Illumination Invariant Color Segmentation Method based on Cluster Center Tree for Traffic Sign Detection

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ABSTRACT
This paper proposes a color segmentation method that can locate candidate regions of traffic signs accurately and reliably from real world images. In the real world, there are various light conditions which make the color segmentation very difficult problem. Hence, we propose an illumination invariant color segmentation method. The proposed method consists of two parts; 1) cluster center tree-based segmentation 2) illumination estimation. Cluster center tree is trained for color segmentation. Illumination estimation algorithm classifies light condition of the input images. We validate the proposed method qualitatively and quantitatively with 1,745 images containing red and blue traffic signs captured with four light conditions; sunny, cloudy, rainy and night. The proposed method achieves the high detection rate of 99.25% in sunny, 98.33% in cloudy, 87.85% in rainy and 88.70% at night.

Categories and Subject Descriptors
I.4.9 [**Image Processing and Computer Vision**]: Application; I.5.1[**Pattern Recognition**] Models – Neural nets; I.5.4 **[Pattern Recognition**]: Application – Computer Vision;

General Terms
Algorithms, Measurement, Experimentation

Keywords
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1. INTRODUCTION
Advanced Driver Assistance Systems (ADAS) are becoming more common in modern vehicles to provide assistance in driving situation. In particular, methods from computer vision field have been emerging as important techniques for intelligent vehicle systems including pedestrian detection, lane detection, vehicle recognition and traffic sign recognition. Since ADAS are directly related to the safety of drivers and pedestrians, they are very important.

The main problem of traffic sign detection is that images captured from a camera cannot keep the color constant as illumination changes.These problems occur when it is rainy, cloudy or at night. Since the color of an image depends on the reflectance of object and illumination, the same objects appear differently as the illumination changes. However, human visual system perceives constant color under the illumination changes. In this paper, we provide a color segmentation method that is invariant to the illumination changes in order to solve light condition problems.

1.1 Related Work
In recent traffic sign detection research area, color has been used to extract region of interest (ROI) of traffic signs. But color based ROI extraction methods are sensitive to illumination changes. Thus preprocessing step such as a color space transform has been introduced to make the system robust to the illumination changes [1]. Many studies that segment the color of target object are in progress already.

Chourasia and Bajaj [2] propose a method using the YCbCr color model. Red, white, blue, yellow colors are segmented by threshold in YCbCr color space. Next, traffic signs are detected regarding the center of segmented channel plane. It is shown to be effective considering illumination changes for detecting traffic signs which have pre-specified color to find. Kiran et al. [3] segment the color by thresholding in HSV color space. After image segmentation, segmented areas of input image are selected as ROIs. To recognize the traffic signs, they use Support Vector Machine (SVM). However, they simply segment input images using a fixed threshold without considering illumination.

Color segmentation has been extensively studied not only for traffic sign detection but also for detecting other interesting objects. For segmentation of the various skin colors under various light conditions, Sinan et al [4] propose a multi-color clustering model method. This method constitutes a region of the color space using the color distributions of the sampled skin, corresponding to the each skin color model. By using the HSV color space, it shows excellent performance in the segmentation of a shaded skin or various human skin types.

Further, Chung and Chan [5] propose an edge extraction method using distribution of color variance that is the difference between the color values. However, it shows quite noisy result when applied to the objects with many colors in various real road environments. Those noises can be reduced by preprocessing methods such as color enhancement.

In previous works, some of them consider the illumination changes, but they just transform the color space or add preprocessing. These methods can deal with the situations only with a single illumination condition. So it is insufficient to be applied to the various environment of real road. In addition, threshold based color segmentation methods are very sensitive to light condition and threshold.

1.2 Proposed Method

This paper presents a color segmentation method that can locate candidate regions of traffic signs and a color enhancement method. Color segmentation is achieved by learning cluster center tree with traffic sign images annotated as four cases: day-sunny, day-cloudy, rainy and night to efficiently handle the illumination changes. A leaf node in lower depth represents dominant cluster which is easy to classify while one in higher depth represents minor cluster which requires longer process. We introduce illumination estimation and color enhancement step to deal with minor clusters.

We use k-means clustering algorithm to model the color distribution of traffic signs. Naïve clustering may group up the colors under different illuminations to the same cluster. Hence we further divide clusters regarding annotated illumination status to generate finer clusters. With given illumination labels, we calculate the ratio of the light status in each generated clusters. When the ratio of the one light status occupies a cluster above a certain level, the cluster can be considered as properly clustered. If major color does not occur and the several light conditions are evenly distributed, the cluster should be further divided because it is not possible to know what color is major. After a single step of clustering is completed, we run secondary clustering recursively using k-means in the clusters not having a dominant color. These clustering steps are repeated until the every cluster consists mostly of a single major light status.

For segmentation of the test image, we calculate distance of each pixel to the center of the clusters and select the closest cluster in HSV space. To make the procedure efficient, we generate a *cluster center tree* which is decision tree whose node is center of each cluster. The cluster centers are generated by above repetition of clustering where the number of iterations equals the depth of the tree. A cluster center tree is trained for each color of traffic signs and we train in two trees for red and blue in our experiments. It decides a color model of each pixel from the input image. However, the results that went through high-depth nodes are not reliable because the number of samples used to generate high-depth node is small.

Thus we introduce an additional color enhancement step to compensate the illumination. In order to decide the underlying light condition, we adopt a method described in Tominaga et al. [6] and Finlayson et al. [7] to generate reference gamut of four illumination conditions and to classify illumination condition using correlation between distributions described in gamut as a cue. It significantly increases the accuracy of target color segmentation from real-life images which have various light conditions.

2. COLOR SEGMENTATION

In this paper, the colors that we are interested in are the red and blue from circular traffic signs. Light condition in the driving environment is actually very diverse. First, it can be divided into day and night, and can be further divided by weathers; sunny, cloudy and rainy. The proposed color segmentation method collects the color value of the manually annotated signs from actual road images for training. And then images are recursively clustered by k-means clustering while halting condition is given by presence of a dominant illumination case. A decision tree is generated with the nodes with the cluster centers obtained after color clustering. The trained decision tree decides a color model of the all pixels from a test image for segmentation.

2.1 Cluster Center Tree

With existing methods, it is difficult to find the color of interest in real road images when they are exposed to various light condition. The proposed method uses the modified k-means clustering algorithm that utilizes the annotation data. In real road image, an identical object may have wide distribution in color space due to weather, time and artificial light. To train a decision tree, we use light condition information which are annotated at each training image to set label of each pixel of traffic sign area and the training samples are the pixel values. The labels for illumination are bright, standard and dark. For training red color, 242 bright, 353 dark, 593 standard traffic sign images are used and 69865, 98030, 155995 pixels are collected respectively. For blue, 153, 113, 283 images are used, 470699, 411352, 1019629 pixels are collected respectively. Fig 1 shows the example of traffic sign images in various light conditions. Collected color values are represented in HSV color space. HSV color space is relatively stable to changes in light

Figure 1. Examples of traffic sign images in various light condition

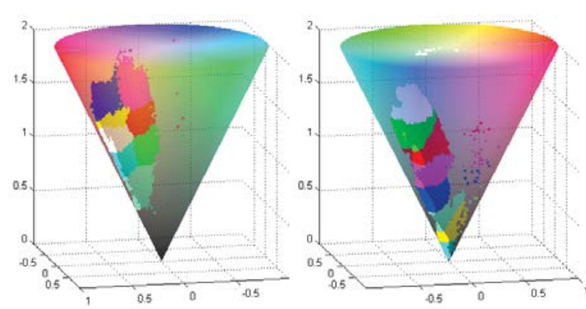


Figure 2. Clustering result in HSV plane (for red and blue respectively)

and follows roughly how humans recognize the color. HSV color space using hue, saturation, brightness value has non-linear relation with RGB color space.

First, we classify the collected pixel values which are represented in HSV color space using k-means clustering. The result of the first clustering iteration is shown in Fig 2. We recursively run the clustering for each cluster until the halting criterion is met. The halting criterion is defined by homogeneity of annotated labels in the cluster and the homogeneity is characterized by a ratio of the samples with the most dominant labels to the entire samples as shown in Equation (2).

$$\boldsymbol{i_{max}} = \underset{\boldsymbol{i}}{\boldsymbol{argmax}}(\boldsymbol{N}(\boldsymbol{C_i})) \tag{1}$$

$$\frac{N(C_{i_{max}})}{N(C)} > \rho \tag{2}$$

where C is a cluster generated after k-means clustering, i is an index of annotated label, $N(C_i)$ is the number of samples which have annotation label i. We impose high homogeneity which means the cluster mostly consist of samples with identical labels because we want each cluster to have colors from the same illumination condition. If homogeneity of annotated labels in cluster C is higher than a given threshold, the interation is stopped. Afterwards, we generate a decision tree using the cluster centers.

2.2 Cluster Center Tree based Color Segmentation

The cluster center tree is used as a decision tree that decides a color of input pixel. The number of iteration is the depth of cluster center tree. The deeper a node is, the more detailed cluster is. At the same time, in cluster center tree, deep node represents ambiguous cluster center which is less reliable.

When an input pixel runs through the cluster center tree and reaches a leaf node, the pixel is classified to the cluster corresponding to the node. Result of classification is represented in grayscale. The higher intensity of segmentation result means that it is more likely to be the color we were looking for.

Because the color segmentation method using cluster center tree is trained by real world traffic sign images for each light condition, it is robust to illumination change. Fig 3 shows the segmentation result of each light condition using the cluster center tree. But there are some noise in complex images that contain various object and colors and it has limitation when we have extremely low light condition with severe noise. In addition, though same object is segmented, sometimes intensity distribution is very diverse. In such cases, we further apply illumination correction by estimating the illumination condition.

3. ILLUMINATION ESTIMATION

This section explains a method for classifying illumination conditions into four cases; sunny, cloudy, rainy and night. We first generate four reference gamuts for each illumination conditions and then calculate correlation between an input gamut and each reference gamut.

3.1 Reference Gamut

Tominaga et al. [6]'s illumination estimation method uses color temperature. The reference gamut is produced using the color temperature of various objects. They use the data that consist of frequency-dependent color values and the reflection coefficient of the objects from Vrhel et al. [8]. They use the collected reflection coefficients and black-body radiation theorem of Plank to calculate color for each temperature.

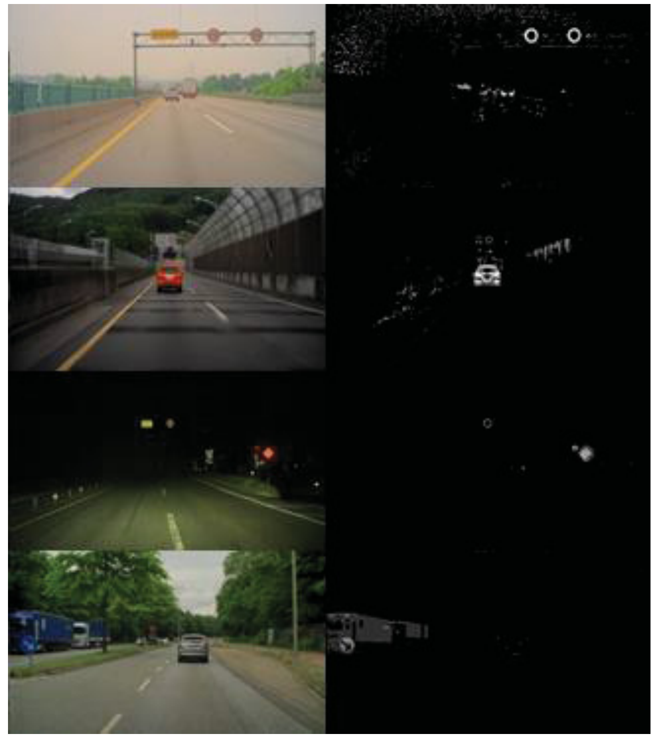


Figure 3. Result of segmentation using cluster center tree before illuminant estimation

The illuminant gamuts are estimated with the three channel of camera sensor. The sensor response are inferred from

$$\begin{bmatrix}\boldsymbol{R}\\ \boldsymbol{G}\\ \boldsymbol{B}\end{bmatrix} = \int_{400}^{700} \boldsymbol{S}(\boldsymbol{\lambda})\boldsymbol{M}(\boldsymbol{\lambda}) \begin{bmatrix}\boldsymbol{r}(\boldsymbol{\lambda})\\ \boldsymbol{g}(\boldsymbol{\lambda})\\ \boldsymbol{b}(\boldsymbol{\lambda})\end{bmatrix} \boldsymbol{d\lambda} \tag{3}$$

where $S(\lambda)$ is the surface spectral-reflectance function, $r(\lambda), g(\lambda), b(\lambda)$ are the spectral-sensitivity functions, and $M(\lambda)$ is the black-body radiator. These RGB values are used to define the illuminant gamuts. Vrhel et al. [8] construct the database of reflectance values with Dupoint paint chip, Munsell chip and 170 objects.

$$\boldsymbol{M}(\boldsymbol{\lambda}) = \boldsymbol{c_1}\boldsymbol{\lambda}^{-5}[\boldsymbol{exp}(\boldsymbol{c_2}/\boldsymbol{\lambda T}) - \boldsymbol{1}]^{-1} \tag{4}$$

Equation (4) is Planck's law of λ. T is the color temperature in Kelvin(K). c_1 and c_2 are the Plank constant.

Reference gamut use the intensity distribution of the images. Tominaga et al. [6] use RB plane that is from sensor response. Let I_i be the intensity of i th pixel,

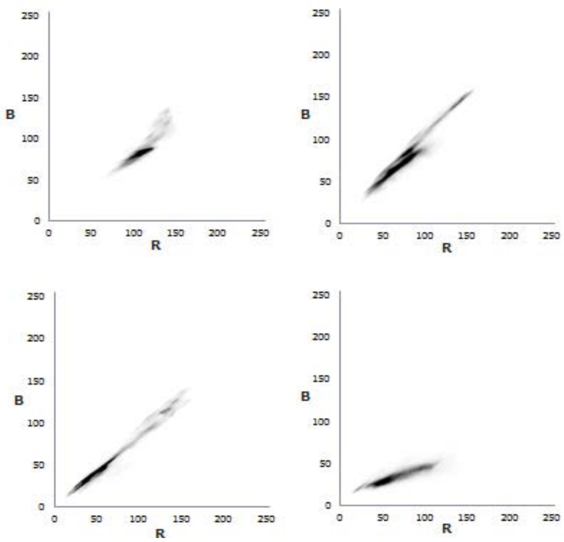


Figure 4. The reference gamuts corresponding each light condition

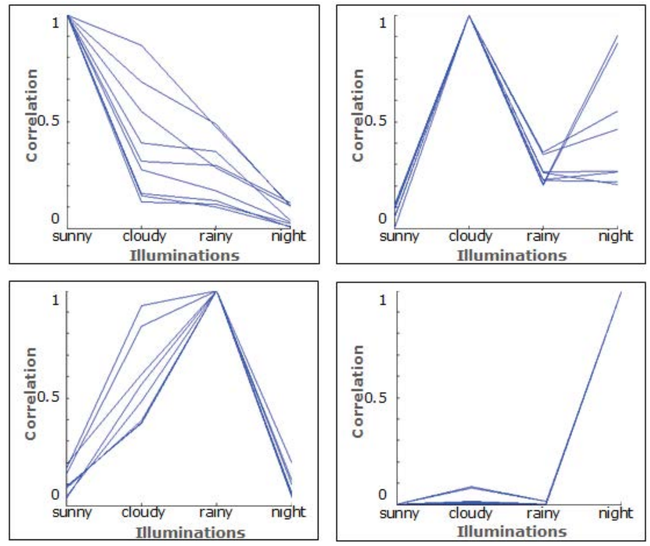


Figure 5. Illuminant classification result

$$I_i = (R_i^2 + G_i^2 + B_i^2)^{1/2} \tag{5}$$

and I_{max} is the maximal value in the image. Then the camera makes a RGB response that are normalized as

$$(\mathbf{R}, \mathbf{G}, \mathbf{B}) = (R/I_{max}, G/I_{max}, B/I_{max}) \tag{6}$$

Through the intensity normalization, the relative intensity information can be preserved. Tominaga et al. [6] proposed a reference gamut as a 256x256 RB plane. The reference gamut is a binary image as shown in Fig 4.

On the other hand, we propose a relative likelihood correlation matrix using 256x256 RB histogram. The intensities of image are allocated RB histogram. Then, the number of pixels in each histogram bin is normalized by the number of pixels that is maximum among all histogram bins.

3.2 Illumination Classification

In order to classify illumination condition of a given image, we follow Finlayson et al. [7] for calculating the overlap between the reference gamut and the gamut of input image. First, we calculate correlation matrix between input gamut and each reference gamut of four illumination cases where the reference gamuts are from the average images of each case. Then we obtain the correlation values for each case by dot product of the matrices. Then the input image is classified to one of illuminations whose correlation value is maximum

4. EXPERIMENTAL RESULT

To evaluate the performance of the proposed traffic sign color segmentation method, we apply our method on a dataset of 1050 images containing traffic signs with various colors and types. The dataset shows images of traffic sign in different conditions such as sun light, cloudy day, rainy day, night time. We compare the proposed method with a threshold based method [4] and a color variance method [5]. The color variance map is represented by difference of neighbor pixels. Because color variance can express subtle difference of color, it is not illumination-robust features. Through we apply illumination estimation, the result of cluster center tree based segmentation methods is improved. After illumination estimation, the images are enhanced by using look up table of R/G, B/G ratio. As shown in Fig 6, the proposed method is invariant to illuminant change.

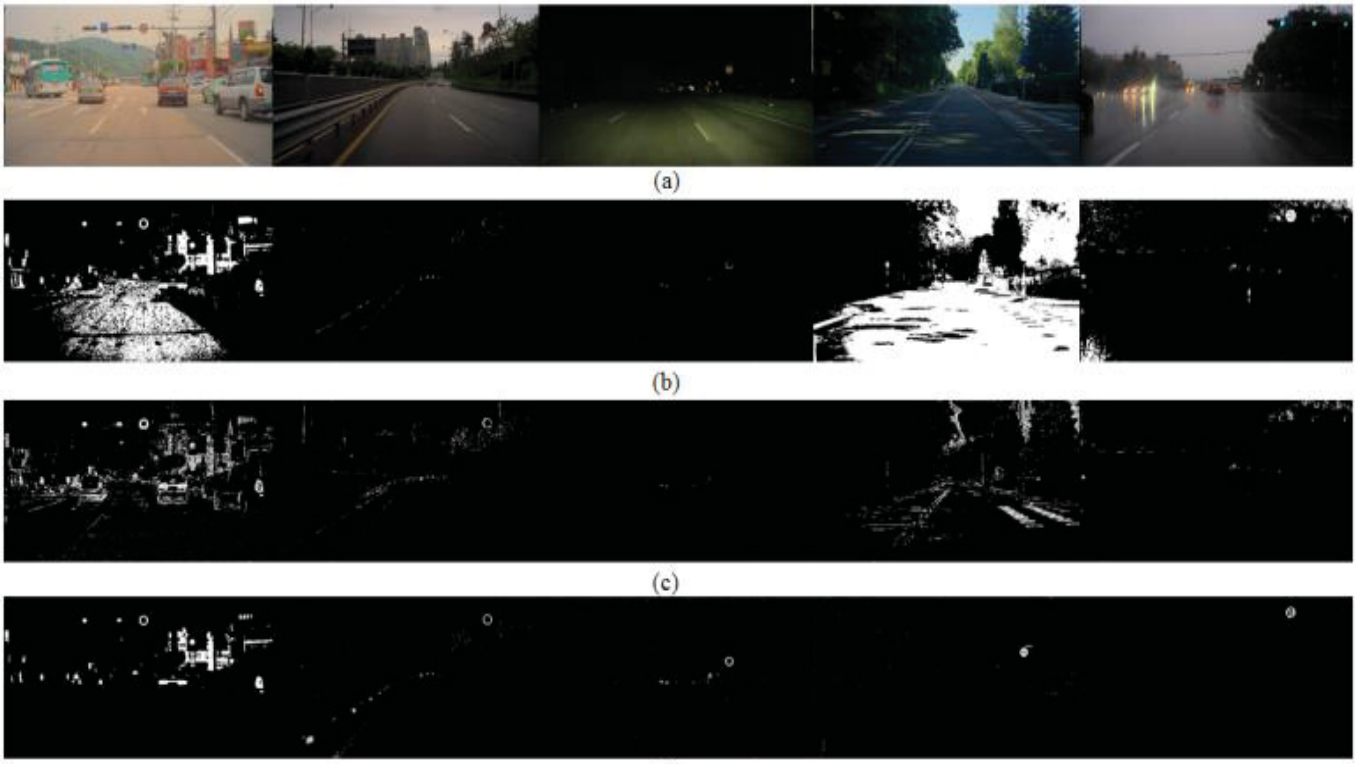
For quantitative analysis of our method, we use radial symmetry detector proposed by Barnes [9]. This method uses a color gradient map. The detection rate of red traffic sign is summarized in Table 1. From red traffic sign images, Detection rate of proposed method is more than 99% in sunny, 98% in cloudy, 87% in rainy and 88% in night. Table 1 shows that proposed method has higher detection rate especially in rainy, night while basic radial symmetry detection method achieves poor performance. In normal light condition, the result is similar. But as the light condition gets worse, the result of proposed method is the better. In the same manner, the result of blue traffic sign shows higher detection rate than other methods in bad light condition as shown in Table 2.

Table 1. Detection performance for red traffic sign

Illuminations	**Detection rate**		
	Barnes	***Color variance***	***Proposed method***
Sunny	99.25%	99.62%	99.25%
Cloudy	65.00%	98.33%	98.33%
Rainy	70.09%	83.17%	87.85%
Night	70.86%	74.34%	88.70%

Table 2. Detection performance for blue traffic sign

Illuminations	**Detection rate**		
	Barnes	***Color variance***	***Proposed method***
Sunny	77.46%	89.11%	94.30%
Cloudy	47.10%	60.29%	86.03%
Rainy	33.33%	95.37%	96.30%
Night	2.63%	63.16%	65.79%



(a) Input images, (b) Segmentation with the threshold based method,
(c) Segmentation with color variance map, (d) Segmentation with the proposed method

Figure 6. Example of segmentation result

The proposed method fails to correctly detect traffic sign when traffic signs are acquired as rotate or too small. In such case, all methods fail to detect the traffic sign.

5. CONCLUSION

In this paper, we propose a color segmentation method that can detect color traffic signs accurately and reliably for real world images. We test proposed method qualitatively using segmentation result and quantitatively using radial symmetry detection algorithm. The proposed method achieves the high detection rate of 99.25% in sunny light condition, 98.33% in cloudy, 87.85% in rainy and 88.70% in night with red and blue traffic sign image dataset.

6. ACKNOWLEDGEMENTS

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