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Traffic light recognition with HUV-histogram from daytime driving-view images.

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Abstract: Signals of traffic lights are important factors in traffic environment analysis. Advanced Driver-Assistance Systems (ADASs), which need to be aware of surrounding traffic environments to assist drivers, are required to be able to recognize signals of traffic lights. We propose robust, Korean-standard-based, computerized methods to recognize traffic lights in daytime driving-view images. The images captured by the camera mounted on the vehicle. To detect traffic lights in the images, we use the Aggregate Channel Features (ACF). To recognize states of traffic lights, we remove irrelevant background pixels in the detected traffic light image patches by using visual saliency analysis, then we train support vector machine (SVM) with HUV-histogram. Our methods do not require any specific sensors such as Lidar or external systems such as car-to-car networks. This makes our methods to be easily ported over to existing automotive control platforms. 13,500 frames of videos were used to test our methods. The traffic light recognition accuracy is 0.97.

Keywords: Advanced Driver-Advanced System, Traffic Light, Object Detection

1. INTRODUCTION

Advanced Driver-Assistance Systems (ADASs) are being developed to assist, supplement and ultimately replace the drivers in complex vehicle-control process [11]. ADASs can increase car safety and more generally road safety, by applying various function such as cruise control, forward collision warning or automotive navigation. To perform such functions, an ADAS requires an ability to recognize the traffic environment around a vehicle in which the ADAS is installed. An ADAS recognizes the traffic environment by using devices such as Lidar, proximity sensors, or video cameras [13], or networks such as car-to-car communication or external network frameworks [5]. Lidar and proximity sensors are used to scan surrounding objects so the vehicle can avoid collision. Driving-view video analysis is a low-cost but less reliable method to recognize general traffic environments. Car-to-car communication or external networks are used to inform a vehicle of traffic status.

States of traffic lights are important components of traffic environments. Knowing states of traffic lights allows automotive navigation system to efficiently identify the best route to a driver's destination and to avoid crashes caused by driver's late detection of stop signals. Some vehicle developers have tried to build a network system in a city to inform vehicles of traffic light signals and traffic flows. Bernais et al. [1] shows a design of a network-based traffic light assistance system. That method is very reliable but has spatial limitations and a high cost problem. We decided to extract traffic light information from driving-view video because this method does not require any external network system.

Jensen et al. [4] shows the performances of the several traffic light recognition algorithms. Most of the state-of-the-art algorithms are designed for their own datasets and are also designed to recognize the traffic lights which are different to the Korean standard traffic lights. We use the Hyundai Contest dataset that contains images of Korean highways and urban areas.

We propose a traffic light recognition method. We installed a camera in a car to capture driving-view images. We detect and extract traffic light image patches from captured driving-view images by using aggregate channel features (ACF) [2]. We remove irrelevant background pixels in the detected image patches by using graph-based visual saliency (GBVS) [3]. We train the support vector machine (SVM) with HUV-histogram to classify the traffic lights in the image patches into four classes: go, warning, stop and stop-left.

2. TARGET ENVIRONMENT

The proposed method is designed to operate in situations where a vehicle is driven in Korean highways and urban areas during the day. The proposed method recognizes Korean standard LED traffic lights which are identifiable by the human eye from a driving view image. Fig. 1 shows two types of Korean standard traffic lights. One is a three-color traffic light, and the other is a four-color traffic light with a left turn signal. We consider four states of a traffic light: go, warning, stop, stop-left. Table 1 shows the detail of the four states of a traffic light. We install a camera under a room mirror of a vehicle to capture driving-view images. The camera captures HD (1280x720) RGB images at 25 fps.

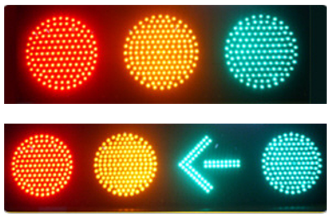

Fig. 1: Two types of standard traffic lights in Korea.

Table 1: States of a traffic light according to lighting lamps.

State	Lighting lamps
go	green
warning	yellow
stop	red
stop-left	red, arrow

3. TRAFFIC LIGHT RECOGNITION

3.1 Extracting traffic light image patches

As a result of analyzing locations of traffic lights in various driving-view images, we assume that traffic lights always appear in the top two-fifths of driving-view images, so we limited the search area to this area. Fig. 3 shows heatmap of traffic light locations. To detect traffic light image patches P from an input image I, we train boosted decision forest classifier with aggregate channel features [9] [2].

3.2 Removing irrelevant background pixels

P contain unnecessary background pixels in addition to a traffic light. See Fig. 4 (a). Complex illuminations or complex objects contained in the background pixel regions interfere with the traffic light recognition method using intensity threshold like Kim et al. [6]. To remove irrelevant background pixels in an image patch $p \in P$, we compute saliency map by using using Graph-Based Visual Saliency (GBVS) [3]. The salient regions in p appears as a high-scored region in the saliency map. Then we filter out low-scored region in the saliency map based on the threshold value obtained by using the Otsu threshold [10]. Finally, we compute the bounding rectangle of the filtered region. This rectangle r contains a traffic light with few background pixels. See Fig. 4 (d).

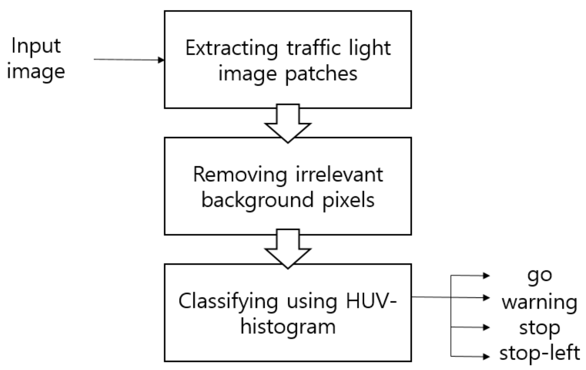

Fig. 2: Workflow of the proposed recognition method.

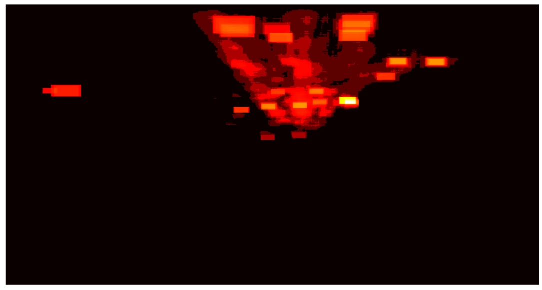

Fig. 3: Heatmap of traffic light locations in the Hyundai Contest dataset.

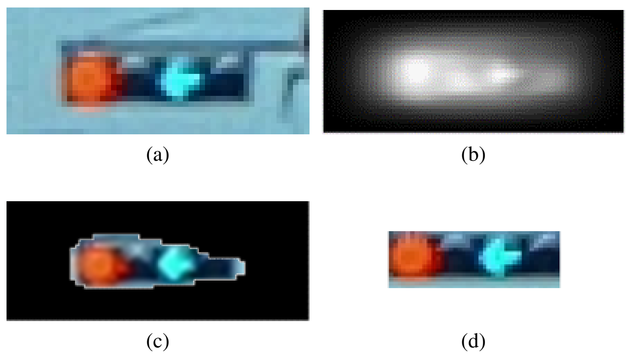

Fig. 4: (a) A detected traffic light image patch. (b) The saliency map for (a). (c) The salient area obtained by applying thresholding to (b). (d) The bounding rectangle region of (c).

3.3 Traffic light states classification

Color is a useful factor to classify states of a traffic light. Fig. 5 and Table. 2 show chromaticity restriction on the colors that the standard Korean traffic lights should display [8]. Green area in XYZ space (and also Y'UV space) is easily distinguishable from yellow and red areas. [7] and [6] use Hue value to classify states of a traffic light.

We split a refined traffic light image r into U and V channel of Y'UV color space and Hue channel of HSV color space. Then we compute 72-bin histogram for each channel and concatenated them. The concatenated 1-D vector is the HUV-histogram. To classify states of *r*, we train support vector machine (SVM) with HUV-histogram. Fig. 7 shows distributions for values of green, yellow, and red in U, V and Hue channels. This classifier distinguishes go, warning, stop and stop-left states.

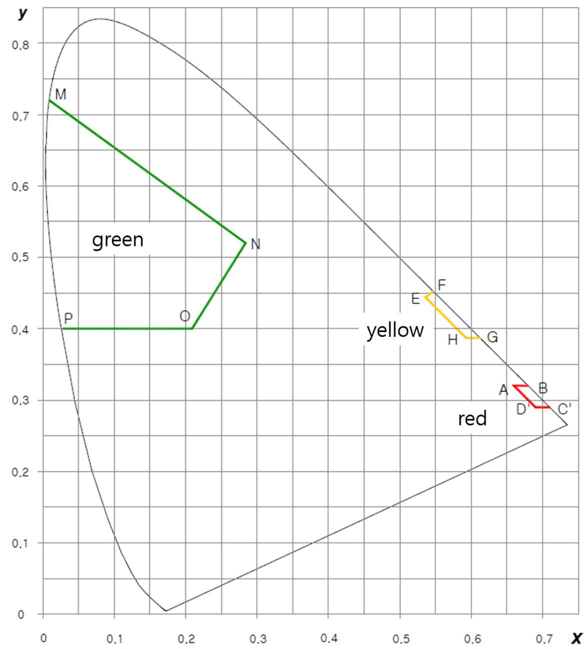

Fig. 5: CIE 1931 (XYZ) chart annotated with Korean LED traffic light standard guideline. This is the same as that of BSI traffic light standard (BS EN12368:2006.)

Table 2: CEI 1931 coordinates for the Korean LED traffic light standard guidlines.

	symbol	A	B	C'	D'
Red	x	0.660	0.680	0.710	0.690
	y	0.320	0.320	0.290	0.290
	symbol	E	F	G	H
Yellow	x	0.536	0.547	0.613	0.593
	y	0.444	0.452	0.387	0.387
	symbol	M	N	O	P
Green	x	0.009	0.284	0.209	0.028
	y	0.720	0.520	0.400	0.400

4. EXMERIMENTAL RESULTS

We use three image sequences in the Hyundai Contest dataset that collected from Korean highways and urban areas during the daytime. Each sequence contains more than 4,500 images. We extract traffic light patches from the dataset and divide them into train set and test set. Fig. 6 shows traffic light patches which are used. Table 3 shows details of experiment data. The accuracy of recognition is 0.97. Table 4 shows traffic light recognition results.

We also perform experiments on LISA dataset. [12] We extract 37,810 traffic light patches from 14,035 images and divide the patches into three groups (red, yellow, and green). Then we use 10-fold cross validation to compute recognition accuracy. The recognition accuracy on LISA dataset is 0.92.

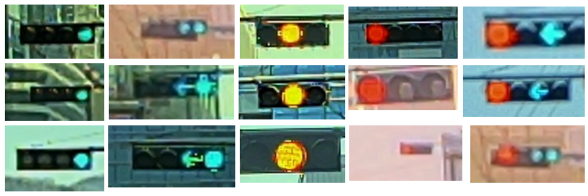

Fig. 6: Example of traffic light image patches.

Table 3: Train set and test set.

	go	warning	stop	stop-left
train set	1997	973	3618	276
test set	760	453	299	270

Table 4: Traffic light recognition results on Hyundai Contest dataset.

		prediction			
		go	warning	stop	stop-left
ground truth	go	518	4	0	0
	warning	52	401	0	0
	stop	1	0	298	0
	stop-left	1	0	2	267

5. CONCLUSION

We studied method to recognize traffic lights in driving-view images. ACF is used to detect traffic light in a driving-view image. GBVS, HUV-histogram, and SVM are used to recognize a state of a detected traffic light image patch. If we make further improvements, our proposed algorithms may be able to replace expensive traffic light informing system using external network.

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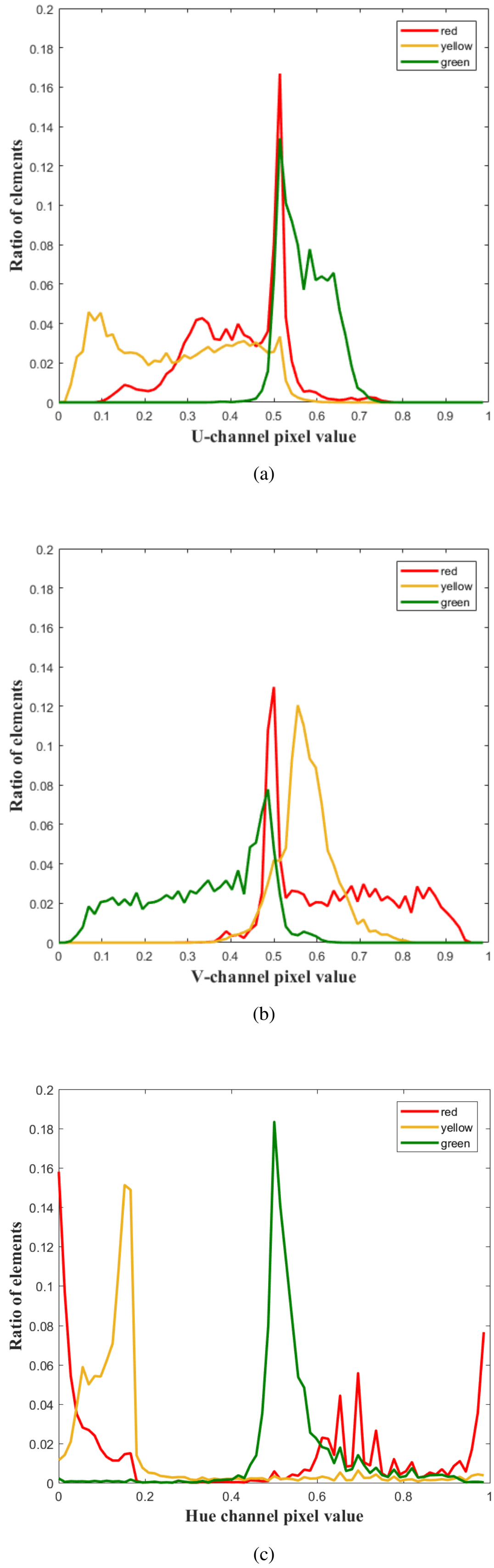

Fig. 7: Distributions of pixel values for red, yellow, and green light region in traffic light images.