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A Method of Fast and Robust For Traffic Sign Recognition

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***Abstract*—This paper proposes a fast and robust algorithm for traffic sign detection and recognition. The algorithm includes two stages: traffic sign detection and recognition. In the first stage, Adaboost algorithm based red pixels model of speed limit sign in the Lab color space is built. Then the model is used to extract area of latent speed limit signs. After that, the improved Hough Transform is used to locate the signs precisely. In the second stage, the template matching algorithm is used to recognize the traffic sign. At the same time, a new method of rejecting non-signs is presented, which improved the recognition rate in the complex outdoor scenes.**

Keywords-traffic sign; color filtering; Hough transform; criterion of rejection; context information

I. INTRODUCTION

Traffic sign recognition is a key step in the intelligent traffic system. It can alleviate the fatigue of drivers and improve traffic safety. For these reasons, many scholars have already proposed lots of methods, such as statistical methods, neural networks, syntax methods[1]etc. These algorithms have shown good performance in certain scenes. However, lots of signs may be fuzzy, shadowed, color and geometric distorted etc. More important, there are kinds of traffic signs and kinds of traffic sign-like logos. So these algorithms cann't not keep their good performance all the time.

In this paper, a new method to detect and recognize speed limit signs is presented. Three new ideas can be found in this methods: the first one is using Adaboost algorithm to model the color features of signs, which can be found in section 2; the second one is a new rejecting way to refuse non-traffic signs, which can be found in section 3; the last one is to use context information to improve the efficiency of the algorithm just as section 3 presented. Experiments in section 4 show that the method presented in this paper is valid in many natural scenes.

II. TRAFFIC SIGN DETECTION

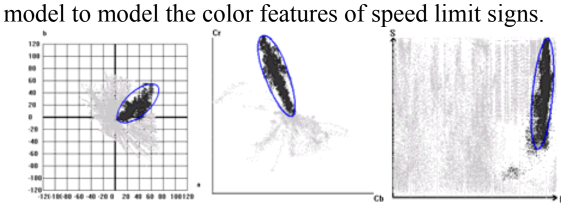
A. Analysis of Sign Characteristics

As shown in Figure 1, speed limit signs in Chinese usually have border of red pixels, white background, black characters and other priori characteristics. The samples obtained from the natural scene are clustered in the Lab color space, YCrCb color space and HSV color space respectively. The results are shown in Figure 2. In the Figure, the dark area is the red pixels clustered region of signs, the light area is the non-red pixels clustered region. As can be seen from the Figure, the cluster effect of red pixels provides better performance in the Lab color space than in other color spaces. Therefore, this paper selects Lab color space to design a filter for red pixels of speed limit signs.

Figure 1. Speed limit sign

B. Analysis of Sign Characteristics

Because the region where the red pixels of speed limit signs clustered in the Lab color space presents elliptic shape, an intuitive way is using elliptical or rectangular model to model the color features of speed limit signs.



(a) (b) (c)

Figure2. The cluster results of the red pixels:
(a) the cluster result in the Lab color space (b) the cluster result in the YCrCb color space (c) the cluster result in the HSV color space

Although this method is simple, it still has some problems such as missing detection and false detection in some cases. In order to overcome these problems, the paper designed a color model based on the Adaboost algorithm. The basic idea is using a series of circular templates of different size cover the cluster region of red pixels more accurately through Adaboost algorithm in the Lab color space.

1) The template and the calculation.

This paper takes a series of circular templates of different size as templates, which can be expressed as following:

$$(x_a - a_j)^2 + (x_b - b_j)^2 = r_j^2 \tag{1}$$

Where j is the sequence number of the templates, $j = 1, 2, \cdots, N$, (a_j, b_j) is the centre coordinate of the $j-th$ circle template, r_j is the radius of the $j-th$ circle template.

Assume that the coordinate of the pixel in the image to be classified in the Lab space is $\vec{x}_i = (x_{ai}, x_{bi})$, Then the $j-th$ template can be calculate as follows:

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$$f(\vec{x}_i)=\sqrt{(x_{ai}-a_j)^2+(x_{bi}-b_j)^2} \qquad (2)$$

2) Construction of Weak Classifier.

Changing the centre and radius of the different circular templates constitutes a series of weak classifiers. Where the center can be changed in the Lab space according to the statistic of the general distribution area where the red pixels of speed limit signs in the real scene. While the radius can be changed according to the external rectangular size which the red pixels of speed limit signs clustered.

According to 1000 frames speed limit signs images taken from different conditions, the statistic of its red pixels cluster area in the Lab color space shows that: the distribution where the red pixels of speed limit signs taken from real scene clustered in the Lab space is as follows:

$$\begin{cases} 3<a<60 \\ -10<b<50 \end{cases} \qquad (3)$$

Therefore, all of the weak classifier's center is included in formula (3); While all of the weak classifier's radius is in accordance with the external rectangular which the red pixels of speed limit signs clustered, which is ranged as:

$$15<r<40 \qquad (4)$$

With (3) and (4), the number of weak classifier can be calculates as 57×60×25=85500. Thus, the weak classifier can be constructed as follows:

$$h_j(\vec{x})=\begin{cases}1 & p\cdot f_j(\vec{x})\le p\cdot r_j \\ 0 & otherwise\end{cases} \quad j=1,2,\cdots,N \qquad (5)$$

Where, if $h_j(\vec{x})$ equals to 1,that means the correct classification for sample $\vec{x}$; if $h_j(\vec{x})$ equals to 0, that means error classification for sample $\vec{x}$; p is bias, $p=1$ if $\vec{x}$ is positive sample, $p=-1$ if $\vec{x}$ is negative sample.

3) Algorithm.

In order to cover the area where red pixels of speed limit signs clustered more accurately in the Lab space, the Adaboost algorithm[2]is used. The algorithm is specifically described as following:

Step 1: Given a set of training samples: $(\vec{x}_1,y_1)$, $(\vec{x}_2,y_2)$, ... $(\vec{x}_i,y_i)$, where $\vec{x}_i=(x_{ai},x_{bi})$ is the $i-th$ training sample, $i=1,2,\cdots,L$; and when the sample $\vec{x}_i$ is positive, $y_i=1$, on the contrary, when $\vec{x}_i$ is a negative sample, $y_i=0$.

Step 2: Initialize the maximum number of iterations: $T=20$.

Step 3: Initialize weights: For any positive samples $\omega_{i,1}=1/2m$, For negative samples $\omega_{i,1}=1/2n$, where m,n are the number of positives and negatives respectively and meet $m+n=L$.

Step 4: For: $t=1,2\cdots T$

a) Normalize the weights:

$$\omega_{t,i}=\omega_{t,i}/\sum_{i=1}^{L}\omega_{t,i} \qquad (6)$$

b) Select the best weak classifier with respect to the corresponding rate of false detect according to the N weak classifiers structured in 3.2 :

$$\varepsilon_t=\min(\sum_{i=1}^{L}w_{t,i}\left|h_t(\vec{x}_i)-y_i\right|) \qquad (7)$$

c) Update the weights: $w_{t+1,i}=w_{t,i}\beta_t^{1-e_i}$,where $\beta_t=\varepsilon_t/(1-\varepsilon_t)$,if $e_i=0$,then $\vec{x}_i$ is classified correct by $h_t(\vec{x})$,if $e_i=1$,then $\vec{x}_i$ is classified wrongly by $h_t(\vec{x})$.

Step 5: Based on the best of the T weak classifiers selected by Step 4, the ultimately color filter is:

$$H(\vec{x})=\begin{cases}1 & \sum_{t=1}^{T}\alpha_t h_t(\vec{x})\ge 0.5\sum_{t=1}^{T}\alpha_t \\ 0 & otherwise\end{cases} \qquad (8)$$

where, $\alpha_t=\ln(1/\beta_t)$.

4) Experimental results and analysis.

In order to verify the validity of the above algorithm, this paper selects training samples from a large number of images taken from the real scenes. The positives samples are 72000 red pixels cropped from 180 images; The negatives samples are 88000 non-red pixels cropped from 220 images. The color model is described with a cluster of circular weak classifiers by the above algorithm and is shown at Figure 3.

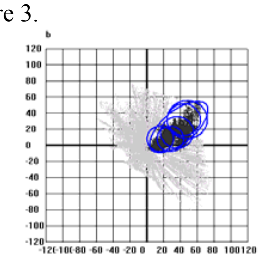

Figure 3. Color Filter

Figure 4 gives results of detection the image which includes a speed limit signs. The Figure 4(a) is a real scene image taken at night; The detection result with the color model and operators of expansion, corrosion is shown at Figure 4(b), and Figure 4(d) is the last candidate sign. The binary image in the RGB color space introduced by literature[2] is shown at Figure 4(c). The experimental results show that the color model presented in this paper can provide a better performance in the complex conditions.

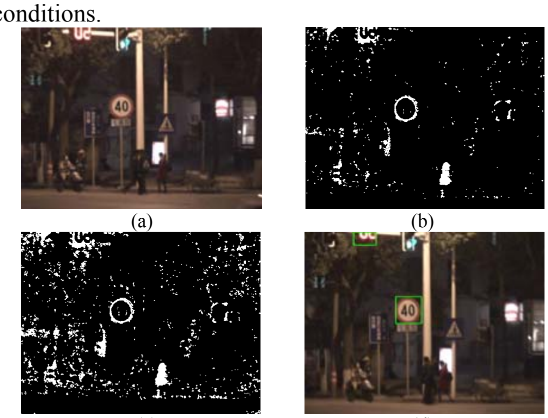

Figure 4.The experimental results:

(a) The preliminary image (b)the result of color filter of this paper (c) the result of literature[2] (d) sign candidates according to the filter result.

C. Hough transform

What worthy of note is that the typical traffic sign detection method is obtaining the final result according to the binary images combined with a number of other constraints such as size of traffic sign, But this method is trustless if the sign is shadowed and so on. The missing detected rate or the false detected rate is relatively high. To overcome these problems, the Hough transform based on the gradient information to detect circles is used in the system. The detailed algorithm is shown in literature[4]. The final detection results in different conditions are shown in Figure 5. As is shown, the using of Hough transform based circle detection with gradient information improved the accuracy of the sign effectively and the system is insensitive to bad conditions.

Figure5. The detection results in different conditions

III. TRAFFIC SIGN RECOGNITION

A. Pre-processing

The pre-processing of character recognition is the process of histogram equalization, contrast enhancement, binary, median filtering, character segmentation and normalization for the extracted sign. Through this approach, we can highlight the number of characters of the speed limit sign for the next step to carry out character recognition. Among them, the character segmentation uses region growing method, the character normalization chooses the way nearest neighbor interpolation in this paper. Figure 6 gives the flow chart example of pre-processing.

(a) (b) (c) (d)

Figure 6. The flow chart example of pre-processing: (a) The extracted sign (b) histogram equalization and contrast enhancement (c) binarization and character segmentation (d) character normalization

B. Feature Extraction

In the experiment, for each normalized character by the size of 20×40 is divided into 25 grids, as is shown in Figure 7. Extract 25-dimensional black pixel density of each grid as follows:

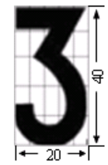

Figure 7. 25-D pixel features

a) Divide the normalized character into small areas by the size of 4×8 pixel;

b) Calculate the proportion of black pixels of each small area. The five proportions of the first line are saved as the first five features, the next five of the second line are saved as the features of 6-10, and so on.

C. Character Recognition

The traditional template matching algorithm is less than the reliability, and the recognition speed performance is poor. To solve these problems, the paper proposes a system to evaluate the reliability of the recognition result and improves the recognition speed performance by other ways.

1) Evaluating the reliability.

First, the paper uses the template matching algorithm to recognize characters of speed limit signs. After that, extract the features such as the number of horizontal line and vertical line at different columns and rows, the times of a line across the black pixels at different columns and rows, the number of holes of the character[5]. As is shown at Tab.1, the total feature is 11.What worthy of note is that these features are extracted according to the different characteristic of 10 types of character and scan the different and appropriate columns and rows according to different characters, while in the past methods, the same columns and rows are scanned although the characters are different. According to these features, we can calculate the reliability of the recognized character by the following formula:

$$P=\sum_{i=0}^{10} \alpha_i f_i \tag{9}$$

Where, i is the $i-th$ feature; α is the weight of the feature; f is the value of the feature, if it is satisfied to the Tab.1, $f=1$,otherwise $f=0$.

TABLE I. CODER OF CHARACTER

Feature	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	α
Top-across	2	1	2	1	1	1	1	1	2	2	0.1
X-across	2	1	1	1	1	1	2	1	1	2	0.1
Bottom-across	2	1	1	2	1	2	2	1	2	1	0.1
Left-across	2	1	2	2	1	2	1	1	2	2	0.05
Y-across	2	1	3	3	2	3	2	2	3	2	0.1
Right-across	2	1	2	2	1	3	2	1	2	1	0.05
Top -horizontal	0	0	0	1	0	1	0	1	0	0	0.1
Bottom -horizontal	0	0	1	0	1	0	0	0	0	0	0.1
Left vertical	1	0	0	0	0	0	0	0	1	0	0.1
Right vertical	1	1	0	0	1	0	0	0	1	0	0.1
Hole	1	0	0	0	1	0	1	0	2	1	0.1

2) Improved Template Matching Algorithm.

We can improve the reliability and computation speed of the template matching algorithm on characters recognition. The whole phases can be described as: Create templates; Extract 25-dimensional pixel density features; Calculate the similarity between template and the character of sign using Euclidean distance; Obtain the preliminary result according the template with highest similarity; Give the reliability assessment of the preliminary result, decide if the characters are numbers; Use the information of sequential images to improve the system's speed. The algorithm is specifically described as follows:

Step 1: Create templates. In this paper, According to the character of the speed limit sign, the templates are constituted by the 25-dimensional pixel density features of 200 samples for each character type from 1-10.

Step 2: Extract features. For the next frame, segment and normalize its character of the detected sign, and extract the 25-dimensional pixel density features. Set $k=0$,and k is the number of successive recognition result according to the information of sequential images.

Step 3: Calculate the Euclidean distance between the characters of signs and the templates of numbers from 1-10 as follows:

$$D(R,I)=\|F_R-F_I\|=\sqrt{\sum_{i=0}^{24}\left|f_i^R-f_i^I\right|^2} \tag{10}$$

Where, R is the character of the sign, I is the character template, the two feature vectors are $F_R=\left\{f_0^R,f_1^R,.......f_{24}^R\right\}$ and $F_I=\left\{f_0^I,f_2^I.....f_{24}^I\right\}$, $D(R,I)$ is the Euclidean distance between the two character.

Step 4: For the every character of signs, using Euclidean distance to obtain a number from 1-10 that is most similar to the character.

Step 5: According to formula (9), give the reliability assessment of the preliminary result. if $P>th_p$, then the preliminary result is correct, and confirm the final recognition result. Then go to Step 6; otherwise, refuse to recognize this characters and go to Step 2.

Step 6: According to the information of sequential images to recognize the next frames. Obtain the next frame, calculating the histogram's Bhattacharyya distance between the current frame and last frame according to the formula (11).if $d<0.2$, the two frames have the same recognition results. Confirm the recognition directly, then go to Step 7 ; otherwise, go to Step 2.

$$d(H_1,H_2)=\sqrt{1-\sum_i\sqrt{H_1(i)\cdot H_2(i)}} \tag{11}$$

Where, H_1 is the histogram of current frame, while H_2 is the last frame's. $d(H_1,H_2)$ is the Bhattacharyya distance between two frames.

Step 7: Calculate the number of frames which is recognized according to the information of sequential images. That's if $k>0$,then go to step 2; otherwise go to step 6.

IV. EXPERIMENTAL RESULTS

A. *Static Image*

Real images in different lighting and weather conditions are taken in order to analyze the robustness and reliability of proposed algorithm. The results are shown in Figure 8.

Figure 8. The results of recognition

B. *Video Images*

All experiments were run on the Pentium-IV 2.6G with 512MB RAM under VC++6.0 environment. We measure the system's performance in terms of its rates which include correct acceptance rate(CAR), false acceptance rate(FAR) , correct rejection rate (CRR) and false rejection rate(FRR). In this paper, video images were taken in different lighting and weather conditions includes day and night. In the experiments, For provide a more accurate representation of the system, a receiver operating characteristic(ROC) curve may be used, as is shown the figure 9, which displays the variations of the FAR as the FRR. According to this curve, so we can deduce the minimum the error rate of the system from this figure and select the appropriate FRR.

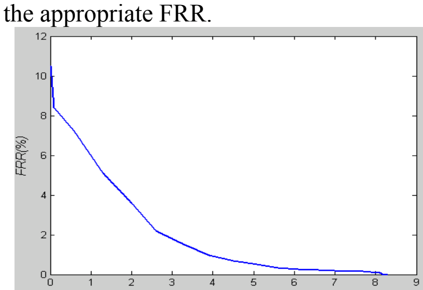

Figure 9. ROC performance curve showing the variations of the FAR as the FRR.

V. CONCLUSION

This paper discussed the method of recognition for speed limit sign from the two stages: Detection and recognition. The experimental results indicate that the proposed method can be used for real-time detection and recognition of traffic signs. The proposed system shows good recognition rate for various lighting and weather conditions. It provides robust results in dark and bad conditions. The system can be used to improve the reliability and reduce computation time.

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