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A Fast Sign Localization System Using Discriminative Color Invariant Segmentation

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Abstract—Building intelligent traffic guide systems has been an interesting subject recently. A good system should be able to observe all important visual information to be able to analyze the context of the scene. To do so, signs in general, and traffic signs in particular, are usually taken into account as they contain rich information to these systems. Therefore, many researchers have put an effort on sign recognition field. Sign localization or sign detection is the most important step in the sign recognition process. This step filters out non informative area in the scene, and locates candidates in later steps. In this paper, we apply a new approach in detecting sign locations using a new color invariant model. Experiments are carried out with different datasets introduced in other works where authors claimed the difficulty in detecting signs under unfavorable imaging conditions. Our method is simple, fast and most importantly it gives a high detection rate in locating signs.

Keywords—Sign localization, color-based segmentation.

I. Introduction

Due to the increasing demand for intelligent aid systems with guidance to users, sign recognition has become a topic of great interest. With sign recognition capability, many applications become feasible, for example, providing information for driver by detecting traffic signs, and system for blind people in navigating on the street, or tourist guidance systems using information on visual signs.

Sign recognition is a very challenging task due to the varieties of the recognition condition in reality such as different viewpoints, different lightning and weather conditions (sunny, cloudy, foggy, rainy etc.), or signs being partially occluded. The success of the recognition step is strongly dependent on the sign detection/localization step. Localization step restricts the search area and should filer out non-sign regions and return potential ones containing signs. Once the sign has been located correctly, the recognition rate will increase. Moreover, being able to localize the sign correctly also helps in speeding up later step in many runtime applications.

In literature, detecting sign location can be classified into two main approaches: shape-based approach and color-based approach. Shape based approach usually first applies edge detection algorithm to obtain an edge image, from there shape information will be used to find certain object [7], [3], [14], [8]. For example, in [3] the authors first apply Canny edge detection, then they employ Hough transform to detect circular and triangular shapes those are supposed to be traffic signs. In [7] edges are extracted from the zero-crossing of a multi-scale oriented B-spline wavelet representation, then a distance set filtering method is proposed to find an appropriate shape that is best matched with a query one. Therefore, they have difficulty when objects are occluded, or viewpoint changed or appeared in a complex scene. The former will produce unclosed shapes especially when a large part of these objects are invisible. In the second case, shapes are distorted, hence are easily misclassified. The last one introduces lots of noise to the edge image, making it much more difficult for later steps in finding the right shape of the objects. Color-based approaches have been used very often as they are rotation invariant, overcome the problem of partially occlusion and changing viewpoint. However, colors are sensitive to lightning condition, and illumination changes. To overcome this disadvantage, most of existing works use color spaces that keep sign color almost invariant. For instance, RGB and normalize color space rgb are used in [1], modified RGB in [16], [11], CIELab is used in [9], YCbCr in [2], YUV in [12], and HSI in [13], [10], [15].

Fig. 1. Examples of signs in our search domain.

Though there are a lot of research works devoted to the sign detection task, many issues are still open. First, the detection of signs is usually treated in a narrow domain i.e. limited types of signs are detected [2], [16], [11]. In [2], the authors only concentrate on detecting speed limit traffic sign. Triangular and circular signs with red color are detected in [16]. Second, restriction and predefined parameters, those suit to the context and location of the signs i.e. range of color, geometric information, area around location of the signs, are often used in most of the detection process. Examples can be found in [16], [12], [11], [15]. In [16], the authors define

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TABLE I
SEVERAL COLOR MODELS AND THEIR INVARIANT UNDER DIFFERENT IMAGING CONDITIONS (+ DENOTES INVARIANT, AND - DENOTES SENSITIVITY).

	Viewpoint direction	surface orientation	highlights	illumination direction	illumination intensity	illumination color	inter reflection
RGB	-	-	-	-	-	-	-
rgb	+	+	-	+	+	-	-
H	+	+	+	+	+	-	-

range of red color, and regions where sign should appear. Grigorescu et al. in [7] consider sign appearance constraint i.e reference object and object in the scene are approximately the same. None of the existing methods works for general sign detections. Therefore, we aim at developing a general technique that detects signs location disregarding of their appearance. We work on signs which may be a notice that instructs, advises, informs or warns people. That includes traffic signs, street sign names, text description under traffic signs etc. In other words, our localization domain is broader which allows for applications with more generalized purposes.

In this broad domain, signs can appear with any colors, and shapes as shown in figure 1 for example. Hence, shape based approaches are not a suitable solution. Signs are usually designed in such a way that they can be distinguishably noticed by their color. These signs, in general, have a common character that they contain a solid color background, and with texts or figures with different colors displayed on them. Because of this property, color segmentation is an appropriate approach to detect candidate regions that may contain signs.

The paper is organized as follows. In the next section, we first give an overview of existing color based method in detecting signs. Then, in section II-B we describe a technique using a new color model in [4]. From there, we present our approach to find the location of signs in section II-C. Experiments are carried out in section III. The datasets used for the experiment are selected from [16], [7] in which they are claimed to be difficult to detect. Finally, conclusions are given in section IV.

II. SIGN DETECTION USING COLOR SEGMENTATION

A. Related work

Signs can appear under different imaging conditions such as illumination, shading, and highlight. For instance, a red object, which is partly under the sun and the other part is in a shade, should be observed as a unique object. This means that a color chosen for segmentation should be invariant under varying viewing conditions.

As mentioned above, different color spaces are used to segment images to find potential area that may contain signs [1], [12], [16], [11], [10], [13], [15]. In [1], apart from RGB, the authors applied the normalized channels rgb and the gray channel $(R+G+B)/3$. Modified RGB is used in [16], [11] to define the range of color that they interested in, for instance, in [16] they define the range of red color to find areas contain warning and forbidding traffic signs, or red, white and black in [11]. The HSI color space is the most commonly used in color segmentation [10], [13], [15].

Overview on color invariance can be found in [5], [6], [4]. In these references, the authors present an extensively research with different color models regarding their invariance property to various imaging condition. Table I is a re-draw of the comparisons given in these references. From their conclusions, RGB is invariant to all conditions namely viewing direction, surface orientation, highlights, illumination direction, illumination intensity, illumination color, and inter-reflection. While Hue is only sensitive to illumination color and inter-reflection. This also explains why Hue is used very often when detecting signs in existing methods.

Moreover, in [4], the authors provide different classes of color invariants under three independent assumption regarding the imaging conditions 1) white or colored illumination, 2) matte, dull object or general object, and 3) uniformly stained object or generally colored object. They provide a set of photometric invariant derivative filters which uses them for invariant edge detection. A discriminative power is used to investigate the invariance of different color classes. The discriminative power is the number of colors which can be discriminated from one another in a color system of 1000 colors. It is proved in the reference that with its insensitivity to different imaging conditions, H gives the lowest discriminative power. However, low discriminative power color class does not give a good segmentation. An example is shown in figure 2. In this examples, we have tested different color classes in [4] with an input image that contains a sign with red color border, and background is a red panel. Low discriminative power color class groups the back ground and the object border into a unique region. The example also show that highest discriminative power namely Ew (measure of spectral edge strength) and Ww (measure of color edge strength) detect all edges. Therefore, a high discriminative power class should be chosen to distinguish signs from the background. But these color classes are sensitivities to all imaging condition. This raises the difficulty with locating signs that are mainly placed in an outdoor environment.

To satisfy both the invariant property and high discriminative power, we employ a color class dichromatic invariant Cw (measure of chromatic edge strength). It is proved in the reference that Cw gives high discriminative power and in the mean time invariant to several imaging conditions such as viewing direction, surface orientation, illumination direction, and illumination intensity. In the next section, we will give a brief description of image segmentation using this chromatic color class.

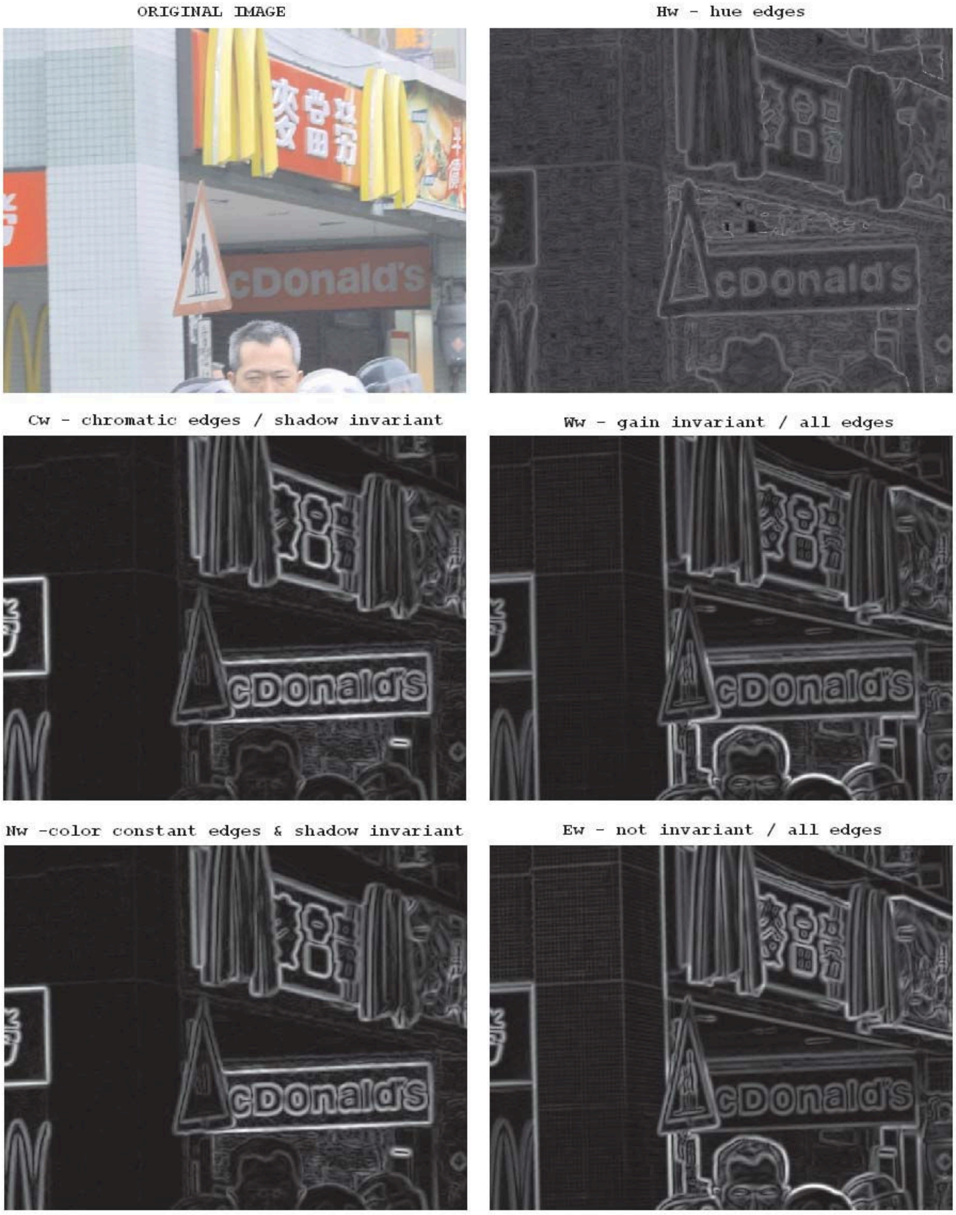

Fig. 2. An example of edge segmentation illustrating the discriminative power. Hue gives the worst segmentation (The input image is taken from [17]).

B. Chromatic edge detection

Given an input image captured by a RGB-camera, the RGB image is first converted to a Gaussian color model as follows:

$$\begin{bmatrix} \hat{E} \\ \hat{E_\lambda} \\ \hat{E_{\lambda\lambda}} \end{bmatrix} = \begin{pmatrix} 0.06 & 0.63 & 0.27 \\ 0.3 & 0.04 & -0.35 \\ 0.34 & -0.6 & 0.17 \end{pmatrix} \begin{bmatrix} \hat{R} \\ \hat{G} \\ \hat{B} \end{bmatrix}$$

where $\hat{E}, \hat{E}_\lambda, \hat{E}_{\lambda\lambda}$ denote the first three components of the Gaussian color model. We obtain $E, E_\lambda, E_{\lambda\lambda}$ of $\hat{E}, \hat{E}_\lambda, \hat{E}_{\lambda\lambda}$ at the give scale σ (the value of σ is set as suggested in the reference, $\sigma = 2.0$). From there, the first spatial and second spectral order expressions are computed by:

$$C_{\lambda\lambda} = \frac{E_{\lambda\lambda}}{E}, C_{\lambda x} = \frac{E_{\lambda x}E - E_\lambda E_x}{E^2}, C_{\lambda\lambda x} = \frac{E_{\lambda\lambda x}E - E_{\lambda\lambda}E_x}{E^2}.$$

where $E_x, E_{\lambda x}, E_{\lambda\lambda x}$ are differential to x of $E, E_\lambda, E_{\lambda\lambda}$, respectively. The same is applied to differentiation of y yields $C_{\lambda y}, C_{\lambda\lambda y}$. Finally, we calculate the total edge strength denoted as C_w:

$$C_w = \sqrt{C_{\lambda x}^2 + C_{\lambda\lambda x}^2 + C_{\lambda y}^2 + C_{\lambda\lambda y}^2}$$

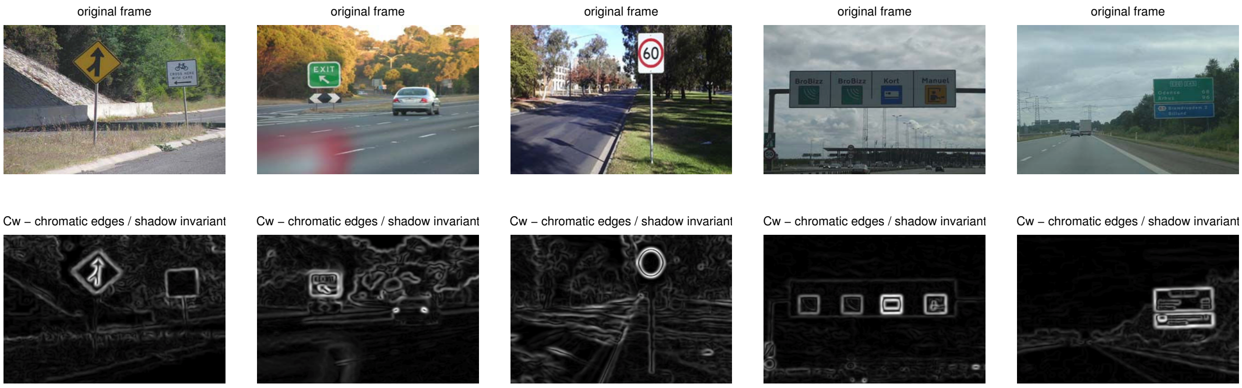

Fig. 3. An example of edge segmentation with C_w. The first row contains original images. The second row shows the corresponding edge segmentation image.

Figure 3 shows some examples of segmentation using chromatic edge detection. The brightness indicates edge strength.

C. Sign localization

After calculating the chromatic edge strength image, in this section, we will allocate signs location. We note that signs in our search domain usually appear with a color on the background and contain text or figures with different color. Most of the signs contains a border with color different from the color of the signs background. For examples, some traffic warning signs and prohibitory signs have a red color border, white background and with or without black color text/figure (figure 4). Based on this color distribution property of signs, we propose an approach to locate candidate regions as follows.

Fig. 4. Examples of signs appearance: with/without border, plain background color, with/without text/figure with different color from the background.

First, a threshold is applied to the given chromatic edge image. This step will filter out all weak edges. The threshold is set to 0.02 with the value of $\sigma = 2.0$ as stated in the previous section. A binary edge image is obtained. Then, all closed edges are filled. The filled image will be subtract with the edge image. At this point, we get a segmented image. The system removes small regions which have border length less than 50 pixels. Remaining regions are candidate ones which are locations of signs. Figure 5 demonstrates the whole process we have described above.

III. Experimental results

To test our system, we collect two different image sets. These datasets are collected from [7], [16]. In [7], the authors provide a set of 48 traffic sign images. In this set, two different traffic signs are captured in complex scenes. The authors first apply edge detection to get an edge image, then a shape matching method is used to extract signs region. The computation for shape matching is rather expensive. In [16], the authors claim that they work with difficult images where traffic signs appear under unfavorable conditions such as viewpoints, and weather conditions (rainy, sunny). We randomly select 60 images out of 167 images for our test.

For the ground-truth, we manually label all images. This means that for each image, we point out which sign locations should be detected. We note here that we only consider signs that have border lengths that are not too short i.e. signs are not too small. In our experiment, we set this threshold by 50 pixels. This setting is reasonable as in reality user can not read and distinguish signs that are too far i.e. appear in small sizes.

Evaluation is carried out by observing all the final segmented images. We count the number of correct sign locations N_c, the number of unlocated signs (missed signs) N_u, and the total number of segmented regions for each image N_r. From these values, we calculate the precision and recall:

$$\text{recall} = \frac{N_c}{N_c + N_u},$$

$$\text{precision} = \frac{N_c}{N_r}.$$

In table II, we report the performance of the detecting system with the two datasets. The first collum shows the total number of signs that are detected correctly. The second collum shows the total number of missed signs. And the last collum shows the total number of segmented regions for each dataset.

Results show that, on average, the system locates two regions per image in both datasets. With the dataset 1, we get 79% recall and precision is 60%. With the dataset 2, the system returns 80% corrrect signs, and achieves 71% in

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Fig. 5. An example of the whole process in locating signs. The first row is an input image. The second row shows sign localization process with our approach using chromatic edge segmentation. For comparison, we test with using Hue color segmentation. Results are shown in the last row. From left to right: chromatic edge images, binary edge images, filled images, final segmented images.

TABLE II
AVERAGED EXPERIMENTAL RESULTS WITH THE TWO GIVEN DATASETS.

	♯ correct signs	♯ unlocated sign	♯ segmented regions
dataset 1	49	13	82
dataset 2	96	23	135

precision. For the dataset 2, it is reported in the reference [7] that all the signs was correctly detected. In [16], with their method, the authors achieved 93% in recall and 78% in precision. In this dataset, only triangular signs are detected under number of restrictions using property of this specific type of sign. With our simple approach and especially no-restriction is involved in the localization process, our system performance is a success. Besides, as we detect different types of signs, we believe that applying the same restrictions in [16] or complicated method in [7] as supplement step, we can improve the detection rate much higher for a specific type of sign. Moreover, another important factor in our system is speed. All computation and processing takes about $\frac{1}{5}$ second per image on average. With this property, the system can be easily employed in a runtime application.

Figure 6 shows some examples of our detection results. Rectangles mark regions located by the system. In these examples, we show some difficult cases such as weather conditions (rainy), different lightning condition (dark light source, sunny, cloudy), blurring images, viewpoint changes. It is observed that our method is rather flexible, and capable of locating signs under different imaging conditions. Since a closed boundary is needed for the filling step, out approach failed to locate signs that are partially occluded. However, the performance can be enhanced by applying the method to a sequence of images instead of a single image, so that the sign is first located when it is not occluded, then a tracking system traces it through out the sequence.

IV. CONCLUSION

In this paper, we have proposed a new system for detecting sign location. Using a new color model in [4] for segmentation, we are able to locate the sign region successfully. This new color model has its advantage over the most common used color model Hue such that it provides a higher discriminative power and invariant to different imaging conditions. Our segmentation method can be applied to detect different signs disregarding of theirs appearances in colors and shapes. Experimental results show that our system provides a high recognition rate. Moreover, due to the simplicity in localization, the processing time has been reduced significantly. We believe that with the processing time in a fraction of second our method can be used in any reality applications such as traffic guidance, or tourist guidance system, etc..

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Fig. 6. Some examples of the experimental results using proposed sign localization method.

References

[1] C. Bahlmann, Y. Zhu, V. Ramesh, M. Pellkofer, and T. Koehler. A system for traffic sign detection, tracking, and recognition using color, shape, and motion information. In *Proceedings of the IEEE conference on Intelligent Vehicles Symposium*, pages 255–260, 2005.

[2] Y.B. Damavandi and K. Mohammadi. Speed limit traffic sign detection and recognition. In *IEEE conference on Cybernetics and Intelligent Systems*, pages 797–802, 2004.

[3] M.A. Garcia-Garrido, M.A. Sotelo, and E. Martin-Gorostiza. Fast road sign detection using hough transform for assisted driving of road vehicles. In R.M. Diaz and et al., editors, *EUROCAST*, LNCS 3643, pages 543–548, 2005.

[4] J.M. Geusbroek, R.v.d. Boomgaard, and A.W.M. Smeulders. Color invariance. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(12):1338–1350, 2001.

[5] T. Gevers and A.W.M. Smeulders. Color based object recognition. *Pattern Recognition*, 32:453–464, 1999.

[6] T. Gevers, J. Weijer, and H. Stokman. Color feature detection. *Color Image Processing: Methods and Applications, editors R. Lukac and K.N. Plataniotis, CRC Press*, 2006.

[7] C. Grigorescu and N. Petkov. Distance sets for shape filters and shape recognition. *IEEE Transactions on Image Processing*, 12(10):1274–1286, 2003.

[8] Y. Liu, S. Goto, and T. Ikenaga. An MRF model based algorithm of triangular shape object detection in color images. *International Journal of Information Technology*, 12(2):55–65, 2006.

[9] L.D. Lopez and O. Fuentes. Color-based road sign detection and tracking. In M. Kamel, A. Campilho, and et al., editors, *ICIAR*, LNCS 4633, pages 1138–1147, 2007.

[10] J.T. Oh, H.W. Kwak, Y.H. Sohn, and W.H. Kim. Segmentation and recognition of traffic sign using shape information. In G. Bebis and et al., editors, *ISVC*, LNCS 3804, pages 519–526, 2005.

[11] L. Sekanina and J. Torresen. Detection of norwegian speed limit signs. In *Proceedings of the 16th European Simulation Multiconference on Modelling and Simulation*, pages 337–340, 2002.

[12] W.G. Shadeed, D.I. Abu-Al-Nadi, and M.J. Mismar. Road traffic sign detection in color images. In *ICECS*, 2003.

[13] P. Silapachote, J. Qeinman, A. Hanson, R. Weiss, and M.A. Mattar. Automatic sign detection and recognition in natural scenes. In J. Coughlan and R. Manduchi, editors, *IEEE workshop on Computer Vision Applications for the Visually Impaired*, 2005.

[14] G. Wu, W. Liu, X. Xie, and Q. Wei. A shape detection method based on the radial symmetry nature and direction discriminated voting. In *ICIP*, 2007.
[15] W. Wu, X. Chen, and J. Yang. Detection of text on road signs from video. *IEEE Transactions on Intelligent Transportation Systems*, 6(4):378–390, 2005.
[16] H.M. Yang, C.L. Liu, K.H. Liu, and S.M. Huang. Traffic sign recognition in disturbing environments. In N. Zhong and et al., editors, *ISMIS*, LNAI 2871, pages 252–261, 2003.
[17] Hsiu-Ming Yang. Traffic dataset in disturbing environment *http://www.cs.nccu.edu.tw/∼chaolin/papers/ismis03/testdata.html*.