to improve detection performance.
Kuang et al. (2017)	Weighted Feature Fusion Technique, Convolutional Neural Network (CNN), HOG, SVM,	95.95%	Detection of the occluded and distant vehicles and fast-tracking of the detection process using integral channel features.
Mo et al. (2019)	CNN, combines multi-scale highlight features and vehicles visual features, label hierarchy,	----------	To extend with acceleration algorithm and model simplification and nighttime road anomaly detection.

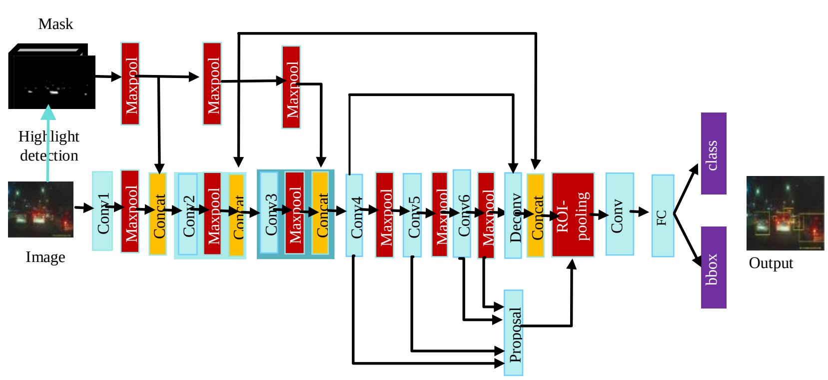

Fig. 33. Overview of the suggested highlight fusion process [19].

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ISSN 1947-5500

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