논문 20-45-05-12 The Journal of Korean Institute of Communications and Information Sciences '20-05 Vol.45 No.05
https://doi.org/10.7840/kics.2020.45.5.842

Haar와 Lab 색상 특징 기반의 야간 차량 전조등 및 후미등 감지 알고리즘

팜뚜안안•, 유 명 식°

A Vehicle Headlight and Taillight Detection Algorithm Based on Haar and Lab Color Features in Nighttime

Tuan-Anh Pham•, Myungsik Yoo°

요 약

온로드 차량 감지는 지능형 운송 시스템에서 중요한 기술이다. 일광 상태에서 차량감지 시스템은 색상, 모양 또는 일반적인 차량 패턴과 같은 차량의 외관 정보를 활용하여 높은 정확도를 얻을 수 있다. 그러나, 야간에는 대부분의 차량 외관 특징들은 차량감지를 하기에는 불충분하고 신뢰성이 낮아, 전조등 및 후미등이 차량감지를 위한 신뢰할 수 있는 특징이 된다. 본 논문에서는 야간 차량 전조등 및 후미등 영역을 모두 검출하는 방법을 제안한다. 감지의 처음 단계로 회색조 이미지를 사용하는 Haar 특징과 Lab 색상 특징을 결합한다. 이후 결합된 두 특징은 Multi-Adaboost를 통하여 훈련된다. 제안된 감지 알고리즘은 실험을 통하여 전조등과 후미등 감지 성능에서 우수함을 증명하였다.

Key Words : headlight, taillight, vehicle detection, feature, training

ABSTRACT

On-road vehicle detection is an important technique in Intelligent Transportation Systems. Under the daylight condition, the vehicle detection system can utilize the appearance information of vehicle such as color, shape, or typical vehicle patterns for vehicle detection with high performance. However, most of vehicle appearance features are insufficient and unstable in nighttime, and headlights or taillights become the reliable features for identifying vehicles. In this paper, a method for detecting both headlight and taillight regions during nighttime is proposed. At first, the Haar-like features using grayscale image and color feature using Lab color space are combined. Then, the Multi-Adaboost is trained with the combined features. The experimental results show the effectiveness of our method in detecting headlights and taillights at night.

Ⅰ. Introduction

In recent years, vehicle detection has played an important role in many applications in Intelligent Transportation Systems (ITS) such as autonomous driving, traffic control, and traffic surveillance.

※ This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF), funded by the Ministry of Education, Science and Technology (NRF-2018R1A2B6004371)
• First Author : Department of ICMC Convergence Technology, Soongsil University, Seoul, South Korea, anhptuit@gmail.com, 학생(석사), 학생회원
° Corresponding Author : School of Electronic Engineering, Soongsil University, Seoul, South Korea, myoo@ssu.ac.kr, 종신회원
논문번호 : 202002-026-C-RN, Received February 11, 2020; Revised February 12, 2020; Accepted February 12, 2020

However, detecting vehicles in nighttime is more challenging than in daytime due to the lack of details of vehicle appearance. In daytime, vehicle detection is based on color, shape, shadow, corners, and edges of the vehicles[1]. Nevertheless, at night, the above features are not visible because of low contrast and luminosity of nighttime images. Under dark conditions, the most salient features to be seen is the light source, and vehicle headlights or taillights become important features which can be used for identifying vehicles.

To detect headlights, various methods have been designed. Most of the methods first segment the image to find the bright blobs which may be the headlights. By using fixed threshold or adaptive thresholding, a set of pixels of bright spots whose gray intensity values are higher than the threshold is retrieved. Then, in order to classify whether the bright blob is the headlight or not, rule-based or machine-learning-based methods are applied. The rule-based methods are the most commonly used ones. Chen. Y. et al[2] constructs a set of rules based on the prior knowledge and statistical laws on contrast, position, size and shape to classify headlights and the other objects. The difficulty of the rule-based method is that the rules should be defined carefully and covered all scenarios to get highly accurate results. Otherwise, machine-learning-based methods have been researched recently because of their good discrimination and better adaptability. In [3], support vector machine (SVM) is deployed to classify headlights and nuisance lights (reflections). The Adaboost and Haar features are used to discriminates headlights from non-headlights in [4].

Unlike headlights, the dominant color of taillights is red, the redness of rear lights can be simply filtered out by using color spaces. In [5], a set of thresholds for filtering red color in taillights is directly derived from automotive regulations and adapted for real-world conditions in hue-saturation-value (HSV) color space. A Y'UV color space[6] is employed to extract the potential taillight candidates in the image. Then, the other areas which may not be the taillights of a vehicle are eliminated by using symmetry and histogram tests.

In this study, we propose a machine-learning-based approach for detecting both vehicle headlights and taillights in nighttime. Our approach is inspired by the method of Satzoda et al.[7]. The approach for training Multi-Adaboost classifiers with Haar features and color feature is implemented in this paper. Then, the results of the classification are evaluated when two kinds of features are fused.

Ⅱ. Proposed method

In this section, the whole learning flow for training Multiclass Adaboost classifier with the proposed features is described as follows using Fig. 1. First, the annotated headlights and taillights are extracted from the given training images. Let H and L be the set of annotated windows of headlights and taillights, respectively. A window $r_H \in H$ or $r_L \in L$ is defined by $[x\ y\ w\ h]$ where (x, y) indicate the top left corner of the window, and w and h indicate the width and the height of the window. Fig. 2 shows examples of annotated headlights and taillights. Negative images which do not contain any headlights or taillights are randomly taken from the given training images. In order to prepare for extracting features, all annotated windows and negative images need to be resized to the same dimension. This dimension depends on the

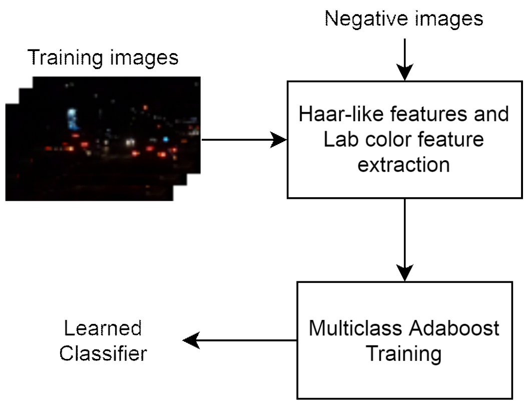

Fig. 1. A learning flow for training Multiclass Adaboost classifier

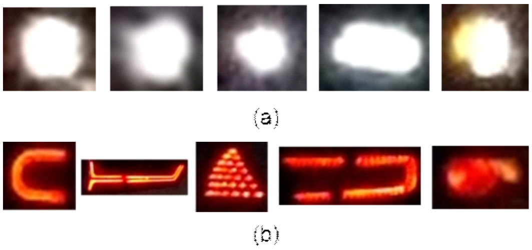

Fig. 2. Examples of annotated windows. (a) headlights. (b) taillights.

experiment. Then, Haar features and Lab color feature are extracted from the resized images. The feature extraction process will be explained in detail in section II-A and II-B. Finally, a Multiclass-Adaboost classifier[8] is trained to discriminate headlights and taillights.

2.1 Haar features extraction

Haar features are digital image features used in object detection and they are good at detecting edges and lines. To extract these features, the resized images must be converted to the grayscale image. In this study, we use two kinds of features (edge and line) which are described in Fig. 3.

Each feature is used to encode local appearance of headlights or taillights. It may consist of two or three rectangular regions. These regions have the same size and shape and are horizontally or vertically adjacent. The value of feature is a scalar value and it can be calculated by subtracting the sum of the pixels under the white rectangle from the sum of pixels under the black rectangle.

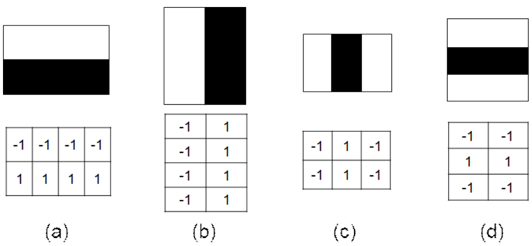

Fig. 3. Examples of two kinds of Haar features and their corresponding numerical representation. (a) horizontal edge feature. (b) vertical edge feature. (c) horizontal line feature. (d) vertical line feature.

2.2 Lab color feature extraction

Lab color space is a 3-axis color system with dimension L for lightness from black to white, a from green to red, and b from blue to yellow. It represents colors by using the coordinates in uniform color space. After analyzing the mean values of channel L, a and b of 100 healight and 100 taillight images, we see that channel a can be employed for identifying the headlights and taillights, the mean values are depicted in Fig 4.

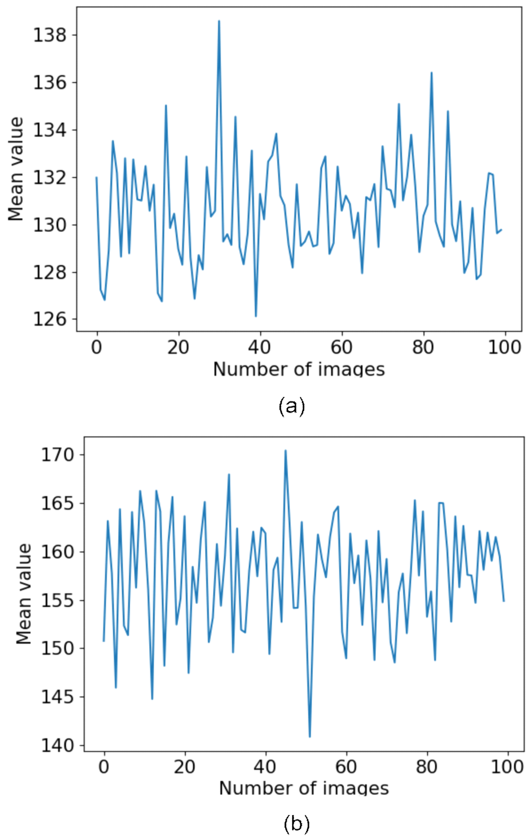

Fig. 4. Mean values of channel a images. (a) headlight. (b) taillight.

Ⅲ. Experimental results

The dataset in our experiment is collected by using camera Sony Cyber-shot DSC-RX100V. We take out 110 frames for extracting 360 annotated headlights, taillights and negative images. The extracted images are resized to 20x20 pixels. Then, all the resized images are used for training and testing Multi-Adaboost classifier. We extract 616 Haar features for training classifier. Each Haar feature describe a local appearance of headlights or taillights. The examples of Haar feature received after training classifier are shown in Fig. 5.

In order to perform the evaluation of classifier, we use two common metrics which are precision and recall. Both of them are calculated as follows:

$$precision = \frac{true\ positive}{true\ positive + false\ positive} \quad (1)$$

$$recall = \frac{true\ positive}{true\ positive + false\ negative} \quad (2)$$

To evaluate the classification, we split the dataset into 80% for training and 20% for testing. By using (1) and (2), two different sets of results are listed in Table 1. The first part of Table 1 lists precision and recall results which are obtained by training Multi-Adaboost without Lab color feature. The second part of Table 1 shows the classification results with Lab color feature. It can be seen that the classifier is unable to classify both headlight and taillight well if it trains with Haar features only. The evaluation results are improved significantly by combining two kinds of features.

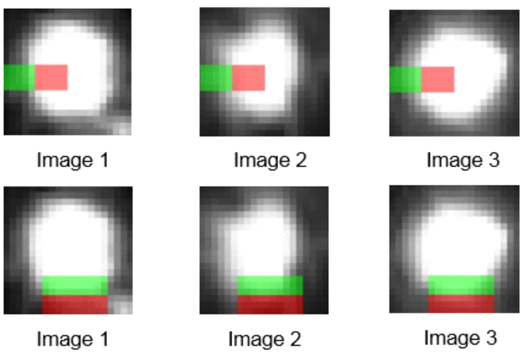

Fig. 5. Examples of Haar features which the Multi-Adaboost learned from training process

Table 1. Classification results

Class	Without color feature		With color feature	
	Precision (%)	Recall (%)	Precision (%)	Recall (%)
Headlight	95	95	100	100
Taillight	85	89	95	100
Negative	85	81	100	95

Ⅳ. Conclusion

In this paper, the proposed method shows the improvement in the classification results. By suggesting a new color feature and combining it with Haar features, the approach can increase the accuracy in detecting both headlights and taillights. In future work, more data will be collected to cover all cases which might happen in night-driving.

References

[1] Z. Sun, G. Bebis, and R. Miller, "On-road vehicle detection: A review," *PAMI*, vol. 28, no. 5, pp. 694-711, 2006.

[2] Y. Chen, B. Wu, H. Huang, and Ch. Fan, "A real-time vision system for nighttime vehicle detection and traffic surveillance," *IEEE Trans. Ind. Electron.*, vol. 58 no. 5, pp. 2030-2044, 2011.

[3] P. Alcantarilla, et al.: "Night time vehicle detection for driving assistance lightbeam controller," in *Proc. IEEE Intell. Veh. Symp.*, pp. 291-296, 2008.

[4] Q. Zou, H. Ling, S. Luo, Y. Huang, and M. Tian, "Robust nighttime vehicle detection by tracking and grouping headlights," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 5, pp. 2838-2849, 2015.

[5] R. O'Malley, E. Jones, and M. Glavin, "Rear-lamp vehicle detection and tracking in low-exposure color video for night condition," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 2, pp. 453-462, 2010.

[6] A. Almagambetov, S. Velipasalar, and S. Member, et al., "Robust and computationally lightweight autonomous tracking of vehicle taillights and signal detection by embedded

smart cameras," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3732-3741, 2015.

[7] R. K. Satzoda and M. M. Trivedi, "Looking at vehicles in the night: Detection and dynamics of rear lights," *IEEE Trans. Intell. Transp. Syst.*, 2016.

[8] T. Hastie, S. Rosset, J. Zhu, and H. Zou, "Multi-class adaboost," *Statistics and its Interface*, 2009.

팜뚜안안 (Tuan-Anh Pham)

Tuan-Anh Pham received the B.Eng. degree in software engineering from the University of Information Technology, Vietnam National University－Ho Chi Minh City, Ho Chi Minh City, Vietnam, in 2018. He is currently pursuing the master's degree with Soongsil University. His research interests include visible light communication and image processing.

유 명 식 (Myungsik Yoo)

Myungsik Yoo received his B.S. and M.S. degrees in electrical engineering from Korea University, Seoul, Republic of Korea, in 1989 and 1991, and his Ph.D. in electrical engineering from State University of New York at Buffalo, New York, USA in 2000. He was a senior research engineer at Nokia Research Center, Burlington, Massachusetts. He is currently a professor in the school of electronic engineering, Soongsil University, Seoul, Republic of Korea. His research interests include visible light communications, sensor networks, Internet protocols, control, and management issues.