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Effective Traffic Lights Recognition Method for Real Time Driving Assistance System in the Daytime

Hyun-Koo Kim, Ju H. Park, and Ho-Youl Jung

***Abstract*—**This paper presents an effective traffic lights recognition method at the daytime. First, Potential Traffic Lights Detector (PTLD) use whole color source of YCbCr channel image and make each binary image of green and red traffic lights. After PTLD step, Shape Filter (SF) use to remove noise such as traffic sign, street tree, vehicle, and building. At this time, noise removal properties consist of information of blobs of binary image; length, area, area of boundary box, etc. Finally, after an intermediate association step witch goal is to define relevant candidates region from the previously detected traffic lights, Adaptive Multi-class Classifier (AMC) is executed. The classification method uses Haar-like feature and Adaboost algorithm. For simulation, we are implemented through Intel Core CPU with 2.80 GHz and 4 GB RAM and tested in the urban and rural roads. Through the test, we are compared with our method and standard object-recognition learning processes and proved that it reached up to 94 % of detection rate which is better than the results achieved with cascade classifiers. Computation time of our proposed method is 15 ms.

***Keywords*—**Traffic Light Detection, Multi-class Classification, Driving Assistance System, Haar-like Feature, Color Segmentation Method, Shape Filter

I. Introduction

DRIVER is able to be a bit of trouble, because he cannot recognize situation of road environment [1]. Recently, to prevent accident due to carelessness of driver and to provide convenient driving environment, research on advanced driving assistance systems (ADAS) to offer road information and caution alarm and to help the driver in its driving process is crucial issue. Examples of such a system are adaptive cruse control (ACC), lane departure warning system (LDWS), collision avoidance system (CAS), vehicle detection system, traffic sign and light detection system, blind spot detection system (BSD), and etc [2, 3].Up to seventy percent of road accident is happen to 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. For this reason, we propose an effective traffic light recognition method for real time driving assistance system at the intersections in the daytime [4]. To introduce our method, paper outline is as follows. A system overview is presented in section 2. In Section 3, main steps of our recognition method are detail. Finally, results on road sequence will be shown and commented in Section 4.

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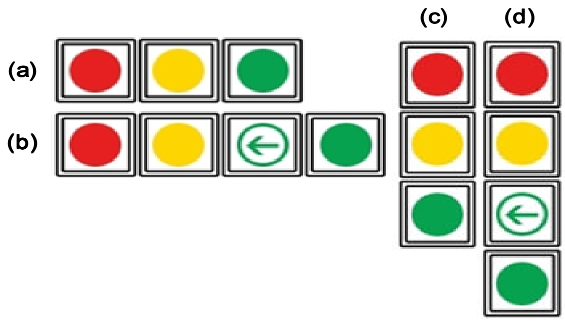

Fig. 1 (a) and (b) pictures are Korean horizontal traffic lights. (c) and (d) pictures are Korean vertical traffic lights

II. System Overview

As shown in Fig 1, traffic lights are very different types in the intersection. However we can distinguish two main types of traffic lights: horizontal traffic light ((a) and (b) pictures of Fig. 1) and vertical traffic light ((c) and (d) pictures of Fig. 1). Almost all the previous researches have been applied only on vertical traffic lights. Therefore, our goal is to design a method for Traffic Lights Recognition that is able to detect horizontal and vertical traffic lights in a dynamic road environment. The layout of our proposed traffic lights recognition method consists mainly of three steps as illustrated in Fig. 2.

Fig. 2 Layout of traffic light detection method

First Step First, Potential Traffic Lights Detector (PTLD) use whole color source of YCbCr channel image and make each binary image of green and red traffic lights.

Second Step After PTLD step, Shape Filter (SF) [5] use to remove noise such as traffic sign, street tree, vehicle, and building. At this time, noise removal properties consist of information of blobs of binary image; length, area, area of boundary box, etc.

Third Step Finally, after an intermediate association step witch goal is to define relevant candidates region from the previously detected traffic lights, Adaptive Multi-class

Classifier (AMC) is executed. The classification method use Haar-like feature [9] and Adaboost algorithm [10, 11].

III. Recognition Process

A. Potential Traffic Light Detector (PTLD)

From the YCbCr image, some regions are extracted as candidates for a traffic light. The decision whether a pixel belongs to one of the candidate regions or not is done by the values of Cb and Cr. We observed the images of the traffic lights and determined the condition that a pixel belongs to a candidate region as follows:

- Green Traffic Lights; Cr < 122 and Cb > 120
- Red Traffic Lights; Cr > 145

In our paper, a traffic signal recognition method uses a color camera. The major challenge at that time was the low dynamic range of color sensors. In order to verify the active traffic light by classification, two inactive traffic lights have to be visible above/below it. To discern this region from the background, the exposure time had to be long enough, which forced the active traffic lights into saturation hence producing white instead of the signal colors. Using high dynamic range CMOS sensors the whole scene is discernable and we still have detectable signal colors. The image resulting from the classification process is blurred and then segmented by the use of a connected component analysis. Scattered noise pixels are filtered out and regions containing the lights of traffic signals are detected.

Fig. 3 PTLD Result of green traffic lights detection. Left picture is original image and right picture is binary image of green lights

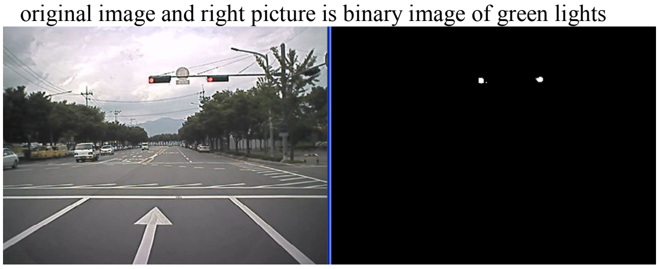

Fig. 4 PTLD Result of red traffic lights detection. Left picture is original image and right picture is binary image of red lights

B. Shape Filter (SF) [5]

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 (Binary Large Object) 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 sum of pixel of the blob is smaller than 160.
- 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 and Fig. 6 shows noise examples of traffic lights by the shape filter. Shape filter remove some other types of noisy bright spot such as traffic sign, street tree, vehicle, and building.

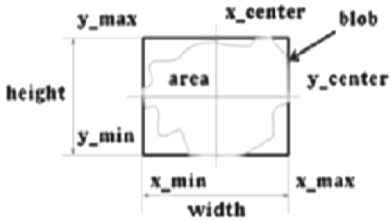

Fig. 5 Blob parameters of labeled potential traffic lights [5]

Fig. 6 Noise example of traffic lights. 1st picture is road lane, 2nd picture is street tree, 3rd picture is building, and 4th picture is vehicle

C. Adaptive Multi-class Classifier (AMC)

In many papers, Haar-Like feature [9] can be used with covariance for pedestrian detection [6], with non-orthogonal feature for matching, reconstruction [7], with stochastic context-free grammar for hand gesture recognition [8]. In this paper, we propose the Adaptive Multi-class Classifier (AMC) method using Haar-Like feature with means of pixels' sum of region witch is removed noise through shape filter for traffic light detection.

A simple rectangular Haar-like feature [9] can be defined as the difference of the sum of pixels of areas inside the rectangle, which can be at any position and scale within the original image. This modified feature set is called two rectangle features. These values indicate certain characteristics of a particular area of the image. Each feature type can indicate the existence (or not) of certain characteristics in the image, such as edges or changes in texture. For example, two rectangle features can indicate where the border between a dark region and a light region lies. The simple features used are reminiscent of Haar basis functions which have been used by Papageorgiou et al. [9]. Moreover, we used eight types of feature. The value of a two-rectangle feature is the difference between the sums of the pixels with two rectangular regions. The regions have the same size and shape and horizontally or vertically neighboring (Fig. 7). In the previous step, blob size of traffic lights is affected by distance between vehicle and traffic lights. Therefore, in this paper, size of the detector is variable.

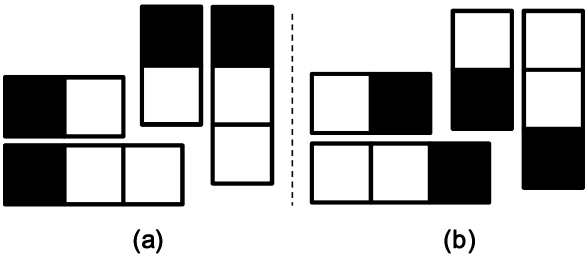

Fig. 7 (a) is prototypes of Haar-like features for red traffic light detection and (b) is prototypes of Haar-like features for red traffic light detection. Black areas have negative and white areas positive weights.

Note that unlike the Haar basis, the set of rectangle features is overcomplete. Denote the feature set as $F = f_i|i = 1, ...,N$ and corresponding feature values on images observation z as:

$V(z) = v_i(z)|i = 1, ...,N.$

Nevertheless, we can calculate them if we have a gathered sum of intensity from origin:

$$S_{acc}(i,j) = \sum_{x=0}^{i} \sum_{y=0}^{j} I(i,j) \tag{15}$$

If a rectangle is defined by the region $[x_{left}, x_{right}] \times [y_{up}, y_{down}]$, the sum of intensity in the rectangle is following:

$$S_{acc}(x_{right}, y_{down}) - S_{acc}(x_{left}, y_{down}) - S_{acc}(x_{right}, y_{up}) + S_{acc}(x_{left}, y_{up}) \tag{16}$$

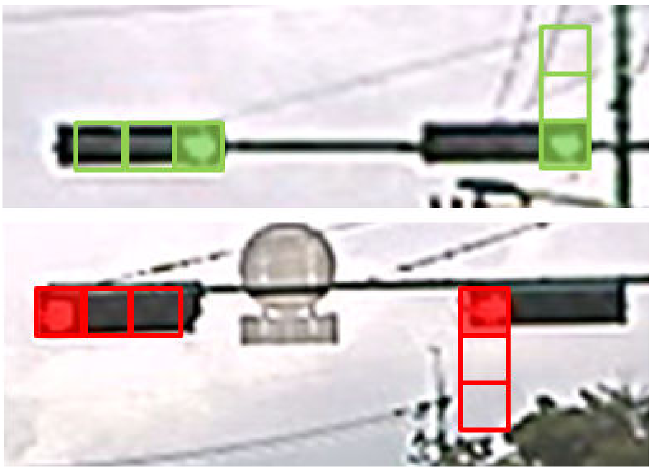

Fig. 8 Examples of traffic lights detection. Top picture is Prototypes of Haar-like feature for green traffic lights detection and down picture is Prototypes of Haar-like feature for green traffic lights detection

Boosting is a technique to improve the performance of any given learning algorithm, generally consisting of sequentially learning classifiers with respect to a distribution and adding them to an ensemble [12, 13]. When classifiers are added to the ensemble, they are typically weighted in some way that is related to their accuracy. After adding classifiers, the data is also reweighted: examples that are misclassified gain weight and examples that are classified correctly lose weight, thus forcing the next classifier to focus on previously hard to classify data points. In this paper, we use serial forming ensemble learning method using four Adaboost algorithms for vertical and horizontal traffic lights detection.

IV. 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 object-marked sequences acquired with an on-vehicle camera, we extracted traffic lights and non-traffic lights samples. Table 1 describes different datasets, number of boosting classifiers, and number of whole week classifiers used for training.

TABLE I
DATASETS AND CASCADE CLASSIFIERS FOR TRAINING

Boosting	Dataset	# of boosting classifiers	# of whole week classifiers
Basis Adaboost 1	6x15, 15x6	9	321
Basis Adaboost 2	13x33, 33x13	11	330
Proposed Method	variable size	1	8

TABLE II
SEQUENCES USED FOR THE TESTS

Sequence	Country	Length	# of frames with traffic lights
Sequence 1	Korea	10’30’’	13,723
Sequence 2	China	6’28’’	2,838

Table II describes the sequences used for the evaluation of our method. Table III describes fully detailed results of those tests and the computation time of our proposed method and other methods.

TABLE III
RESULTS OF THE FRAME PER FRAME MATCHING AND COMPUTATION TIME

Boosting	Sequence 1	Sequence 2	Computation Time
Basis Adaboost 1	75.52 %	81.34 %	22 ms
Basis Adaboost 2	88.20 %	91.65 %	37 ms
Proposed Method	93.52 %	94.07 %	15 ms

Results detailed in Table 3 show that our method based on image processing achieves better recognition results than learning processes. In addition to that our method is capable of recognizing traffic lights from other countries since it is very easy to add new traffic lights templates. Conversely, to recognize other traffic lights with learning processes we would need to extract new samples from sequences to train the classifiers with these new samples. Result of the tests, our proposed method can be applied in real-time systems by computation time is 15 ms and easily achieve better performance. For instance, our proposed method reaches 93.52 % and 94.07 % in the sequence 1 and 2.We proposed in this paper, an image processing method to recognize real-time Traffic Lights in urban and rural environment. The proposed method is fully modular and capable of recognizing traffic lights from various countries and types. We are compared with our method and standard object-recognition learning processes and proved that it reached up to 94 % of detection rate which is better than the results achieved with cascade classifiers.

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