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Research paper

Development of Nighttime Vehicle Detection System using 5-stage Cascade Classifier

Ranganathan Venkatasubramanian[1]*, Elangovan M.[2]

[1,2] Department of Mechanical Engineering, Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, INDIA
**Corresponding author E-mail: ranganathan.kec@gmail.com*

Abstract

There is one death in every four minutes due to road accidents in India. This paper is a contribution towards the development of Advanced Driver Assistance Systems such as overtaking assistance system, Adaptive cruise control system, etc., which in turn could reduce the number of road accidents. This paper proposes a three-step method to detect the vehicles in front during nighttime in one-way road. In the first step, the classifier is trained with negative samples and Region of Interest (ROI) marked positive samples. In the second step, input images are acquired and enhanced. In the third step, the enhanced input images are fed into the trained 5-stage cascade classifier, where the vehicles in front are detected and visually presented. This method can detect the vehicles in front during nighttime in one-way road with 65.6% accuracy.

Keywords: *ADAS; Cascade Classifier; Computer vision; Image-processing; Overtaking Assistance system; Vehicle detection during Nighttime;*

1. Introduction

The objective of this work is to detect four wheeled non-commercial vehicles (Example: Hatchback, Sedan, SUV, compact SUV, etc.,) in front during nighttime in a one-way road using 5-stage cascade classifier.

According to survey results of 2017 (https://goo.gl/Nmas56), 1,46,377 people have died due to road accidents in India. The death count in 2017 is around 16,000 more than the death count of 2016. The increase in vehicle sales every year leads to increase in traffic on road, which in turn increases the number of road accidents every year.

Lots of researches are being performed in the area of "Advanced Driver Assistance System (ADAS)" that improves the safety, drivability and comfort in a vehicle. This work is a contribution towards the development of such safety features. This work could be deployed in Overtaking assistance system, Adaptive cruise control system and several related applications.

Overtaking assistance system is a comfort and safety feature that aids the driver to perform an overtaking maneuver. Adaptive cruise control system is a comfort feature that lets the driver to cruise at a constant speed, automatically brakes the vehicle if any other vehicle appears within defined boundary. Both the above-mentioned systems need the information on the vehicles in front. This work could be deployed among those systems to provide the information on the vehicles in front.

1.1. Literature survey

In addition to the daytime vehicle detection, lots of researches are being performed on vehicle detection during nighttime. Some of the researches that are relevant to this work are briefed below:

1.1.1. Fusion of Laplacian of Gaussian (LoG) and diffused light intensity

Jiann-Der Lee [2] detects the vehicles in front during nighttime by applying diffused light intensity, optical flow and LoG (Laplacian of Gaussian) techniques. Each frame from the input video are first converted from RGB color image to gray scale image. Based on the gray scale image, two intermediate images are derived. The First intermediate image is derived by applying LoG (Laplacian of Gaussian) filter. This filter detects the corners of the light sources. The second intermediate image is derived by applying diffused light intensity technique. By this technique, the propagation of light from the source is tracked. The two intermediate images are merged. When the optical flow algorithm is applied on the merged image, vehicles are detected.

1.1.2. AdaBoost classifiers

The method by Ravi Kumar Satzoda [4] detects all the signaling lights – braking, turn right and turn left using a 10 stage 'AdaBoost classifiers'. A new dataset 'LISA-N' is created to train and test the developed model.

1.1.3. Deformable part model

The method by Zhiyong Cui [7] detects the vehicle tail lights by applying Deformable part model combined with optical flow algorithm. In addition to the detection of taillights, this paper also proposes a method to read the taillights and identify the signals (brake, indications) by applying Hierarchical Matching Pursuit (HMP) technique on the detected taillights.

1.1.4. Symmetrical SURF

Li-Chih Chen [3] detects the vehicles in front by applying Symmetrical SURF technique.

2. Methodology

The proposed method detects the vehicles in front based on the below flow diagram:

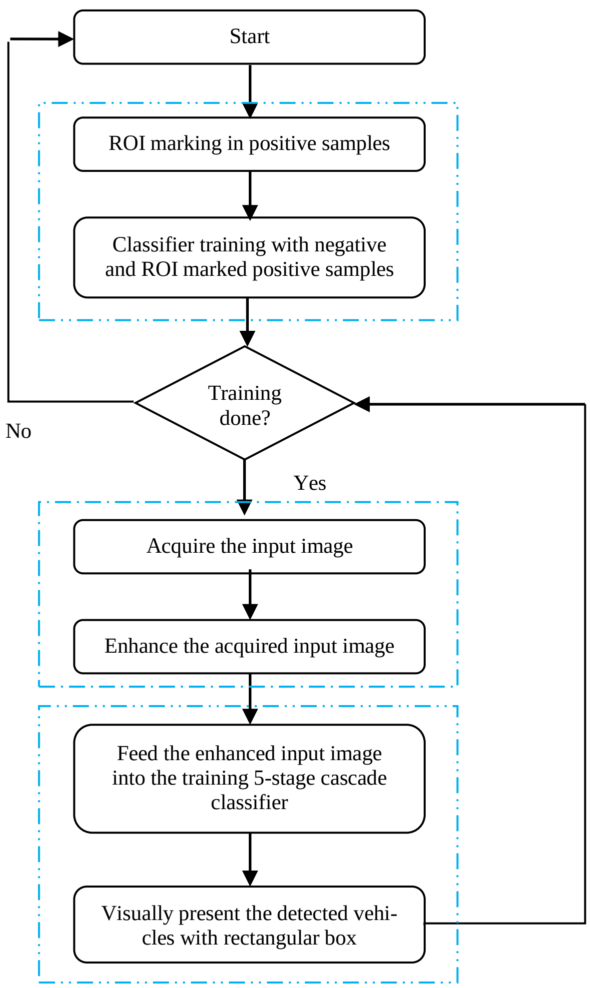

Fig. 1: Flow diagram

2.1. Tools used

1. MATLAB
2. Training image labeler

2.2. Training the Classifier

The Classifier is trained with negative and ROI marked positive samples. It is known that the more the number of training samples, higher will be the accuracy of vehicle detection. In this work, 450 ROI marked positive samples and 2000 negative samples are used to train the Classifier.

For this application, the positive samples are the images of rear end of the different types of non-commercial vehicles at nighttime under varying lighting conditions. The negative samples are the images with objects other than non-commercial vehicles and the images captured during daytime.

Fig. 2a: Positive sample

Fig. 2b: Negative sample

2.2.1. Determining ROI of positive images

ROI (Region of Interest) are the areas within the image that contain the object of interest. For this work, the rear part of the vehicles is the ROI in an image.

It is also possible to mark the ROI interactively using a GUI in MATLAB with the tool 'Training image labeller'. For this work, this tool is used to determine the ROI in all the positive images.

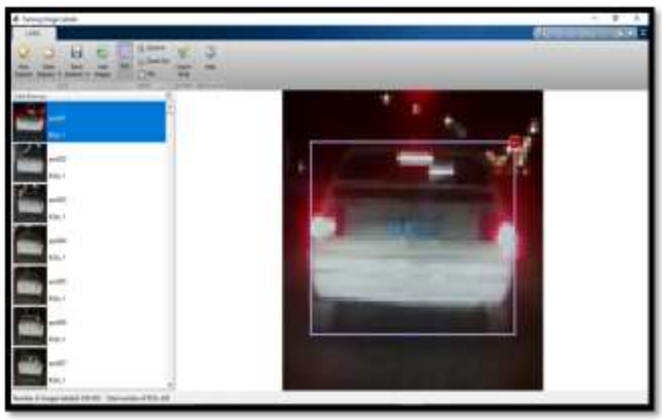

Fig. 3: ROI marked positive sample in 'Training image labeller'

2.2.2. Parameters of cascade classifier

The following parameters of the cascade classifier need to be configured before beginning the training. These parameters decide the quality of the training, which in turn affects the accuracy in vehicle detection:

1. Number of cascade stages
2. Acceptable false alarm rate

2.2.2.1. Number of cascade stages

The Number of cascade stages to train the Classifier is specified as a positive integer. More the number of stages, higher the accuracy of detection. However, for a given set of training images, the accuracy saturates at one point. After the saturation point, the accuracy is constant irrespective of the number of stages. Optimum number of stages is derived for a given set of training samples by trial and error method. If the number of stages is lower than the optimum point, accuracy of vehicle detection is affected. If the number of stages is higher than the optimum point, Classifier training time increases. For this work, number of stages is chosen as '5' based on trial and error method.

2.2.2.2. Acceptable false alarm rate

The Acceptable false alarm rate is specified as a value ranging from 0 to 1. The false alarm rate is the fraction of negative samples incorrectly classified as positive samples. A lower value for False Alarm Rate increase complexity and computation time in each stage but increases the accuracy. For a given number of stages, false alarm rate saturates at one point beyond which accuracy is constant. In this work, the false alarm rate is fixed as '0.2' and the number of stages are adjusted to the optimum value.

2.3. Acquiring and processing the input image

The below steps are performed on the acquired input image to improve the accuracy of detection:

1. Image cropping
2. Image sharpening

2.3.1. Image cropping

Image cropping is the process of removing certain parts of the digital image that are not necessary for the analysis to improve the accuracy of the vehicle detection. In this work, the input images of size 360x640 is cropped to 115x360 from 'x' coordinate of 140 and 'y' coordinate of 145 (pixel coordinate = [140,145]) to remove unwanted information like bonnet of vehicle, street lights etc.,

Fig. 4: Original input image (360x640)

Fig. 5: Cropped input image (115x360)

2.3.2. Image sharpening

Image sharpening is the process of sharpening the corners of the objects in the image to aid in object detection and extraction. The cropped image is sharpened in this step.

Fig. 6: Sharpened image

2.4. Vehicle detection and visual presentation

An input image is fed into the trained 5-stage cascade classifier.

Fig. 7: Vehicle detection and visual presentation

Figure 7 shows that the Classifier detects the rear end of the vehicles in front and visually present them with a rectangular box.

3. Simulation results

3.1. Dataset

A standard benchmark open source dataset for nighttime vehicle detection "SYSU Dataset - Nighttime Vehicle (with Ground truth)" is used for evaluating the model. All the images in the dataset are in RGB color model. The dataset contains

1. 450 images of rear of different vehicles during nighttime (positive images).
2. 2000 images with nighttime and daytime road scene without vehicles in the frame (negative images)
3. 400 images captured in real road at nighttime containing a total of 634 vehicles (test images) and Ground truth report for all the images.

3.2. Success results

3.2.1. Single vehicle in front with less noise

Fig. 8, 9, 10 and 11: Single vehicle in front with less noise

The figures 8, 9, 10 and 11 show the successful detection of single vehicle in front with less noise. The detected images clearly shows that, this model can differentiate the street lights and reflecting boards from the vehicle taillights.

3.2.2. Single vehicle in front with more noise

Fig. 12, 13, 14 and 15: Single vehicle in front with more noise

The figures 12, 13, 14 and 15 show the successful detection of single vehicle in front with more noise in the image like

1. Street lights
2. Head lights of vehicle coming in opposite direction
3. Display boards on the sides of the road
4. Reflection of ego vehicle's head lights on adjacent vehicle
5. Street lights pattern resembling like vehicle taillights.

3.2.3. Multiple vehicles in front with less noise

Fig. 16, 17, 18 and 19: Multiple vehicles in front with less noise

The figures 16, 17, 18 and 19 show the successful detection of multiple vehicles in front with less noise like

1. Head lamps
2. Street lights
3. Reflections from bonnet of the ego vehicle.

3.2.4. Multiple vehicles in front with more noise

Fig. 20, 21, 22 and 23: Multiple vehicles in front with more noise

The figures 20, 21, 22 and 23 show the successful detection of multiple vehicles in under complex lighting environment.

3.3. Failure results

The figures 24 to 27 show a few failure cases of the model. The model produces less accurate results in complex and dynamic road scenes.

Fig. 24, 25, 26 and 27: Failure results

3.4. Results table

Table 1 shows the performance of the proposed method.

Table 1: Performance of proposed method

Total cars (ground truth)	614
Detected cars	403
True positive rate	65.6%
Detected 'non-cars'	114
False positive rate	18.5%

4. Conclusion

In this paper, a method to detect the vehicles in front of the ego during nighttime is proposed. Nighttime vehicle detection is usually performed by tracking the light sources. The method proposed in this paper is a different approach to detect the vehicles in front during nighttime. As this method relies on correlating the objects present in an image with a known object rather than tracking the light source, it performs well in differentiating non-vehicle light sources from vehicle taillights under complex and dynamic environments. This method poses disadvantage in low true positive rate (65.6%). The true positive rate could be improved by combining another detection method with the proposed method and it may be considered as a direction for a future study.

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