Night Time Vehicle Detection Using Machine Learning

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Abstract: ***Monitoring traffic using camera networks is crucial, especially at night when visibility decreases and accident risks rise. Existing methods often struggle with the erratic nature of vehicle lights in low - light conditions, where lights appear as flashes or complex patterns across disconnected image regions. This study introduces a real - time vehicle detection algorithm designed for night time scenarios, leveraging machine learning with a grid of foveal classifiers. These classifiers use a single global image descriptor to predict vehicle locations based on their positions within the grid and ground - truth data. By requiring only point - based annotations for training, the algorithm accelerates database creation. Experimental validation on a new nighttime dataset demonstrates the effectiveness of this approach in accurately detecting vehicles under challenging lighting conditions.***

Keywords: Databases, Vehicle detection, Real - time systems, Lighting, Annotations, Cameras.

1. Introduction

Night - time vehicle detection using machine learning with a forward classifier represents a significant advancement in enhancing road safety and traffic management in low - light conditions. Detecting vehicles at night poses unique challenges due to reduced visibility and varying lighting conditions. Traditional methods often struggle to accurately identify vehicles in the darkness. However, leveraging machine learning techniques, particularly with the integration of a fuzzy classifier, offers a promising solution to this problem.

Inspired by the human visual system's ability to focus attention on specific areas of interest, the foveal classifier dynamically allocates computational resources to relevant regions within the image, enhancing the detection of vehicles. This introduction explores the significance of night - time vehicle detection, the challenges it presents, and the potential of integrating machine learning with a forward classifier to address these challenges effectively.

Night - time vehicle detection is a crucial aspect of traffic monitoring, autonomous driving, and road safety applications. Detecting vehicles in low - light conditions presents unique challenges compared to daytime detection due to reduced visibility, headlight glare, and varying illumination levels. There are some challenges we are facing with night - time vehicle detection:

- Night - time scenes have low ambient light, making it difficult to detect and identify vehicles.
- The bright glare from vehicle headlights can obscure other parts of the vehicle and surrounding area, complicating detection.
- Street lights, reflections, and other light sources create non - uniform lighting, which can affect detection accuracy.
- Low - light conditions often increase sensor noise, further complicating image processing tasks.

Night - time vehicle detection is essential for various reasons related to safety, efficiency, and technological advancement. Night driving significantly impacts traffic safety, as detecting oncoming vehicles in low - light conditions is challenging yet crucial. Effective night - time vehicle detection can greatly enhance traffic safety by alerting drivers early, encouraging them to stay focused on the road, and reducing the likelihood of accidents.

Night - time vehicle detection is critical for enhancing road safety, improving traffic management, supporting autonomous vehicles, advancing driver assistance systems, aiding law enforcement, and facilitating comprehensive data collection. By addressing the unique challenges of low - light conditions, effective night - time vehicle detection systems ensure safer and more efficient roadways, contributing to overall societal benefits.

Detecting vehicles at night requires specialised techniques to address the challenges posed by low visibility, headlight glare, and varying lighting conditions. Night - time vehicle detection is a critical component of modern traffic management and road safety systems. The unique challenges posed by low visibility and varying lighting conditions at night have led to the development of various approaches. The proposed method consists of two key components: a feature extraction system to identify vehicle characteristics, as well as a vehicle detection system that minimizes interference from complex background lighting. We adjust the light parameters to accurately isolate vehicles from streetlights and eliminate their effects. This dual approach ensures precise detection by focusing on vehicle - specific features while mitigating background light distractions.

Different approaches
1) Infrared (IR) Imaging
2) Visible light imaging
3) Sensor Fusion
4) Machine learning and deep learning
5) Pre - processing Techniques

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6) Feature Extraction and Analysis
7) Post - Processing

The picture translation module uses a generative adversarial network (GAN) to transform a nighttime image into a daytime image, enhancing visibility. During the vehicle detection stage, we apply advanced algorithms like Faster R - CNN and YOLOv5 to extract intricate features from the enhanced daytime image, ensuring precise vehicle identification even in low - light conditions. This integrated approach leverages both image translation and robust detection algorithms to improve nighttime vehicle detection accuracy and enhance overall safety on the roads.

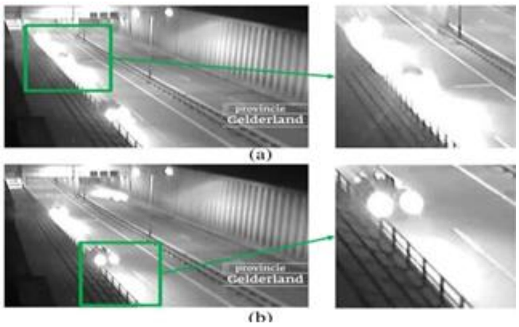

Figure 1: Examples of nighttime images with flashes and complex illumination patterns.

Machine learning (ML) significantly enhances night - time vehicle detection by addressing the challenges posed by low visibility and varying lighting conditions. ML algorithms can automatically enhance image quality by reducing noise and adjusting contrast, improving the visibility of vehicles in low - light environments. Advanced ML models, such as convolutional neural networks (CNNs), can learn to extract relevant features from nighttime images, such as vehicle headlights and shapes, enabling accurate detection. Diverse datasets can train these models to effectively generalize across various lighting conditions.

Additionally, ML algorithms can integrate data from multiple sensors, such as infrared cameras and LiDAR, to improve detection accuracy and robustness. The real - time processing capabilities of ML models enable quick detection and response, which is crucial for applications like autonomous driving and advanced driver - assistance systems (ADAS). Overall, ML empowers night - time vehicle detection systems to operate effectively and ensure road safety in challenging lighting conditions.

A foveal classifier for nighttime vehicle detection is a classification system that mimics the human visual system's foveal vision mechanism. In this approach, the classifier focuses on specific regions of interest within the image, similar to how the fovea in the human eye concentrates on high - detail areas. For night - time vehicle detection, the forward classifier dynamically allocates more computational resources to relevant parts of the image, such as regions with potential vehicle features like headlights or tail lights, while allocating fewer resources to less important areas. This selective attention mechanism allows for more efficient processing and accurate detection of vehicles in low - light conditions, improving overall performance while reducing computational load.

2. Literature Survey

Visual vehicle surveillance is a critical research area due to its numerous traffic applications, particularly at night when accidents surge. Traditional methods rely on segmenting bright image regions from vehicle lights, which often fails with large, undefined flashes. This paper introduces a real - time vehicle detection algorithm that overcomes these challenges. It uses a single image descriptor for the whole image and employs a grid of field classifiers to estimate vehicle positions by analysing complex light patterns. We also created a new nighttime database to evaluate the effectiveness of this method. [1]

Vehicle detection is crucial for monitoring and managing traffic on roads, highways, parking lots, and other areas. It is especially important in Intelligent Transportation Systems (ITS), where identifying and recognising moving vehicles at night poses significant challenges. With the increasing number of vehicles, road accidents have become more frequent, particularly at night when visibility is poor. The absence of illumination makes the whole vehicle body invisible, and high - intensity headlights from oncoming vehicles can cause glare and temporary blindness, leading to accidents. Nighttime vehicle detection is therefore vital for enhancing road safety. This review paper examines and summarises various proposed methods and techniques for nighttime vehicle detection, aiming to develop new strategies to reduce accidents and maintain safe distances between vehicles. We aim to guide future research and the development of improved detection algorithms with the presented findings and discussions. [2]

Vehicle detection is crucial for the development of automatic driving systems (ADS), which have seen significant advancements recently. Detecting vehicles at night, however, remains difficult due to subtle vehicle features and interference from complex road lighting or other vehicles' lights. This paper introduces a high - accuracy vehicle detection algorithm designed for nighttime scenarios. It uses an improved generative adversarial network (GAN), called Attentive GAN, to enhance vehicle features in nighttime images. The method uses multiple local regressions to guess multiple bounding box offsets and a better Region of Interest (RoI) pooling method based on Faster R - CNN for distinguishing features to make detection even more accurate. We apply cross - entropy loss to enhance classification accuracy. We evaluate the proposed algorithm using a dataset of selected nighttime images from the BDD - 100k dataset, which demonstrates superior performance compared to state - of - the - art detectors in nighttime vehicle detection. [3]

Night driving has a significant impact on traffic safety, so detecting oncoming vehicles at night is critical for preventing accidents. Early recognition of oncoming vehicles can encourage drivers to stay focused on the road. This paper presents an approach for nighttime vehicle detection using a single onboard camera. The system detects vehicle headlights by recognizing their shapes using an SVM classifier designed for this task. A pairing algorithm ensures that detected headlights belong to the same vehicle, and a multi - object tracking algorithm tracks cars as they move through the scene. Trained with 503 single objects and tested on 144, 587 objects from 1, 410 frames in 15 videos featuring 27 moving vehicles, the system achieved a recognition accuracy of 97.9% and a vehicle recognition rate of 96.3%, demonstrating its high robustness and effectiveness. [4]

This paper introduces a novel vehicle detection algorithm tailored for night - time conditions, employing pre - processing and lamp detection techniques. Initially, we apply contrast enhancement to enhance the visibility of salient features in low - exposure night - time images. Subsequently, the algorithm identifies pairs of rear lamps in the processed images. Finally, the algorithm detects forward vehicles by analysing lamp pairings. Experimental evaluations confirm the algorithm's capability to achieve robust and accurate vehicle detection under challenging night - time conditions. [5]

This article suggests real - time monocular - vision methods for finding vehicles and figuring out the distance between them. The goal is to get around the high computational costs and calibration problems of stereo - vision methods. The system's performance remains competitive, even on challenging benchmark datasets. The paper introduces a collision warning system that detects vehicles ahead and calculates safety distances to alert distracted drivers before potential crashes occur. Some important new ideas are adaptive global Haar - like features for finding vehicles, tail - light segmentation, virtual symmetry detection, and a good way to combine multiple features from a single sensor. The algorithm demonstrates robust detection capabilities day and night, across short- and long - range distances, validated through extensive experiments in diverse weather and lighting conditions, surpassing current state - of - the - art algorithms. [6]

In recent years, night time detection of pedestrians and vehicles has become a pivotal focus in computer vision. Traditional camera algorithms struggle in dim lighting. Utilising infrared images, which enhance the visibility of pedestrians and vehicles against darker backgrounds, this study introduces a rapid saliency mapping technique for swift target identification. It proposes refining and accurately delineating candidate bounding boxes based on these maps. This method uses a multi - feature fusion approach along with SVM classification to confirm the presence of people and cars in certain areas. Experiments have shown that it works well in real - life road situations. [7]

3. Proposed Method

This work introduces a framework for detecting vehicles at night using a grid of foveal classifiers. These classifiers focus on specific image zones, called foveas, and process global image data to adaptively learn the fovea's size and shape during training. This method allows for accurate vehicle detection, even when vehicles appear as large, bright regions in images. We employ point - based annotations instead of bounding boxes, which expedites and reduces the cost of the annotation process, particularly in poor lighting conditions. The framework is capable of utilising a variety of global image descriptors and classifiers, including the efficient use of Histogram of Oriented Gradients (HOG) for image descriptors and Support Vector Machines (SVM) for classifiers on a standard PC. The paper also discusses other descriptors and classifiers, such as Haar wavelets, LBP, and neural networks, and provides comparative results.

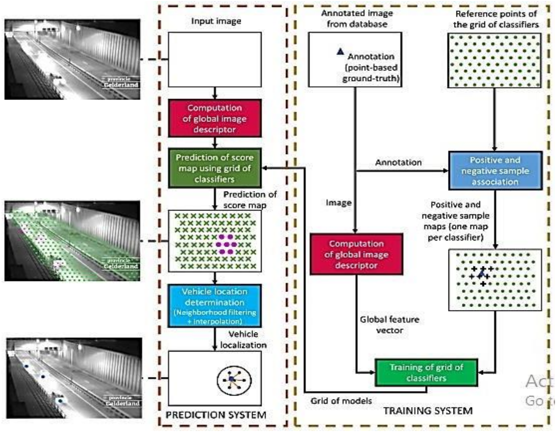

Figure 2: Block Diagram of the Proposed Solution.

The proposed machine learning framework is illustrated in Fig.2 and consists of two main phases: the prediction system and the training system.

1) **Prediction System**: This phase is responsible for predicting vehicle locations in input images using models developed during the training phase. It includes three stages:
   a) **Computation of the Global Image Descriptor**: This stage involves generating a feature vector that represents the entire image.
   b) **Prediction of a Score Map**: A grid of classifiers uses the global image descriptor to create a score map.
   c) **Vehicle Location Determination**: Based on the score map, the locations of vehicles are identified.

2) **Training System**: This phase consists of three stages aimed at preparing the models used in the prediction phase:
   a) **Computation of Global Image Descriptor**: Similar to the prediction phase, this stage computes a GHOG (Global Histogram of Oriented Gradients) vector for each image in the training database.
   b) **Positive and Negative Sample Association**: This stage involves associating each GHOG vector with a positive or negative label for each foveal classifier, indicating the presence or absence of a vehicle.
   c) **Training of the Grid of Classifiers**: The foveal classifiers are trained using the labeled GHOG vectors to distinguish between images with and without vehicles.

4. Result Analysis

Proposed method is implemented using python and Flask web framework. The results for night time vehicle detection and count classification is done below,

When we run the main code flask code will give us an URL which is the link for local host web - page.

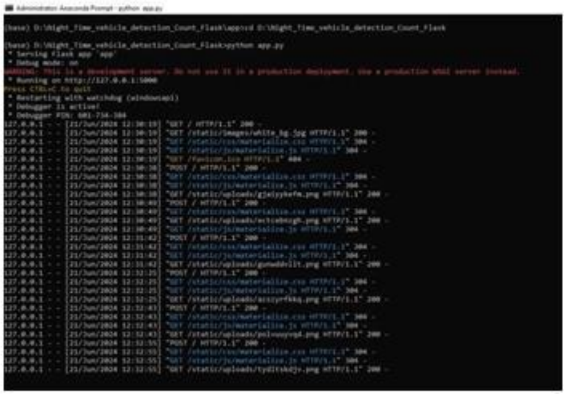

Figure 4.1: Flask Web frame execution

Figure 4.2: Car found and No bus found

We uploaded image to the proposed web page. The response obtained from the web page is, ‘the image contains 1 Car and O bus found’.

Similarly, we are going to upload different images to identify is there any buses and cars.

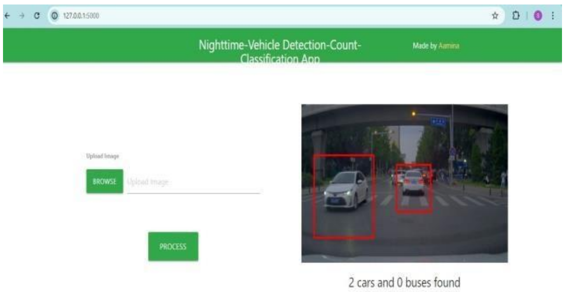

Figure 4.3: 2 cars and 0 buses found

In above results it is observed that 2 cars detected while buses count is 0. There is red bounding box applied for detected vehicles. The condition considered here is for night time.

Figure 4.4: 0 cars and 0 buses found

In above image there is no bus or no cars, its empty road. Night time vehicle detection an classification is complex task and in proposed application we have applied computer vision techniques and python software to implement the proposed model.

5. Conclusion

Visual vehicle surveillance is essential for traffic management, especially at night when accident risk is highest. This study introduces a real - time vehicle detection algorithm tailored for night time conditions, addressing challenges where images predominantly contain flashes occupying large regions, often disconnected from the light sources, obscuring vehicle shapes. The algorithm employs a global image descriptor and a grid of foveal classifiers, each trained to detect vehicles in specific regions by analysing complex light patterns. Unlike traditional sliding window methods, this approach uses a shared global image descriptor for all classifiers. The system requires only point - based annotations for training, simplifying database creation. The algorithm's output can assist in managing traffic congestion and preventing collisions. We have developed a new publicly available nighttime database with point - based annotations to validate the method. Although designed for nighttime use, the system shows potential for daytime use with minimal modifications, suggesting an area for future work.

References

[1] Bell, Andrés, Carlos Roberto del - Blanco, Fernando Jaureguizar, and Narciso García. "Robust Nighttime Vehicle Detection Based on Foveal Classifiers. " In 2020 IEEE International Symposium on Circuits and Systems (ISCAS), pp.1 - 5. IEEE, 2020.

[2] Parvin, Shahnaj, Md Ezharul Islam, and Liton Jude Rozario. "Nighttime Vehicle Detection Methods Based on Headlight Feature: A Review. " IAENG International Journal of Computer Science 49, no.1 (2022).

[3] Liu, Yan, Tiantian Qiu, Jingwen Wang, and Wenting Qi.2021. "A Nighttime Vehicle Detection Method with Attentive GAN for Accurate Classification and Regression" Entropy 23, no.11: 1490. https: //doi. org/10.3390/e23111490

[4] Fleyeh, Hasan, and Iman A. Mohammed. "Night time vehicle detection. " Journal of Intelligent Systems 21, no.2 (2012): 143 - 165.

[5] J. - W. Park and B. C. Song, “Night - time vehicle detection using low exposure video enhancement and lamp detection, ” in Proc. Int. Conf. Electron., Inf., Commun. (ICEIC), Jan.2016, pp.3–4.

[6] S. E. Shladover, J. Vanderwerf, and D. R. Ragland, “Robust vehicle detection and distance estimation under challenging lighting conditions, ” IEEE Trans. Intell. Transp. Syst., vol.16, no.5, pp.2723–2743, Oct.2015.

[7] Xue, Tao and Zhang, Zunqian and Ma, Weining and Li, Yifan and Yang, Aimin and Ji, Tianhao “Nighttime Pedestrian and Vehicle Detection Based on a Fast Saliency and Multifeature Fusion Algorithm for Infrared Images”

[8] W. Tian, L. Chen, K. Zou, and M. Lauer, “Vehicle tracking at nighttime by kernelized experts with channel - wise and temporal reliability estimation, ” IEEE Trans. Intell. Transp. Syst., vol.19, no.10, pp.3159–3169, Oct.2018.

[9] C. - C. Yu, H. - Y. Cheng, and Y. - F. Jian, “Raindrop - tampered scene detection and traffic flow estimation for nighttime traffic surveillance, ” IEEE Trans. Intell. Transp. Syst., vol.16, no.3, pp.1518–1527, Jun.2015.

[10] R. Gallen, A. Cord, N. Hautiere, E. Dumont, and D. Aubert, “Nighttime visibility analysis and estimation method in the presence of dense fog, ” IEEE Trans. Intell. Transp. Syst., vol.16, no.1, pp.310–320, Feb.2015.

[11] X. Dai, X. Yuan, J. Zhang, and L. Zhang, “Improving the performance of vehicle detection system in bad weathers, ” in Proc. IEEE Adv. Inf. Manage., Communicates, Electron. Autom. Control Conf. (IMCEC), Oct.2016, pp.812–816.

[12] H. Kuang, X. Zhang, Y. - J. Li, L. L. H. Chan, and H. Yan, “Nighttime vehicle detection based on bio - inspired image enhancement and weighted score - level feature fusion, ” IEEE Trans. Intell. Transp. Syst., vol.18, no.4, pp.927–936, Apr.2017.

[13] R. K. Satzoda and M. M. Trivedi, “Looking at vehicles in the night: Detection and dynamics of rear lights, ” IEEE Trans. Intell. Transp. Syst., vol.20, no.12, pp.4297–4307, Dec.2019.

[14] G. Rätsch, T. Onoda, and K. - R. Müller, “Soft margins for AdaBoost, ” Mach. Learn., vol.42, no.3, pp.287–320, 2001.

[15] P. Dave, N. M. Gella, N. Saboo, and A. Das, “A novel algorithm for night time vehicle detection even with one non - functional taillight by CIOF (Color inherited optical Flow), ” in Proc. Int. Conf. Pattern Recognit. Syst. (ICPRS), 2016, pp.2–7.

[16] P. Dave, N. M. Gella, N. Saboo, and A. Das, “A novel algorithm for night time vehicle detection even with one non - functional taillight by CIOF (Color inherited optical Flow), ” in Proc. Int. Conf. Pattern Recognit. Syst. (ICPRS), 2016, pp.1–6.

[17] D. - Y. Chen, Y. - H. Lin, and Y. - J. Peng, “Nighttime brake - light detection by Nakagami imaging, ” IEEE Trans. Intell. Transp. Syst., vol.13, no.4, pp.1627– 1637, Dec.2012.

[18] W. Zhang, Q. M. J. Wu, G. Wang, and X. You, “Tracking and pairing vehicle headlight in night scenes, ” IEEE Trans. Intell. Transp. Syst., vol.13, no.1, pp.140–153, Mar.2012.