# Night-Time Traffic Light Detection Based On SVM with Geometric Moment Features

Hyun-Koo Kim, Young-Nam Shin, Sa-gong Kuk, Ju H. Park, and Ho-Youl Jung

Abstract—This paper presents an effective traffic lights detection method at the night-time. First, candidate blobs of traffic lights are extracted from RGB color image. Input image is represented on the dominant color domain by using color transform proposed by Ruta, then red and green color dominant regions are selected as candidates. After candidate blob selection, we carry out shape filter for noise reduction using information of blobs such as length, area, area of boundary box, etc. A multi-class classifier based on SVM (Support Vector Machine) applies into the candidates. Three kinds of features are used. We use basic features such as blob width, height, center coordinate, area, area of blob. Bright based stochastic features are also used. In particular, geometric based moment's values between candidate region and adjacent region are proposed and used to improve the detection performance. The proposed system is implemented on Intel Core CPU with 2.80 GHz and 4 GB RAM and tested with the urban and rural road videos. Through the test, we show that the proposed method using PF, BMF, and GMF reaches up to 93 % of detection rate with computation time of in average 15 ms/frame.

*Keywords*—Night-time traffic light detection, multi-class classification, driving assistance system.

#### I. INTRODUCTION

**D**RIVER may have some troubles, when he or she could not recognize the situation of road environment [1]. Up to seventy percent of road accident occurs in intersection. If driver handle an appropriate action before several second of accident, traffic accidents can reduce to less than 50 % or turn a minor accident. Recognizing traffic lights are important for safety driving. If it is possible to detect and recognize a traffic light, it will give useful information to a driver to understand the road ahead. However, it is not easy to detect a traffic light in a scene image since the traffic light is very small compared to other objects and there are many objects of which colors are similar to one of the traffic lights. Therefore, there are not so many researches on this topic.

Few researches have been conducted on traffic light

detection based on video cameras for intelligent vehicle applications. There are two kinds of frameworks in the traffic light detection. The one uses color information, but the other one do not use it. In the researches using color information, Masako and Shinichiro [2] proposed an algorithm to detect daytime traffic light detection. This algorithm uses normalized RGB to select as candidates of a traffic light. Then Hough transform is applied to detect an exact region. Park [3] also proposed daytime traffic lights detection by judging the shape and size of an object, in which the arrow-shaped traffic light was not discussed. Chung [4] adopted HIS model to recognize daytime and nighttime traffic lights, in which the road scene was simple and some interference problems such as vehicle lamps, street lamps were not considered. Moises et al. [5] proposed a technique to detect suspended traffic lights, based on colors and features such as black area of traffic lights or area of lighting lamps in the daytime. Additionally, the traffic light distance is estimated aiming at slowing down and stopping in the correct position, in case of red light. Cai et al. [6] proposed a algorithm to resolve the problems of detection and recognition of arrow traffic lights in the daytime. To get the regions of candidates of blackboards, the color space conversion, binarization and morphology features filtering methods are performed. For getting the regions of arrow of traffic lights, segmentation based on the YCbCr color space is used in the cropping image, which is cropped from original image by the region of blackboard. To recognition types of traffic light, Gabor wavelet transform and 2D independent component analysis are used to extract traffic light candidate's features for features of the arrow traffic lights. In the researches using non color information as gray image, Raoul and Fawzi [7, 8] proposed a daytime traffic light recognition using spot detection and adaptive traffic lights templates. This algorithm is able to detect lights from a long distance.

Recently, most of the researches have focused on daytime traffic light detection and recognition, but only few did on nighttime traffic light detection and recognition. For this reason, we propose an effective night-time traffic light detection method for real time driving assistance system. This paper outline is as follows. A system overview is presented in section II. In Section III, main steps of our detection method are detail. Finally, test results on road sequence will be shown and commented in Section IV.

## II. SYSTEM OVERVIEW

As shown in Fig. 1, there exist two different types of traffic

Hyun-Koo Kim is Ph.D Student with Department of Information and Communication of Engineering - Yeungnam University - Korea (phone: +82-10-8610-8032; fax: +82-53-810-4742; e-mail: kim-hk@ynu.ac.kr).

Young-Nam Shin, Mr, E/E Research Team Research Engineer, SL Corporation - Korea (e-mail: ynshin@slworld.com).

Sa-gong Kuk, Mr, Director, SL Corporation - Korea (e-mail: ksakong@@slworld.com).

Ju H. Park is Ph. D, Professor, with Department of Electrical Engineering, Yeungnam University, Kyongsan, South Korea (Email: jessie@yu.ac.kr).

Ho-Youl Jung is (Corresponding Author), Ph. D, Professor, Department of Information and Communication of Engineering, Yeungnam University -Korea (phone: +82-53-810-3545; e-mail: hoyoul@yu.ac.kr.

lights. In this works, we focus only on horizontal types of traffic lights in the night-time dynamic road environment.



Fig. 1 Left picture is horizontal traffic lights and right picture is vertical traffic lights

The proposed traffic lights detection method consists mainly of three steps as illustrated in Fig. 2.

**Candidates Region Selection Step** extracts candidates region of traffic lights from RGB color image. To extract red and green color, Input image is represented on the dominant color domain by using color transform proposed by Ruta. Then, red and green color dominant regions are separated by labeling process.

**Noise Reduction Step** carries out shape filtering to reduce noisy blob using information of blobs in binary image such as length, area, area of boundary box, etc.

**Multi-class Classifier Step** classifies real traffic light blobs from the candidate blobs. SVM (Support Vector Machine) is used with three kinds of features, i.e., BF (Basic parameter Feature), BMF (Brightness (or intensity) based Moment Feature) and GMF (Geometric based Moment Feature).

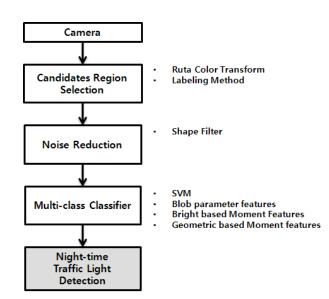


Fig. 2 System overview for night-time traffic light detection

## III. PROPOSED METHOD

## A. Candidates Region Selection

For valuable traffic light detection at night-time, it is important to find blobs with red color and green color lights. A simple thresholding on a color channel image does not work well to extract candidates of traffic lights, since there are lots of noisy objects on urban road environments. There exist many noisy self-emitted lights which is similar color to traffic lights. For examples, neon-sign with red and/or green color, rear-lamp of other vehicles, street lamps, indoor light of building, and so on are included. Moreover, there are various reflectors such as traffic signs, fences, poles, and etc. In addition, blooming effects often appear on self-emitted lights. These noise and blooming effects make it difficult to detect real traffic lights. Clearly, it is very important to reduce such noisy blobs as many as possible in the first step, candidate region selection.

In the proposed method, a dominant color representation technique is used to effectively extract candidate blob of traffic lights with green and/or red color. Blobs with dominant red and green color are selected by using color transform proposed by Ruta et al. [9].

For each pixel with RGB colors  $X = [X_R, X_G, X_B]$ , red-dominant component  $f_R(x)$  and green-dominant component  $f_G(x)$  are obtained by respectively,

$$f_{R}(x) = \max(0, \min(X_{R} - X_{G}, X_{R} - X_{B})/s)$$
  
$$f_{G}(x) = \max(0, \min(X_{G} - X_{R}, X_{G} - X_{R})/s)$$

where  $S = X_R + X_G + X_B$ .

Each dominant color image is transformed into binary image using pre-defined threshold and segmented by labeling process.



Fig. 3 Results of green traffic lights detection. Top picture is original image and bottom picture is binary image of green dominant color

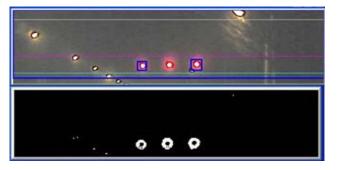


Fig. 4 Results of red traffic lights detection. Top picture is original image and bottom picture is binary image of red dominant color

## B. Noise Reduction [10]

Scattered noisy blobs are filtered out and regions containing other types light such as street light, traffic sign, and vehicle lamps are detected. Assuming that the shape of traffic lights is circle type, we eliminate inconsistent blobs that can be regarded as noisy. The following criteria are used in this work. The blob of extracted spotlight is regarded as noisy:

- If width of the blob is smaller than 1.5 times of height, or if height is smaller than 1.5 times of width.
- If area of the blob is smaller than 1.5 times of the area of bounding box.

Fig. 5 shows blob parameters of labeled potential traffic lights.

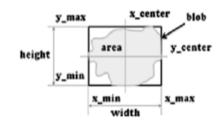


Fig. 5 Blob parameters of labeled potential traffic lights

## C. Multi-class Classifier (MC)

**Multi-class classifier using learning scheme:** For traffic light detection, we use multi-class classifier with Support Vector Machine (SVM) algorithm [11]. This learning scheme is binary classifier separating two classes and best solution maximizes distance to both classes. To classify, this algorithm compute dot product with separating hyper-plane and use quadratic programming to find optimal solution of maximizes the separating margin. In the works, linear SVM is applied. Three types of features are used in the classifier: BF (Basic parameter Feature), BMF (Brightness (or intensity) based Moment Feature) and GMF(Geometric based Moment Feature).

**Basic features (BF):** The width, height, length, center coordinate, area, and area of boundary box of blob in the binary image are included.

Bright moment features (BMF): The mean, variance, skewness, and kurtosis of brightness of blobs are included.

Note that these features can be fast computed by using integral image [12].

**Geometric moment features (GMP):** Using the coordinates of blob, the following geometric (n-th, m-th order) moments are calculated and used as features. For more details of geometric moment, refer to [13].

$$\Delta_{10} = \mu_{\chi} = E[X],$$
  

$$\Delta_{01} = \mu_{Y} = E[Y]$$
  

$$\Delta_{11} = \frac{E[(X - \mu_{X})(Y - \mu_{Y})]}{\sigma_{X}\sigma_{Y}}$$
  

$$\Delta_{20} = \sigma_{X}^{2} = E[(X - \mu_{X})^{2}]$$
  

$$\Delta_{02} = \sigma_{Y}^{2} = E[(Y - \mu_{Y})^{2}]$$
  

$$\Delta_{21} = \frac{E[(X - \mu_{X})^{2}(Y - \mu_{Y})]}{\sigma_{X}^{2}\sigma_{Y}}$$
  

$$\Delta_{12} = \frac{E[(X - \mu_{X})(Y - \mu_{Y})^{2}]}{\sigma_{X}\sigma_{Y}^{2}}$$

where, E[] means expectation.  $\Delta_{10}$  and  $\Delta_{01}$  respectively means center of x and y coordinate of labeled object.  $\Delta_{20}$ ,  $\Delta_{02}$ each means length of width and height of labeled object.

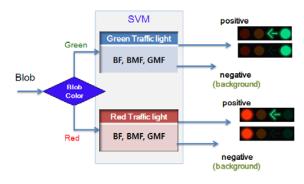


Fig. 6 Layout of Multi-class Classifier

Fig. 6 shows layout of our proposed multi-class classifier for night-time traffic light detection. Depending on the dominant color of blob, three kinds of features are calculated and induced into one of two different SVM classifiers. Each classifier distinguish positive and negative blob. In the case of green color dominant blobs, green circle or green circle with green arrow is classified as positive. For red blobs, red circle or red circle with green arrow as positive.

#### IV. SIMULATION RESULTS

The proposed system is tested on Intel Core CPU with 2.80 GHz and 4 GB RAM tested in the urban and rural road environments. The frame rate of test videos is 30 frames per second and the size of each frame of grabbed image sequences is 620 pixels by 480 pixels. Using sequences acquired with an on-vehicle camera, we extracted traffic lights and non-traffic lights samples. For training of traffic light, the number of positive samples is 2,354 and the number of negative samples is 23,422.

 
 TABLE I SEQUENCES USED FOR THE TESTS

 Sequence
 Length
 # of frames
 # of frames with traffic lights

 Sequence
 8'56"
 16,080
 12,703

In the test, we carry out three times on the same video sequence to evaluate the performance depending on the types of feature. Table I describes the sequences used for the evaluation of our method. Table II describes fully detailed results of those tests and the computation time of our proposed method according to three different combinations of features. In the computation of detection rate, if traffic light is detected at least during its timeline, traffic detection is regarded as success.

TABLE II

RESULTS OF THE FRAME PER FRAME MATCHING AND COMPUTATION TIME		
Features	Sequence 1	Average Computation Time/frame
BF	73.51 %	7 ms/frame
$\mathbf{BF} + \mathbf{BMF}$	87.20 %	10 ms/ frame
BF + BMF + GMF	93.53 %	15 ms/ frame



Fig. 7 (a) and (b) show red traffic light detection of red circle type and type of red circle and green arrow (c) and (d) show green traffic light detection of green circle type and type of green circle and green arrow

Results in Table II show that the proposed method using combined features of BF, BMF, and GMF achieves better detection rate than the others. Also this method can be applied in real-time systems by average computation time is 15 ms/frame. The proposed method reaches 93.53 % in the sequence 1.

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