Color-Based Traffic Sign Detection

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***Abstract*—According to the characteristic of traffic signs, several color components are used to extract several kinds of traffic signs, which improved the detection efficiency in pre-processing. Then the regions of interest (ROI) are set not only to save process time but also to increase the accuracy of road recognition. Meanwhile the geometric characters of the road signs are represented by morphological skeleton based on which the decision tree is designed to classify road signs. The presented methods are tested on some complex traffic images which are captured under different weather conditions.**

Keywords-traffic sign; color space; hough transfer; region of interest; morphological skeleton; decision tree

I. INTRODUCTION

The perception of the traffic environment is the most important issue that guarantees safe driving of intelligent vehicle. Machine vision is the most effective way to access traffic information due to the rich information and easy installation of cameras, which has drawn the attention of many scholars. And it requires fast processing speed and high accuracy because of the particularity of the vehicle system.

In the early days, researches on traffic sign detection were basically established in the grayscale image processing. Later color image have been widely adopted because of the abundant information it contains. Traffic sign detection is based on some significant features, such as color [1-5], texture [6], edge [7-9], shape [10,11], and etc. Reference [12] used both color and texture features, and [13] adopted the features of intensity and texture for road sign detection. However, because of the high request on computing speed, complicated image processing techniques cannot yet be widely applied to this field. And the existing traffic sign recognition algorithm is influenced by the surrounding environments e.g. shadows of vegetation or buildings and changing illuminations may change the color and brightness of the object. The robust of traffic sign detection algorithm is a challenging work.

In a traffic scene, traffic signs usually have attractive colors and brighter intensities, therefore researchers use luminance component instead of gray image to extract traffic signs from complex traffic scene. Luminance component cannot be used to distinguish a certain color such as red, yellow and white, which are the most important colors in traffic scene. Moreover, Luminance based traffic sign detection methods is sensitive to illumination changes and only work well in some certain conditions such as adequate light and constant illumination.

To describe the geometric features of traffic signs, the algorithm has to overcome translation, rotation, scaling and some other geometric distortions, due to the changing capture position of the camera.

Considering the issues discussed above, this paper introduces the three color components method to extract different traffic information according to the features of traffic scene while meeting the requirement of processing speed and robustness. It also applies one-dimensional maximum entropy method to segment the lane marking and traffic sign. This method effectively inhibits the complex noise of the traffic scene and improves the robustness of the algorithm from the aspect of image preprocessing. Moreover, this paper uses the skeleton algorithm to extract the features of lane markings. In addition, it introduces multiple classifiers to recognize five most common road markings. Finally we test our methods to various traffic scenes and prove the robustness and effectiveness of our method.

II. COLOR-BASED OBJECT EXTRACTION

In urban surroundings, traffic signs are attractive because of their high brightness. Therefore, it's an easy way to extract traffic sings according to this feature. However in order to classify traffic signs more effectively, color is adopted as another significant feature in our work. The most important colors in traffic scene are red, yellow and white which indicate prohibiting, warning, and guidance separately. Among these colors, white is the most used color in traffic sign such as lane lines, road markings, crosswalk and etc. Color spaces are analyzed based on our experiments which show that the B component in the RGB color space is very sensitive to color white. So this component can be used to detect the white markings. And V component in YUV color space is very sensitive to color yellow and red which can be used to extract warning traffic signs from the complicated traffic scene. And the YUV color space is easy to get by linear transformation from RGB color space.

Particularly, the road boundaries in Fig. 1 (a) are extracted and shown in Fig. 1 (c). The V component in YUV color space is shown in Fig. 1 (b) in which pixels with larger values are shown as peaks. One-dimension maximum entropy algorithm is used to do segmentation on Fig. 1 (b). Besides the road boundaries, some other objects in red or yellow are extracted as well. But white lines in (a) are treat as back ground, therefore, signs in different colors can be distinguished.

Similarly, segmentation result of white road markings which is based on the B component in the RGB color space is shown in Fig. 2.

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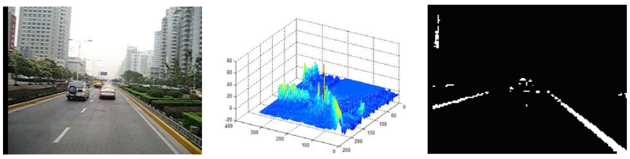
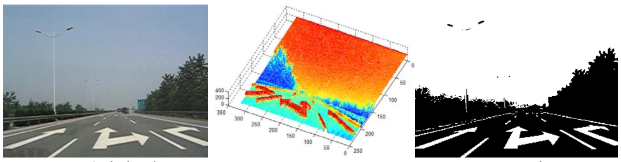


(a) Original (b) V component (c) Segmentation result

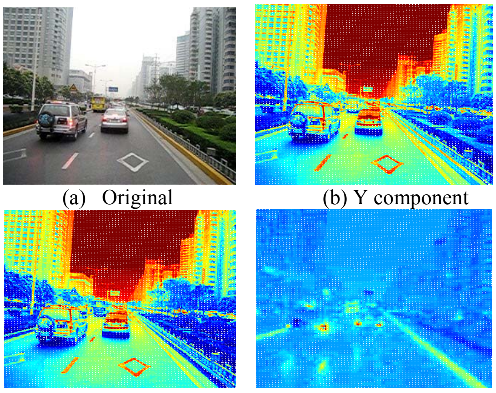
Figure 1. Road markings (in yellow) extracting.



(a) Original (b) B component (c) segmentation result

Figure 2. Road markings (in white) extracting.

Fig. 3 (a) is a complex urban traffic scene image. Its Y and V components in YUV color space and B component in RGB color space are shown in Fig. 3 (b), (c), (d). It can be seen that pixels with higher brightness in (a) have greater values in (b), while pixels with lower brightness corresponding to smaller values. The white lane marking areas in (a) have greater values in (c), while yellow lane markings in (a) corresponding to smaller values in (c). In figure (d), only yellow marking and stoplight areas have greater value while other areas have smaller values. We utilize the features of the three color components to distinguish different kinds of traffic lanes and signs.



(a) Original (b) Y component

(c) B component (d) V component

Figure 3. A traffic image and its three color components.

III. ROAD DETECTION

In this paper we only discuss the detection algorithm of straight lanes. Identification of the straight lane can be transferred into a straight line extraction problem which is achieved by Hough transform algorithm [14] in our experiment. The big advantage of Hough transform is that it can detect edge pixels in a line, even the independent pixels. And the algorithm can reduce the impact of under segmentation and over segmentation. Therefore it is widely used in complex traffic scenes. Extracting a straight line by Hough transform is described as follows:

- Step1. In the minimum and maximum values of a Build a discrete parameter space of ρ and θ;
- Step 2. Build an accumulator and elements in the accumulator are 0;
- Step 3. Do Hough transform to each pixel in image, that is to calculated its curve on the $\rho-\theta$ plane, and count 1 to the corresponding accumulator element;
- Step 4. Find out local maximum value in $A(\rho,\theta)$ which provides the parameters of the line on the polar coordinates.

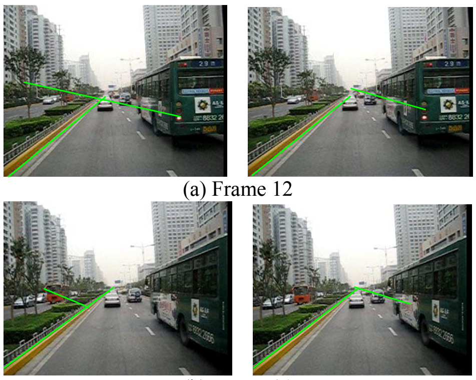
To reduce the heavy calculation of Hough transform, we take the following measures: First, use Hough transform to one row of pixels in every two rows which halved the processing calculation. Secondly, set search ranges for both lane lines. base on our observation of abundant captured images in moving vehicles, the search areas are set as:

$$\begin{cases} \rho > 0 \,\&\, 15^\circ < \theta < 75^\circ, left\ \ lane\ \ line \\ \rho < 0 \,\&\, -15^\circ < \theta < -75^\circ, right\ \ lane\ \ line \end{cases}$$

In addition, to further reduce the computational complexity, the regions of interests are set according to the detected lane lines in the previous frame. Assuming in the previous frame, the polar coordinates of the detected lane lines are (ρ_l, θ_l) (left line) and (ρ_r, θ_r) (right line). Then the local values in Hough transform which are the polar parameters of the lines are searched in the following regions;

$$\begin{cases} \rho_l - \Delta\rho < \rho < \rho_l + \Delta\rho \,\&\, \theta_l - \Delta\theta < \theta < \theta_l + \Delta\theta, left \\ \rho_r - \Delta\rho < \rho < \rho_r + \Delta\rho \,\&\, \theta_r - \Delta\theta < \theta < \theta_r + \Delta\theta, right \end{cases}$$

The experimental results of two frames in a video sequence are shown in Fig. 4. The figures on the left in both (a) and (b) are the lane detection results by Hough transform algorithm, and the right figures are lane detected in regions of interests. We can see that setting of the region of interests can not only improve processing speed, but also the detection accuracy.



(a) Frame 12

(b) Frame 20

Figure 4. Traffic line detection results before and after ROI are set ($\Delta\rho = 20, \Delta\theta = 8$).

IV. ROAD MARKING RECOGNITION

Since road regions and road markings are already detected in the previous sections. In this section, the road marking recognition algorithm is introduced. Because of the complexity of the traffic environment, some information of traffic markings may be lost in the segmentation processing, e. g. the edges may be inconsecutive after over segmentation. Furthermore, different from the general traffic sign recognition which contains plane deformation, such as translation, rotation, scaling, and etc, road marking recognition need to solve more geometric distortions due to the height and angle camera installed and the movement of the vehicles. Therefore, some features such as moment invariant, proportion, edge and shape which are frequently adopted in traffic sign recognition cannot be used in road marking recognition. However the main geometric information would not change a lot. Thus we use morphological skeleton character to describe road markings.

A. Feature Extraction

Morphological skeleton [15] is an important and effective way to describe the topological features (shape and orientation) of objects. It can not only represent the internal structure, but also the geometric characters of the object contour. Morphological skeleton has several definitions, and the most commonly used one is geometric place of the centers of all at least bi-tangent circles.

Let X be the set on Euclidean Space Z^2 and its skeleton as $S(X)$. So the skeleton can be described as:

$$S(X)=\bigcup_{n=0}^{N}S_n(X)=\bigcup_{n=0}^{N}\left[(X\Theta nB)-((X\Theta nB)\circ B)\right] \quad (1)$$

Where $S_n(X)$ is the n_{th} skeleton subset of X. N is the value of n that satisfies $X\Theta nB\neq\Phi$ and $X\Theta(n+1)B=\Phi$, and $nB=B\oplus B\oplus\cdots\oplus B$.

The selection of structural elements is a key aspect to the skeleton extraction, which guarantees connectivity of the object structure and invariance. We applied the template $\mathrm{A}=\{\mathrm{A}_1,\mathrm{A}_2,\mathrm{A}_3,\mathrm{A}_4\}$ and $\mathrm{B}=\{\mathrm{B}_1,\mathrm{B}_2,\mathrm{B}_3,\mathrm{B}_4\}$ to achieve the maximum skeleton algorithm.

$$\underset{\mathrm{A}_1}{\begin{bmatrix}0&0&1\\0&\otimes&1\\1&1&1\end{bmatrix}}\underset{\mathrm{A}_2}{\begin{bmatrix}1&0&0\\1&\otimes&0\\1&1&1\end{bmatrix}}\underset{\mathrm{A}_3}{\begin{bmatrix}1&1&1\\1&\otimes&0\\1&0&0\end{bmatrix}}\underset{\mathrm{A}_4}{\begin{bmatrix}1&1&1\\0&\otimes&1\\0&0&1\end{bmatrix}}$$

$$\underset{\mathrm{B}_1}{\begin{bmatrix}1&0&1\\1&\otimes&1\\1&1&1\end{bmatrix}}\underset{\mathrm{B}_2}{\begin{bmatrix}1&1&1\\1&\otimes&0\\1&1&1\end{bmatrix}}\underset{\mathrm{B}_3}{\begin{bmatrix}1&1&1\\1&\otimes&1\\1&0&1\end{bmatrix}}\underset{\mathrm{B}_4}{\begin{bmatrix}1&1&1\\0&\otimes&1\\1&1&1\end{bmatrix}}$$

where, $\otimes$ is the center; 1 represents the point of object; 0 represents the point of background.

Based on the maximum skeleton extraction algorithm in Mathematical Morphology, we denote the iteration process as follows:

$$S_n(X)=\bigcup_{i=1}^{4}\Big\{\left[(X\Theta nA_i)-(X\Theta nA_i)\circ A_i\right]$$
$$\cup\left[(X\Theta nA_{i+1})-(X\Theta nA_{i+1})\circ A_{i+1}\right]$$
$$\cup\left[(X\Theta nB_i)-(X\Theta nB_i)\circ B_i\right]\Big\}$$

$$S(X)=\bigcup_{n=0}^{N}S_n(X) \quad (5)$$

Where, $A_5=A_1$.

B. Road Marking Recognition

The road markings on highway are mainly guiding arrows, such as straight, left/right turn, straight and left/right turn (as shown at the top of Fig. 5). A decision tree is designed in our work to classify roads markings into these five classes. It is shown in Fig. 5.

Assuming the enclosing rectangle of the direction marking has its four borderlines as y_t, y_b, x_l, x_r, respectively. Then the level midline is $y=y_b+\frac{y_t-y_b}{2}$, and the central axis is $x=x_l+\frac{x_r-x_l}{2}$. The peak has the largest y value of the skeleton, with coordinate as $x=x_l+\frac{x_r-x_l}{2}$.

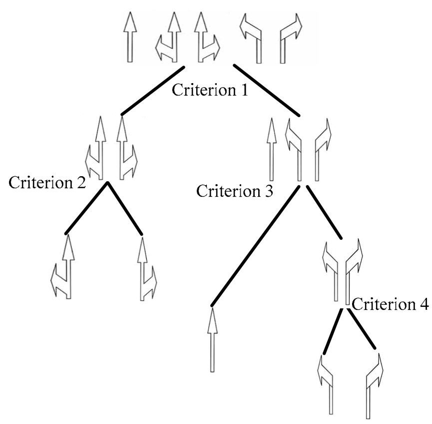


Figure 5. Multi-level classifier.

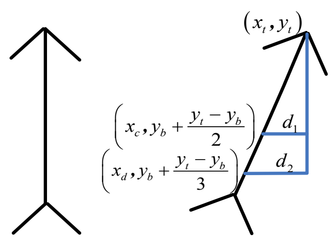


Figure 6. Criterion three.

where, Criterion 1: If there more than two points of intersection between the skeleton and the level midline, then go to Criterion 2; otherwise to Criterion 3;

Criterion 2: Straight or left turn if the skeleton peak stands on the right of the central axis. Straight or right turn otherwise;

Criterion 3: As shown in Figure 6, peak of the direction marking for going straight lies on the same straight line with the random two points of the skeleton backbone. We select the intersection between the level midline and the skeleton which is $\left(x_c, y_b + \frac{y_t - y_b}{2}\right)$, and a point on the skeleton 1/3 from the bottom which is $\left(x_d, y_b + \frac{y_t - y_b}{3}\right)$. Then d_1 and d_2 denote the horizontal distance between the peak and the two points selected above. Therefore if d_1/d_2=3/4 or d_1=d_2=0, the lane marking is for straight; otherwise go to Criterion 4;

Criterion 4: Right turn if the skeleton peak stands on the right of the central axis. Otherwise, left turn.

In our experiment, we firstly extract the road signs in road regions, and then extract their skeletons. The recognition process is according to the criterions above. The results are shown in Fig. 7.

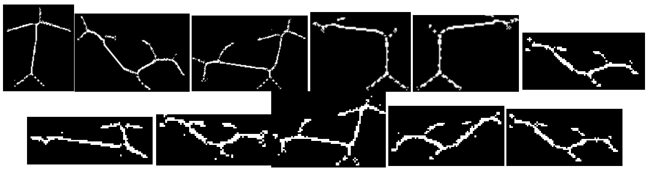


Figure 7. Road markings represented by morphological skeleton.

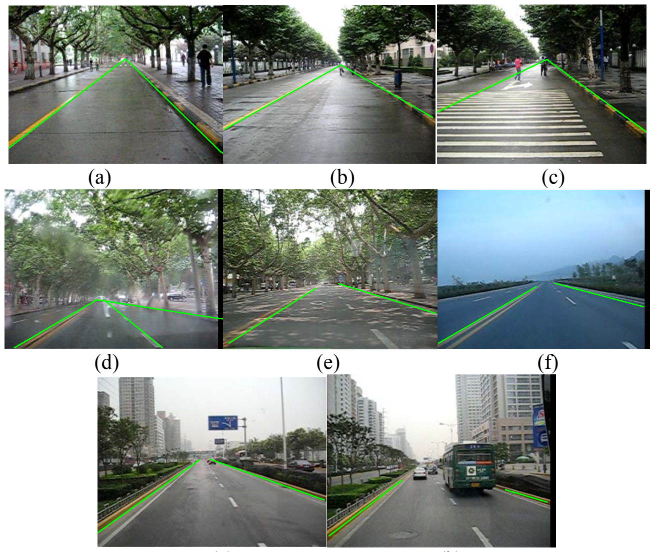
V. Experiment Results

A. Road Detectioin Under Various Weather Conditions

Fig. 8 (a) shows the road image after rain. The hydrous on road changes the brightness and texture of local areas due to the reflection and tree shadow. And the right boundary of the lane comes with alternate black and yellow stubs which makes the feature points discontinuous. In Fig. 8 (c), the detection of the yellow lane boundary was greatly affected by the white speed bump and the pedestrian in red. Fig. 8 (d) shows the image taken when vehicles drive fast. Fig. 8 (e) has a strong sunshine and plenty of tree shadow which invalidate the method using brightness component. Fig. 8 (f) shows the scene at dusk with a low saturation and brightness of the lane marking. Fig. 8 (g) is a simple environment in sunny days. Fig. 8 (h) still succeeds in dismissing the noise under shielding condition due to the division of interested areas. However, the lane detection algorithm works well in all these particular situations.

B. Traffic sign Detection

According to the previous analysis on different color components, we use the Y factor in YUV color space as the detection object. The segmentation results are shown in Fig. 9. The white rectangle is the interested area being set and gives the red prohibitory sign, blue direction sign and yellow alert sign, respectively.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 8. Road detection results in different environments.

Figure 9. Traffic sign detection results.

Fig. 10 shows the traffic sign image in different environments and weather conditions. In Fig. 10, (a) and (b) are the test results of a complex province road in a overcast sky which causes the reduction of detection accuracy of the sign borderline. (c) and (d) are taken in a city traffic scene with hard light. Mountain road experiments are conducted as shown in (e) and (f). And sign detection under a relatively simple traffic scene in city is shown in (g) and (h). All the results show that our proposed method is robust to different traffic conditions.

VI. Conclusion

To adapt to complex traffic scenes and improve the robustness of the traffic information detection, we analyze a variety of color spaces so as to detect traffic prohibitive signs, alert signs and guide signs. Our discussion provides a well-designed platform for post processing such as segmentation and recognition. The ROI is set to improve Hough transform based lane recognition algorithm. Based on that, road markings are detected, and described by the morphological skeleton algorithm. A decision tree is designed recognize the road signs. Experiment results show the robustness and efficiency of our method.

Figure 10. Traffic signs detection results in different environments.

REFERENCES

[1] K. Chiu and S. Lin, "Lane detection using color-based segmentation," In Proceedings of IEEE Intelligent Vehicle Symposium, pp. 706-711, 2005.

[2] V. Andrey, "Automatic detection and recognition of traffic signs using geometric structure analysis," In Proceedings of International Joint Conference, pp. 1451-1456, 2006.

[3] K. Chiu and S. Lin, "Lane detection using color-based segmentation," In Proceedings of IEEE Intelligent Vehicles Symposium, pp. 706-711, 2005.

[4] H. Cheng, N. Zheng, and T. Liu, "An approach of road recognition based mean shift and feature clustering," In Proceedings of ICSP, pp. 1059-1062, 2005.

[5] S. M. Bascon, "Road-sign detection and recognition based on support vector machines," Intelligent Transportation System, vol. 8, no. 2, pp. 264-278, 2011.

[6] C. Rasmussen and T. Korah, "On-vehicle and aerial texture analysis for vision-based desert road following ," In Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 66, 2005.

[7] J. Collado and C. Hilario, "Adaptative road lanes detection and classification ," In Proceeding of ACIVS, pp. 1151-1162, 2006.

[8] C. Rotaru and T. Graf, "Extracting road features from color images using a cognitive approach," In Proceedings of IEEE Intelligent Vehicles Symposium, pp. 298-303, 2004.

[9] J. Lee and U. Yi, "A lane-departure identification based on LBPE," Computer Vision and Image Understanding, vol. 99, no. 3, pp. 659-383, 2005.

[10] F. Moutarde and A. Bargeton, "Robust on-vehicle real-time visual detection of American and european speed limit signs, with a modular traffic signs recognition system," In Proceedings of Intelligent Vehides Symposium, pp. 1122-1126, 2007,

[11] M. G. Garrido, M. Sotelo, and E. M. Gorostiza, "Fast traffic sign detection and recognition under changing lighting conditions," In Proceedings of Intelligent Transportation System, pp. 811-816, 2006.

[12] S. Konishi and A. Yuille, "Statistical cues for domain specific image segmentation with performance analysis," In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 125-132, 2000.

[13] P. Jeong and S. Nedevschi, "Efficient and robust classification method using combined feature vector for lane detection," IEEE Transactions on Circuits and Systems for Lane Detection, vol. 15, no. 4, pp. 528-537, 2005.

[14] J. Illingworth and J. Kittler, "A survey of the hough transform," Computer Vision, Graphics, and Image Processing, vol. 44 no. 1, pp. 87 -116, 1988.

[15] Z. Zhou and A. Venetsanopoulos, "Morphological skeleton representation and shape recognition," In Proceedings of Acoustics, Speech, and Signal Processing, pp.948-951, 1988.