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Traffic Signs Color Detection and Segmentation in Poor Light Conditions

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Abstract

This paper presents a new algorithm for color detection and segmentation of road signs in poor light conditions. The images were taken by a digital camera mounted in a car. The RGB channels of the digital images were enhanced separately by histogram equalization, and then a color constancy algorithm was applied to extract the true colors of the sign. The resultant image was then converted into HSV color space, and segmented to extract the colors of the road signs. The method was tested on outdoor images in different poor light conditions such as fog and snow, and they show high robustness. This project is part of the research taking place at Dalarna University - Sweden in the field of the Intelligent Transport Systems (ITS).

1 Introduction

In most parts of Europe, and especially in Scandinavia, winter is a long season, during which daylight hours are few, and weather conditions are generally foggy, rainy, or snowy. Since color information is very sensitive to the variations of light conditions, the need for improved algorithms to deal with such weather conditions represent a high priority in the future work of traffic sign recognition and computer vision.

Road signs and traffic signals define a visual language which can be interpreted by drivers. They represent the current traffic situation on the road, show danger and difficulties around the drivers, give them warnings, and help them with navigation by providing useful information which makes driving safe and convenient [1, 2]. Giving this information in good time to drivers can prevent accidents, save lives, increase driving performance, and reduce the pollution caused by vehicles [3, 4].

Colors represent an important part of the information provided to the driver to ensure the objectives of the road sign. Therefore, road signs and their colors are selected to be different from the nature or from the surroundings in order to be distinguishable. Detection of these signs in outdoor images from a moving vehicle will help the driver to take the right decision in good time, which means fewer accidents, less pollution, and improved safety.

Color segmentation was achieved by Vitabile et. al. [5, 6] using priori knowledge about color signs in the HSV system. de la Escalera et al. [7] built a color classifier based on two look-up tables derived from hue and saturation of an HSI color space. Fang et al. [2] developed a road sign detection and tracking system in which the color images from a video camera are converted into the HSI system. Color features are extracted from the hue using a two-layer neural network.

The remaining of the paper is organized as follows. Section 2 shows the difficulties behind working traffic signs in the outdoor scenes. Section 3 describes how the color varies in the outdoor images. In Section 4, color constancy is presented. The new detection and segmentation algorithm is introduced in Section 5, and Section 6 shows the result and future research.

2 Traffic Signs: Potential Difficulties

Due to the complex environment of roads and the scenes around them, the detection and recognition of road and traffic signs may face some difficulties. The color of the sign fades with time as a result of long exposure to sunlight, and the reaction of the paint with the air [1, 4]. Visibility is affected by weather conditions such as fog, rain, clouds and snow [1]. The color information is very sensitive to the variations of the light conditions such as shadows, clouds, and the sun. [1, 4, 8]. It can be affected by the illuminant color (daylight), illumination geometry, and viewing geometry [9]. The presence of objects similar in colors to the road signs in the scene under consideration, like buildings, or vehicles. Signs may be found disoriented, damaged or occulted. If the image is acquired from a moving car, then it is often suffers from motion blur and car vibration.

3 Color Variations in Outdoor Images

One of the most difficult problems in using colors in outdoor images is the chromatic variation of daylight. As a result of this chromatic variation, the apparent color of the object varies as daylight changes. The irradiance of any object in a color image depends on three parameters:

The color of the incident light: Daylight's color varies along the CIE curve. It is given by:

$y = 2.87x - 3.0x^2 - 0.275 \qquad for\ 0.25 \le x \le 0.38$.

The variation of daylight's color is a single variable which is independent of the intensity.

The reflectance properties of the object: The reflectance of an object $s(\lambda)$ is a function of the wavelength λ of the incident light. It is given by: $s(\lambda) = e(\lambda)\phi(\lambda)$. Where $e(\lambda)$ is the intensity of the light at wavelength λ, and $\phi(\lambda)$ is the object's albedo at each wavelength.

The camera properties: The observed intensities depend on the lens diameter d, its focal length f, and the image position of the object measured as angle a off the optical axis. This is given by: $E(\lambda) = L(\lambda).(\pi/4)(d/f)^2 \cos(4a)$. According to this equation, the radiance $L(\lambda)$ is multiplied by a constant which will not affect object's observed color. By cancelling the camera's lens chromatic aberration, only the density of the observed light will be affected.

As a result, the color of the light reflected by an object located outdoors is a function of the temperature of the daylight and the object's albedo, and the observed irradiance is the reflected light surface scaled by the irradiance equation [9, 10].

4 Color Constancy

Color constancy represents the ability of a visual system to recognize an object's true color across a range of variations of factors extrinsic to the object, such as light conditions [11]. This definition means that the purpose of color constancy algorithms is to generate illumination-independent descriptors of the scene colors measured in terms of the camera's RGB coordinates.

The response of a sensor at position $\mathbf{P}_s$ measuring the light reflected from Lambertian surface is given by:

$$I_{color}(\mathbf{P}_s) = \mathbf{n}_l.\mathbf{n}_o \int_\lambda E(\lambda)S(\mathbf{P}_o,\lambda)C_{color}(\lambda)d\lambda \quad ;color = R,G,B$$

Where $I_{color}(\mathbf{P}_s)$ is the response of the sensor which is located at position $\mathbf{P}_s$ to the RGB colors, $\mathbf{n}_l$ is a unit vector pointing in the direction of the light source, $\mathbf{n}_o$ a unit vector corresponding to surface normal, $E(\lambda)$ is the spectrum of the incident illumination, $S(\mathbf{P}_o,\lambda)$ is the spectral reflectance of the surface located at position $\mathbf{P}_o$, and $C_{color}(\lambda)$ is the spectral sensitivity of the camera in the RGB color. The integration is done over all wavelengths to which the sensor responds. By assuming ideal sensors for the RGB light, and light source which illuminates the surface at a right angle, the above equation can be simplified to:

$$I_{color}(\mathbf{P}_s) = E(\lambda)S(\mathbf{P}_o,\lambda) \quad ;color = R,G,B$$

Color constancy can be achieved by independent scaling of the RGB color bands, if it is assumed that the camera sensors are close to ideal [12].

A study by Funt et al. [13] showed that machine color constancy algorithms are *not* good enough for color-based object recognition. In spite of this disappointing result, many new algorithms were developed after Funt's paper, namely, Sridharan and Stone [11], Ebner [12, 14]. These algorithms are not yet tested and assessed by an independent study, and no one knows how effective they are for applications to traffic and road sign detection and recognition.

5 The Color Segmentation Algorithm

In order to be able to change the levels of the RGB channels for each pixel, color segmentation algorithm is carried out by treating the RGB channels of the digital image separately. For this reason, the image acquired by the digital camera is separated into three different images, one in each of the RGB channels, and then each channel is histogram equalized by using histogram equalization technique. The resultant RGB images are then forwarded to the color constancy algorithm to extract the true color of the road signs. The block diagram shown in figure 1 describes this algorithm.

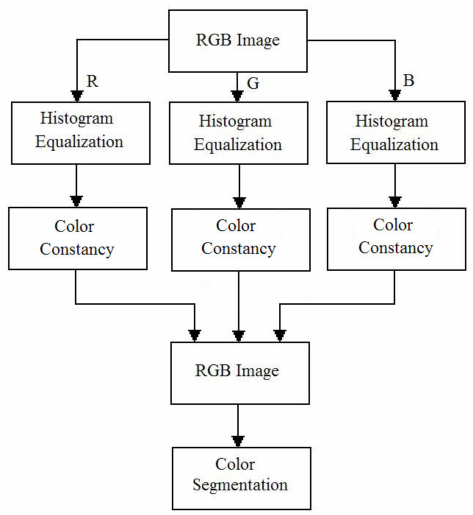

Figure 1. Block Diagram of the Color Segmentation Algorithm.

Color constancy is carried out like a convolution process for serial computers, but it is a parallel process in origin. It is applied separately for each of the RGB channels. Let $a_i(x,y); i \in \{R,G,B\}$ be the current estimate of the local space average color of channel i at position (x,y) in the image, $c_i(x,y)$ be the intensity of channel i at position (x,y) (this represents the input image in either of the RGB channels), and p be a small percentage of current pixel intensity greater than zero ($p = 0.0005$), the algorithm is implemented in four steps.

- Copy $c_i(x,y)$ to $a_i(x,y)$, and normalize both images to the range [0,1].
- Iterate the following two operations a large number of times (10000 times):

$$a_i'(x,y) = (a_i(x-1,y) + a_i(x+1,y) + a_i(x,y-1) + a_i(x,y+1))/4.0$$

$$a_i(x,y) = c_i(x,y) \cdot p + a_i'(x,y) \cdot (1-p)$$

- Calculate the output image as $out_i(x,y) = c_i(x,y)/(2 \cdot a_i(x,y))$
- Normalize the RGB channels of the output image to the range [0,255], Ebner[12, 14].

Color segmentation is carried out by converting the RGB image from the former step into the HSV color space. The global normalized mean $Nmean$ of the V image, in the range $[0,1]$, is calculated by:

$$Nmean = \frac{1}{256 \cdot m \cdot n} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} V(x,y)$$

where m and n are the image dimensions, $V(x,y)$ is the brightness of the current pixel.

The normalized global mean specifies the threshold at which the Euclidian distance is specified. The hue angle and saturation are affected by the light conditions at which the image is taken. Therefore, the threshold is calculated as:

$$thresh = e^{-Nmean}$$

The reference color and the unknown color are represented by two vectors by using the hue and saturation of these two colors as shown in figure 2.

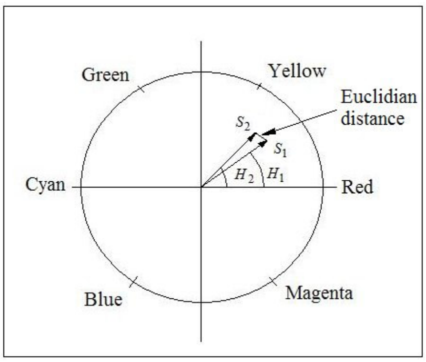

Figure 2. The Vector Model of the Hue and Saturation.

The Euclidian distance between the two vectors is then calculated by the following equation:

$$d = \left((S_2 \cos H_2 - S_1 \cos H_1)^2 + (S_2 \sin H_2 - S_1 \sin H_1)^2 \right)^{1/2}$$

The pixel is considered to be the object pixel if the Euclidian distance is less than or equal to the threshold; otherwise it is considered as background. The main idea here is to develop a dynamic threshold which is related to the brightness of the image. When the brightness of the image is high, the threshold is small, and vice versa. This will allow the brightness image to control the relation between the reference pixel, and the unknown pixel.

6 Results and Conclusions

This paper shows a new method for color segmentation of traffic signs in poor light conditions. The method is based on invoking the histogram equalization, color constancy, HSV color space, and the use of hue, saturation, and value images to generate a binary image containing the road sign of a certain color. The method was tested on about hundred images taken in poor light conditions; first row of figure 3 shows sample images, and it shows high robustness. Almost all the images could be segmented by this method. The second row shows the images after the enhancement by histogram equalization and color constancy. It is very clear that the colors of the signs are enhanced in these images. Row 3 of figure 3 shows the results of the segmentation.

Ebner's color constancy algorithm is tested for the color detection of traffic signs, and it shows very good results. The algorithm is easily implemented as a convolution process in a serial computer; however it is designed for parallel processing.

Combining these results with shape recognition of the road signs, and pictogram recognition, which are parts of the future work, will provide a good means to build a complete system to provide drivers with information about the signs in real time. The other key point for further study is the stability of colors in night images, and the possibility to recognize them in night shots. This paper is part of the sign recognition project conducted by Dalarna University Sweden jointly with the Transport Research Institute – Napier University Edinburgh Scotland to invoke digital image processing and computer vision in the ITS field.

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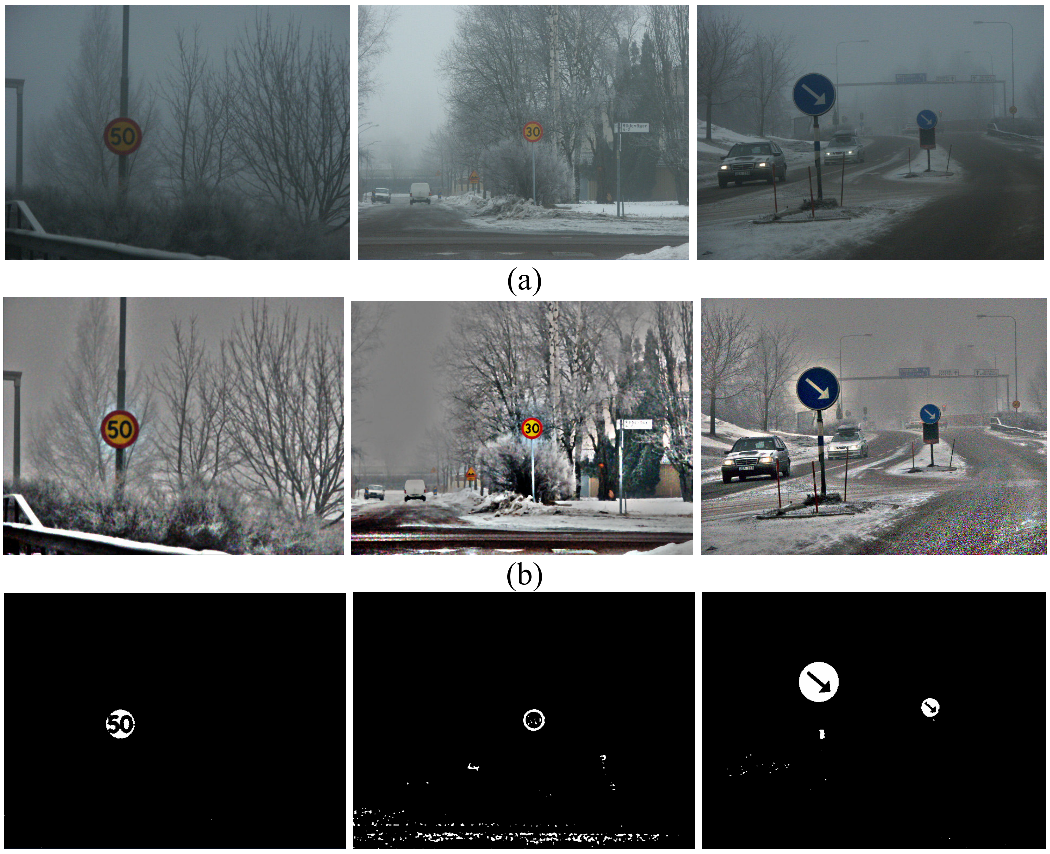

(a)

(b)

(c)

Figure 3. Results of applying Color Segmentation. (a) Original Images. (b) Applying histogram equalization and color constancy. (c) The segmented images.