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Speed Limit Sign Detection Based On Gaussian Color Model And Template Matching

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***Abstract*—Traffic sign detection and recognition play crucial roles on the Intelligent Transportation System(ITS). Firstly, in YCbCr color space, color segmentation of the traffic scene images using Gaussian color model is calculated , and traffic sign regions are obtained. Secondly, the morphology processing is utilized on the segmented image to extract the candidate traffic signs with a rectangle region in the original image to be selected according as its shape property. Finally, template matching is applied for speed signs classification. The performance of the proposed method is evaluated on Norwegian speed limit signs in natural environment. Experiment results show that this algorithm can effectively improve the traffic sign detection efficiency, which is used in traffic signs recognition and tracking of intelligent vehicles.**

Keywords-Traffic sign detection, Gaussian color model, Thresholding segmentation, Image segmentation

I. INTRODUCTION

In a road traffic scenario, Intelligent Transportation Systems(ITS) can be applied for tasks such as recognition and interpretation of the significant objects in a traffic situation. Traffic signs represent the current traffic situation on the road, show danger and difficulties around the drivers, give them warnings, and help them with their navigation by providing useful information that makes driving safe and convenient. Recognition of speed signs – studied in this paper, could inform the driver of the current speed limit and give an alarm for the driver if the car is driving faster than the speed limit. Because color and shape are basic characteristics of traffic signs, the common technique for detecting and recognizing traffic signs can be divided into shape-based and color-based. Color-based methods which using simple thresholding or more advanced image segmentation methods are usually fast and invariant to translation, rotation and scaling. There are different color models such as RGB [1], CIELab [2] HSV and other color spaces have been used for segmentation of traffic signs [3]. The typical problems of such a method lies in the fact that color tends to be unreliable owing to the time of day, weather conditions, shadows, or camera sensitivity produce a change in the apparent color of the sign, while the shape-based methods is another powerful visual feature to deal with these problems better. In [4], the author ignores color information and instead use only shape information from grayscale images for traffic signs detection. Hough transform is a broad class of shape detectors, which can detect circles and other shapes robustly [5]. However, Hough transform is computationally expensive and not suited for systems with real-time requirements. Some improved Hough transform algorithm have been proposed based on radial symmetry to reduce the computational complexity [6].

In this paper, we are proposing to detect road signs in YCbCr color space, modeling the pixel intensity values using Gaussian color model. color segmentation or color thresholding is applied to emphasize possible signs in an image. After that, the morphology processing is utilized on the segmented image to extract the candidate traffic signs. Finally, Histogram of Oriented Gradient features is applied for the feature extraction of these segmented image of traffic sign and utilize support vector machine for the automatic recognition.

II. GAUSSIAN COLOR MODEL METHOD

A. The YCbCr Color Space

Color is a prominent feature of traffic signs. The choice of color space can be considered as the primary step in traffic signs detection. The YCbCr color space is widely used in digital video, image processing, etc. [7]. In this format, luminance information is represented by a single component (Y), Y defined to have a nominal 8-bit range of 16-235, and color information is stored as two color-difference components, Cb and Cr . Component Cb is the difference between the blue component and a reference value, and component Cr is the difference between the red component and a reference value respectively, which are defined to have a nominal range of 16-240. Some research studies [8] found that the chrominance components of the sign color are independent of the luminance component. Hence, in our implementation, the Cb and Cr components are used to model the distribution of traffic signs colors.

The transformation used to convert from RGB to YCbCr color space can be expressed as equation (1):

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$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.996 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.241 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

A total of 500 samples from traffic signs color images were used to determine the color distribution of speed limit in YCbCr color space. As shown in the figure 1, the signs color values form quite compact space, and give a better clustering effect.

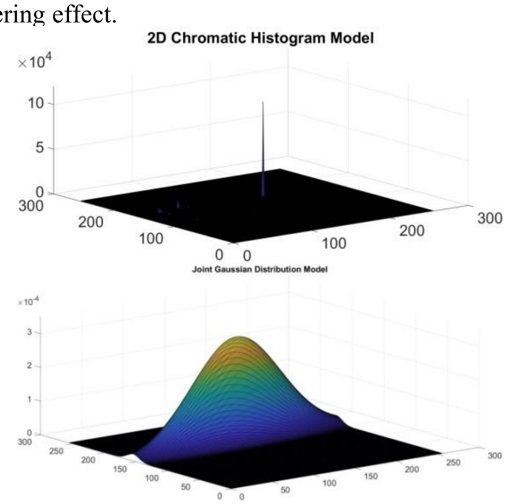

Fig.1. The Chromatic distributions of Cb and Cr

B. Gaussian color model

Since the RGB color space does not closely match the human visual perception and has no ability to describe the spatial structures, the Gaussian color model, which uses the spatial and color information in an integrated model, is used to obtain more complete image features.

In the case of the unimodal Gaussian model, the form of signs class-conditional pdf can be expressed as equation (2):

$$\begin{aligned} p(x|sgin) &= g(x; m_s, C_s) \\ &= (2\pi)^{-d/2} |C_s|^{-1/2} \exp\left\{ -\tfrac{1}{2}(x-m_s)^T C_s^{-1}(x-m_s) \right\} \end{aligned} \quad (2)$$

where d is the dimension of the feature vector, vector x represents the random measured values of the chrominance in an image, m_s is the mean vector and C_s is the covariance matrix of the traffic signs class. If we assume that the non-traffic signs class is uniformly distributed, according Bayesian rule reduces to the following: a color pixel x is considered as a traffic signs pixel if its features can be formulated as equation (3)

$$(x-m_s)^T C_s^{-1}(x-m_s) \le t \quad (3)$$

where t is a threshold and the left hand side is the squared Mahalanobis distance. Eq.3 can easily be shown that x is a sign pixel if its features can be formulated as equation (4) :

$$(x-m_s)^T C_s^{-1}(x-m_s) - (x-m_{ns})^T C_{ns}^{-1}(x-m_{ns}) \le t \quad (4)$$

where t is a threshold, m_{ns} and C_{ns} are the mean and the covariance of the non-sign class, respectively. Figure 2 shows an initial segmentation map of a test image produced by the proposed Gaussian color model segmentation method

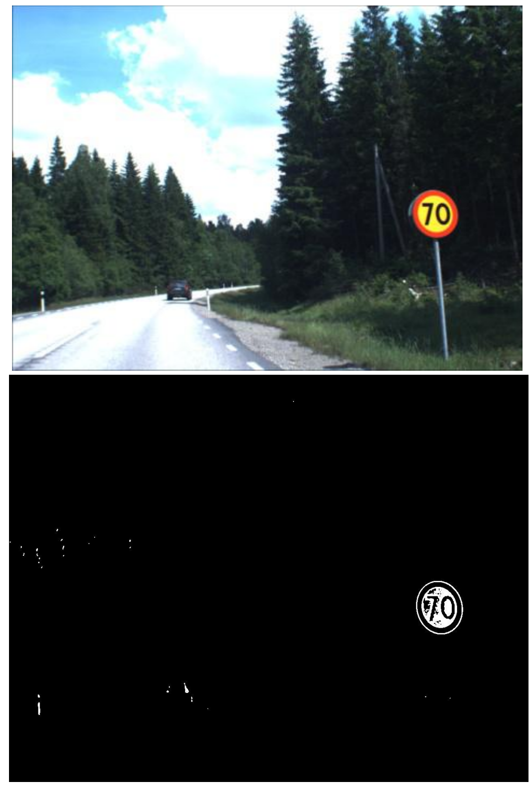

Fig.2 Original image and its binary segmentation image produced by the proposed skin segmentation.

After color image has become a binaryzation image, many non-traffic signal areas will also be shown. To remove noises away from the possible candidates, we need to isolated traffic signs into separate regions by a series of morphological operations. After that, several features of the detected connected component (called blobs) regions are used to determines which regions should be passed to the next stage for final detection. we choose those blobs' area and aspect ratio as equation (5) :

$$160 \le Area \le 10000 \;\; 0.5 \le Heigh / Wide \le 1.6 \quad (5)$$

Once the presence of a traffic sign is detected, its recognition takes place through template matching.

The detail experimental procedure can be summarized as follows:

1) Conversion of color image to YCbCr image.
2) Segmentation image using Gaussian color model
3) Image thresholding using Ostu's methods.
4) Label connected components in 2-D binary image.
5) Morphological operations to filter regions.
6) Resize the extracted region to 40×40, use Histogram of Oriented Gradient to capture features.
7) Utilize support vector machine for the traffic sign automatic recognition.

Fig.3 is a briefly flow chart of the framework of road sign detection.

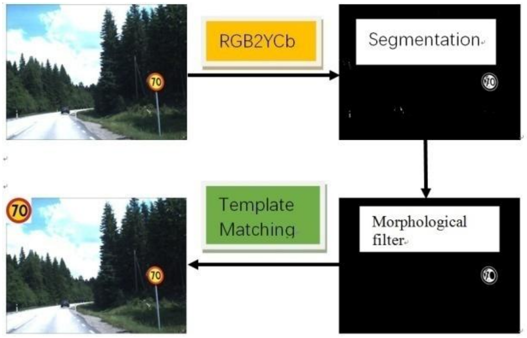

Fig.3 Road Sign detection framework

III. HOG FEATURES AND A MULTICLASS SVM CLASSIFIER

After segment those traffic sign from different road scenes. The next step is to recognize those segmented signs. It is a challenging task to do so owning to the variable lighting conditions that occur in road scenes. The first need is a robust algorithm that allows all those different appearances of traffic sign could be discriminated clearly, even under poor lighting conditions or signs for deterioration.

We study different kinds of feature sets for traffic s ign detection, showing that HOG (Histogram of Oriente d Gradient) features show an excellent performance to other methods including edge orientation histograms, sca le-invariant feature transform descriptors, and shape cont exts. The features are constructed by calculating and ge t statistics of histogram from gradient direction in local region of image. In order to get the features, we initi ally divide the image into small connected regions calle d cells, then the gradient histograms of the gradients or edges for each pixel in the cell are collected. By com bine these histograms together, we can constitute the fe ature descriptor. For simplicity and speed, we use multi class SVM classifier to classify these images.

The traffic sign detection procedure based on the HOG feature and a multiclass SVM classifier is shown in Fig.4

A. Feature definition

The purpose of using features instead of pixels to define an image is to improve the efficiency of machine learning, so that we can get the characteristics of the target region from raw images and make it easier to further detection. In this section, the appearance and shape of the local target can be well described by gradient or directional density distribution of the edges. To obtain these features, we divide the image into small connected regions called cells, then collect the direction histogram of each pixel's gradient or edge in every cell unit. As our feature description is mainly based on those cell unit, so HOG features can adapt the deformation and lighting condition well.

To obtain the HOG feature descriptor, we first make the original image to the grayscale image. To adjust the contrast of the image and reduce the impact of shadow and light, we use adaptive method for image binarization.


Fig.4 the result of image binarization

Next step is to calculate the gradient of all direction in the image, with which we can capture the contour of the digit in the traffic sign. For a pixel (x,y), its gradient can be calculated as equation (6):

$$G_x(x,y) = H(x+1,y) - H(x-1,y)$$
$$G_y(x,y) = H(x,y+1) - H(x,y-1) \quad (6)$$

In the equation, $G_x(x,y)$, $G_y(x,y)$, $H(x,y)$ are the Horizontal gradient, vertical gradient and pixel value of the input image. So the strength of the gradient at the point (x,y) can be calculated as equation (7):

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \quad (7)$$

The orientation of the edge at the point (x,y) is can be calculated as equation (8):

$$\theta(x,y) = \arctan\frac{G_y(x,y)}{G_x(x,y)} \quad (8)$$

A commonly used way access to the gradient component is convolving the image with a gradient operator. [-1 0 1] and $[-1\ 0\ 1]^T$ are two gradient operators for gradient component on x and y direction.

We divide the image into cells with the same size, for example 6*6 pixels per cell, and use several histograms to describe the gradient information within the cell. That is the same as divide the gradient direction into N pieces, and weighted projection will provide the histogram of gradient direction for the whole cell and the N-dimensional feature vector. Fig.5 is an example of divide the gradient direction into 9 pieces.

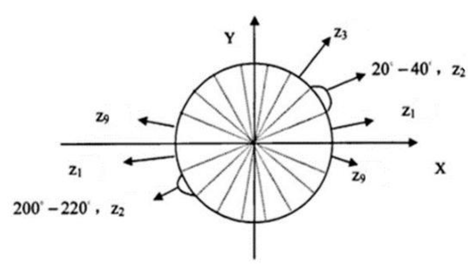

Fig.5 an example of divide the gradient direction into 9 pieces

The number of features for an image could be changed by the size of cell used to divide it. We will get more features if we choose a smaller size. However, a large size, like [8 8], dose not encode much shape information while a cell size of [2 2] encodes a lot of shape information but increases the dimensionality of the HOG feature vector significantly and cost too much computing time. A good compromise is a [4 4] cell size. This size setting strike a balance between the accuracy of the shape and the speed of training. Fig.6 is an example of origin image of traffic sign and Fig.7, Fig.8, Fig.9 are feature images with different cellsize.

Fig.6 origin image of traffic sign

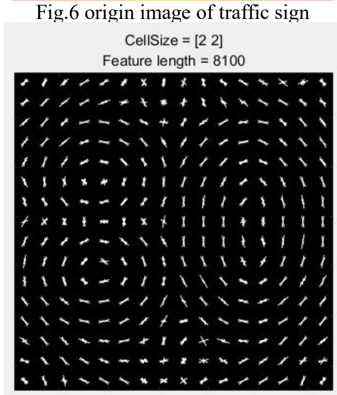

Fig.7 feature image with cellsize of [2 2]

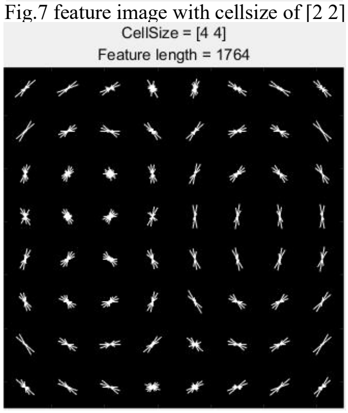

Fig.8 feature image with cellsize of [4 4]

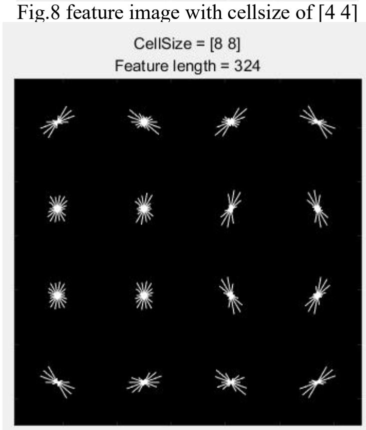

Fig.9 feature image with cellsize of [8 8]

B. *Support vector machine*

After definite the features in the image of traffic sign, we can distinguish them according to the number on those traffic sign by the features we obtained from HOG.

Support vector machine is a wildly used supervised learning model. By using a nonlinear mapping, we can map the sample space into a feature space of higher dimension so that the nonlinear problem in the original sample space transform into a linear one in a feature space. It has been proved to be compute friendly and high accuracy on the field of classification.

IV. Experimental Results and Discussions

One of the most widespread databases which created by recording sequences from over 350 km of Swedish highways and city roads has been used for evaluation of the algorithm objectively [10].

TABLE I. Performance on the Manually ROIs dataset for the method presented in [11] and the proposed algorithm.

Speed Signs	Total Number	Signs Detected	Detection rate (%)
30	9	0	0
50	193	81	41.96
70	215	133	61.86
80	193	93	48.18
100	108	72	66.67

Table I shows the detection and segmentation rate of the traffic signs from Swedish database. The unsatisfactory result mainly owing to the raw image. As we said, our database is the true reflection of actual road condition. None of them pay special attention to the traffic signs, so the traffic signs in those images are non-focusing in most cases. They are small and blur with a lacking brightness or overexposure lighting condition. Many traffic signs are similar in color to the surrounding environment or those easily confused blocks in the background. Under such circumstances, the algorithm is much more likely to fail the detection process.

In our approach, color combinations are the key to an efficient detection of traffic signs. Color combinations have enough discriminative power to reduce the search space significantly.

From the detected images we can establish a database and use it to build our classifier. There are four speed limits: 50, 70, 80 and 100. We established a training set with a scale of around fifty and a testing set with the similar size.

Start by extracting HOG features from the training set and use these set to train the classifier. After that, we evaluate the traffic sign classifier using those images from the testing set and judge the classifier according to the result.

TABLE II. PERFORMANCE OF SVM CLASSIFIER WHEN APPLIED TO TESTING SETS

Speed of Sign	Total Number	Signs classified	Correct rate
50	36	31	86.1%
70	72	66	91.7%
80	48	45	93.8%
100	37	29	78.4%

Misclassification result distribution mainly come from poor lighting condition, Table III describe misclassification in detail.

TABLE III MISCLASSIFICATION OF TRAFFIC SIGN RESULT DISTRIBUTION

Value	Error 50	Error 70	Error 80	Error 100
50		1	3	1
70	0		6	0
80	1	1		1
100	0	0	8	

From the detail record we can arrival at a conclusion that for 50, 70 and 100 there is a dominated misclassification direction 80. A typical traffic sign of 80 and its HOG feature map with a cellsize of [4 4] is in Fig.8. As we can say, the HOG features have a close relationship with the position and texture of the target, and number 8 got a similar texture with other numbers, so there is a higher possibility for the misclassification happen on it. By the way, many of our sources of error come from low quality images. If the image has a very low resolution or is too blurry, the algorithm is much more likely to fail the detection process.

V. CONCLUSIONS

Traffic sign is an indispensable part of the road traffic system. Its function is to prompt the direction, instruct the driver to operate, and ensure the traffic safety. Driving behavior is largely based on visual information processing. Whether it is automatic driving system, semi-automatic driving system or other functional equipment, traffic signs can transmit some useful road information in real time, and ensure driving safety. Such as banning the turn, passage, whistle, danger warning, and driving speed restrictions, which can help the driver obtain information about the environment in which he is currently living.

The key to a real time traffic sign recognition system is a fast and reliable traffic sign detection algorithm. The goal is to detect regions which are likely to contain traffic signs. This allows the recognition process to focus on a limited amount of small search areas, and thus speeding up the whole process significantly. With a detected image of sign, we can recognize the speed limit and transmit it to the driver.

To achieve it, a variety of algorithms are used. Firstly, color segmentation or color thresholding is applied to emphasize possible signs in an image. Afterwards, restricting the search area in the image. Third, specific signs are classified using HOG features and SVM.

We use YCbCr color space to pretreat these images, make it easier for use to distinguish target traffic sign from background. And Gaussian color model, which uses the spatial and color information in an integrated model, is used to obtain more complete image features. With these features, we can detect the boundary of target and finally separate them from background.

After the detection, we capture the features of those signs by HOG. In this way, we can acquire the texture and shape features of those numbers and they will help the SVM to recognize these signs,

However, there are many problems our classifier still cannot handle. They mainly come from the original images. The way to deal with the target images in a confusing background and improve the accuracy of image detection are the next problems to be tackled.

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REFERENCES

[1] De, la Escalera, A, et al. "Road traffic sign detection and classification." IEEE Transactions on Industrial Electronics 44.6(1997):848-859.

[2] Fang, Chiung Yao, S. W. Chen, and C. S. Fuh. "Road-sign detection and tracking." IEEE Transactions on Vehicular Technology 52.5(2003):1329-1341.

[3] Prasad, Dilip K., M. K. H. Leung, and Q. Chai. "ElliFit: An unconstrained, non-iterative, least squares based geometric Ellipse Fitting method." Pattern Recognition 46.5(2013):1449-1465.

[4] Loy, G, and N. Barnes. "Fast shape-based road sign detection for a driver assistance system." Ieee/rsj International Conference on Intelligent Robots and Systems IEEE, 2004:70-75 vol.1.

[5] Garcíagarrido, Miguel A., et al. "Complete Vision-Based Traffic Sign Recognition Supported by an I2V Communication System." Sensors 12.2(2012):1148-69.

[6] Barnes, Nick, et al. "Regular polygon detection." Tenth IEEE International Conference on Computer Vision IEEE, 2014:778-785 Vol. 1.

[7] Shaik, Khamar Basha, et al. "Comparative Study of Skin Color Detection and Segmentation in HSV and YCbCr Color Space." Procedia Computer Science 57(2015):41-48.

[8] Gao, X. W., et al. "Recognition of traffic signs based on their colour and shape features extracted using human vision models." Journal of Visual Communication & Image Representation 17.4(2006):675-685.

[9] Ishak, K. A., M. M. Sani, and N. M. Tahir. "A Speed limit Sign Recognition System Using Artificial Neural Network." Research and Development, 2006. Scored 2006. Student Conference on IEEE, 2007:127-131.

[10] Zttp://www.cvl.isy.liu.se/research/traffic-signs-dataset. Swedish Traffic Signs Data set (STS Data set) [25];

[11] Larsson, Fredrik, and M. Felsberg. "Using Fourier Descriptors and Spatial Models for Traffic Sign Recognition." Scandinavian Conference on Image Analysis Springer-Verlag, 2011:238-249.