An Efficient Framework for Road Sign Detection and Recognition

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Abstract: Road sign detection and recognition is a significant and challenging issue not only for assisting drivers but also navigating mobile robots. In this paper, we propose a novel and fast approach for the automatic detection and recognition of road signs. First, we use Hue Saturation Intensity (HSI) color space to segment the road signs color. And then we locate the road signs based on the geometry symmetry, as almost all the shapes of road sign shapes are symmetrical such circle, rectangle, triangle and octagon. The proposed shape feature is further applied to classify the shape initially. Finally, the road signs are exactly recognized by support vector machine (SVM) classifiers. We test our proposed method on real road images and the experimental results show that it can detect and recognize road signs rapidly and accurately.

Keywords: Road sign recognition, Shape symmetry, Shape detection.

1. Introduction

Road sign detection and recognition is a fundamental and significant topic in robot navigation and computer vision. As road sign detection and recognition system provides meaningful navigation information, it plays an important role not only in notifying drivers the current state of the road but also in the navigation of mobile robots and other unmanned vehicles. The system warns drivers about danger of the traffic situation, and reduces traffic accidents effectively. On the other hand, the system can automatically navigate robots and vehicles by identification of road signs, which is urgently needed in warehouse storage industry and many scientific research fields.

The detection and recognition system faces multiple difficulties and challenges because of the complex environment of roads where there are a lot of different objects on the roads such as pedestrians, vehicles, buildings and trees. The low quality of images including light variation and motion blur also brings many challenges to the system. Another key difficulty of this system is how to detect and recognize road signs rapidly and in real-time. Due to the significance and difficulties of the road sign detection and recognition, a great amount of research has been done to solve this problem.

Usually, there are two major phases the road sign recognition algorithms:

1) Detection - locate road signs from real images,
2) Recognition - identify the types of the road signs.

A road sign has three most important characteristics: color, shape, and pattern, which are designed to be different from each other. The information of road sign is acquired from the basic meaning through the combination of these three

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properties. Thus, most of the solutions rely heavily on these features of road signs [1].

In the detection phase, color segmentation is the most common method. RGB space is used for the color segmentation in [2, 3]. As the RGB space is susceptible to the change of the light, HIS space is preferred. The factors of hue and saturation are invariant to brightness and shadow. [4, 5] use HIS space to extract color feature. Many other methods focus on the shape feature of road signs, which is another significant and visible feature of road sign.

Shape is an important attribute of road signs both in detection and recognition sections. Color information is no need in shape detection. As the contour and the pattern of road signs are both different, a number of approaches based on shape have been proposed. [6] detects circular signs by two-time Hough Transform algorithm. The algorithm classifies the edge points and uses the geometry feature of circle to reduce the transform dimensions. In [7], the radial symmetry feature is adopted for locating road signs. Individual pixels vote for a common centre of symmetry with their results accumulating in a common voting map. A shape symmetry method operating on the gradient of gray-scale images is proposed in [8]. In [9, 10], template matching approach is proposed to search for road signs. All road sign shapes are stored in the database. Each potential sign is normalized in size and compared with every template of the same shape. This method can be easily modified to include new classes of signs. [11] detects the triangular and rectangular road signs by passing lines intersection.

In the second phase, neural networks are the most widely used, due to their powerful classification capability [12, 13]. When the algorithms are applied in road sign classification, neural networks can be trained to recognize road signs within a region of interest. In [14], the road signs are identified by template matching approach. A lot of research based on SVM [15-17] with different extracted features has been applied in many applications. In addition, Fuzzy logic [18] and Zernike Moments [19] are also employed in the recognition of road signs.

Although many road sign detection and recognition algorithms have been proposed, there are still many problems. Most of detection methods like Hough Transform, radial symmetry and template matching are complicated to operate and also not fast enough, especially for large images. In addition, the recognition approaches are usually depending on statistical theory. Lots of samples are needed and the calculation is large. Thus, an efficient and rapid road sign detection and recognition algorithm is very important.

In this paper, we propose an efficient and rapid road sign detection and recognition algorithm. In the detection step, we firstly apply the HSI color segmentation to obtain the Region of Interest (ROI), and then propose a novel method based on the shape symmetry to detect the road sign accurately. In the recognition step, we propose a shape symmetry feature to classify the shapes of detected road signs and then apply SVM classifier to recognize road sign accurately.

The proposed system is much more stable and efficient comparing to the traditional methods. Especially, our detection algorithm based on the shape symmetry is fast and efficient. The algorithm sets central axes in the segmented ROI and analyzes the symmetry by calculating the area ratio from different sides of the axis. In this way, we locate the road signs accurately from initial ROIs segmented by the color segmentation. To classify the road signs rapidly, the interesting regions are divided into four parts by the vertical axis and the horizontal axis, which are through the centre of their bounding boxes. The shape categories are classified by analyzing whether they are symmetric and the values of area ratios. To prove the effectiveness of our framework, we test the proposed method on the database from [22]. The experiments show that our system is very efficient to be used in real application.

2. Methodology

In this paper, we present a fast and intelligent detection and recognition method which is broadly illustrated in Fig. 1. The details of each phase are presented as bellow:

![Flow diagram of the proposed methodology.](image)

The approach consists of two phases: detection and recognition. And each phase has two steps. In the detection phase:

1) Step 1: color segmentation: extract the regions of road signs from real background by using HSI color thresholding.
2) Step 2: symmetry detection of ROI: keep road signs as candidate blobs and removes non-road signs objects by geometry symmetry of the shapes.

In the recognition phase:
3) Step 3: shape classification: further use geometry symmetry and area to classify the different shapes.
4) Step 4: SVM recognition: identify exact road sign types based on SVM.

2.1. Color Segmentation

Color is often the main cue explored to find the areas where road signs appear. The main defect of the color-based approaches is that outdoor illumination that might affect the color acquired by the image sensor. Compared to RGB space, HSI space is more similar to human sensitivity of colors. The HSI system encodes color information by separating out an overall intensity value from two values including hue and saturation to make it more immune to lighting changes. Therefore, thresholding in HSI color space is an efficient way due to its strong robustness against lighting variation. The RGB space is converted to HSI space by the following formulas (1)-(4):

$$\theta = \cos^{-1}\left\{\frac{(R-G)+(R-B)}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\},$$  \hspace{1cm} (1)$$

$$\text{Hue} = \begin{cases} \theta & B \leq G \\ 360 - \theta & B > G \end{cases}$$  \hspace{1cm} (2)$$

$$\text{Saturation} = 1 - \frac{3\min(R,G,B)}{R+G+B}$$  \hspace{1cm} (3)$$

$$\text{Intensity} = \frac{(R + G + B)}{3}$$  \hspace{1cm} (4)$$

where R, G, B represent the red, green and blue brightness of a pixel with ranges from 0-255. The hue and saturation components take values ranging from 0 to 360 and from 0 to 255, respectively. After image conversion into suitable color model for processing, segmentation process is carried out to identify the possible candidate blobs. The thresholds for the criterion are fixed by a series of tests. After the color segmentation, Minimum-Maximum method is applied for filtering the blobs from the noisy environment and then the image is analyzed using pre-processing methods like median operation and morphological operation. The result of this color segmentation step is a binary image with some candidate blobs.

2.2. Symmetry Detection of ROI

After color segmentation in Step 1, most segmented regions are still not the road sign regions which we want. Road signs will be very difficult and slow to be detected or recognized by classifier in these noise regions. Thus, it is very necessary and important to remove the regions without road signs in order to achieve better performance and increase the speed of the process of detection and recognition.

In the step, we propose an effective and fast method to detection the road signs from the segmented regions based on that most of the road sign shapes are symmetrical.

We know that most of the road sign shapes are triangle, rectangle, circle or octagon and the same characteristic of these shapes is axial symmetry. To detect the symmetrical in the binary regions, the candidate blobs are divided into left and right parts by the vertical central axis of their bounding boxes as Fig. 2. The bounding box is the smallest rectangle which contains the object. According to the setting of µ, road signs are detected. µ is the difference between ratio of the pixels in the left part of ROI to the pixels in the left part of bounding box and ratio of the pixels in the right part of ROI to the pixels in the right part of bounding box. The pixels in the region refer to its area.

Fig. 2. The road sign shapes are divided into left and right parts by the vertical central axis.

$$\mu = \frac{l_{ROI}}{l_{box}} - \frac{r_{ROI}}{r_{box}} = \frac{l_{ROI} - r_{ROI}}{\frac{1}{2}b}, 0<\mu<1,$$  \hspace{1cm} (5)$$

where \(l_{ROI}\) represents the pixels in the left part of ROI, represents the pixels in the right part of ROI. \(r_{ROI}\) is equal to pixels in the left part of bounding box and \(l_{box}\) is equal to pixels in the right part of bounding box, actually they are both 1/2 pixels in the bounding box(b). The theoretical value of µ is 0, considering the breakage and deflection of road signs, the value of µ can be setting based on a lot of experiments. The result of symmetry detection is shown in Fig. 3.

This shape detection approach has strong robustness as it detects shapes based on edges, and will efficiently reduce the search for road signs from the whole image to a small number of pixels. The advantage of saving processing time is described as follows:

- The detection algorithm operation is no longer complex as other methods.
- This approach does not search for all the image and pixels, it just computes the area of candidate blobs after color segmentation with low calculation.
First, the interesting regions are divided into four parts by the vertical axis and the horizontal axis which are through the centre of their bounding boxes as Fig. 4.

![Image](Fig. 4. The road sign shapes are divided into four parts by the vertical central axis and the horizontal axis.)

Then we use $\mathcal{S}_i$ to classify the shapes according to Table 1.

$$\mathcal{S}_i = r_i / b_i, \ i = 1, 2, 3, 4,$$

where $r_i, b_i$ represent the area of the interesting region and the bounding box in part $i$, respectively.

<table>
<thead>
<tr>
<th>Shape</th>
<th>$\mathcal{S}_1$</th>
<th>$\mathcal{S}_2$</th>
<th>$\mathcal{S}_3$</th>
<th>$\mathcal{S}_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circle</td>
<td>$0.75 &lt; \mathcal{S}_1 = \mathcal{S}_2 = \mathcal{S}_3 = \mathcal{S}_4 &lt; 0.80$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Triangle</td>
<td>$\mathcal{S}_1 = \mathcal{S}_2 &lt; \mathcal{S}_3 = \mathcal{S}_4$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rectangle</td>
<td>$\mathcal{S}_1 = \mathcal{S}_2 &gt; \mathcal{S}_3 = \mathcal{S}_4$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Octagon</td>
<td>$0.96 &lt; \mathcal{S}_1 = \mathcal{S}_2 = \mathcal{S}_3 = \mathcal{S}_4 &lt; 1.00$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Octagon</td>
<td>$0.81 &lt; \mathcal{S}_1 = \mathcal{S}_2 = \mathcal{S}_3 = \mathcal{S}_4 &lt; 0.85$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Through the simply comparing of $\mathcal{S}_i$ and confirming the range of the values, circle, triangle, rectangle and octagon can be distinguished precisely. The four ratios of circle, rectangle and octagon are in common in theory. According to this point, the triangle road signs are identified. Furthermore whether the triangle is regular or inverted can be known at the same time by making sure that $\mathcal{S}_1, \mathcal{S}_2$ are bigger or not. Then different values of ratio are used to recognise circle, rectangle and octagon.

In this step, we divided the region into four parts, which results in exact classification. It is more accurate than the approach using the whole area ratio. And few pixels are examined in this method. In general, shape classification is efficient and fast.

Fig. 3. Detection of ROI.
(a) - real road image from [22]; (b) - segmentation result by blue thresholding; (c) - detection result based on geometry symmetry; (d) - segmentation result by red thresholding; (e) - detection result based on geometry symmetry; (f) - road sign detection results.

2.3. Shape Classification

Road sign recognition is a hard and complex task. In this step, the shape of road signs is classified by using the part area ratio after the detection phase.
2.4. SVM Recognition

The recognition step is used to classify the exact sign types based on Super vector machines (SVMs). SVMs are pattern classifiers with high generalization ability compared with conventional ones. The aim is to find an optimal hyperplane in the higher dimension feature space that can separate the data in the best way.

SVMs are formulated to solve binary classification [20]. In the case of two separable classes, the training data are labeled \( \{x_i, y_i\} \), where \( y_i \in \{-1, 1\} \), \( x_i \in \{R^d\} \), \( i = 1, 2, ..., n \). The vectors \( x_i \) are HOG features, which will be introduced later. The values \( y_i \) are “1” for one class and “−1” for the others, \( d \) is the dimension of the vector, and \( n \) is the number of training vectors. If a hyperplane \( \{w, b\} \) separates the two classes, the points that lie on it satisfy:

\[
x \cdot w^T + b = 0,
\]

where \( w \) is the normal to the hyperplane, \( |b|/w \) is the perpendicular distance from the hyperplane to the origin. In order to obtain the optimal hyperplane, the following quadratic constraint optimization problem is needed to solve:

\[
\min \varphi(w) = \frac{1}{2} \|w\|^2
\]

A nature way to assign extra cost for errors is to change the objective function to be minimized from \( \|w\|^2 /2 \) to \( \|w\|^2 /2 + C \left( \sum \xi_i \right)^k \), where \( C \) is a parameter to be chosen by the user. A large \( C \) corresponds to assignment of higher penalty to errors.

However, in many cases, the data cannot be separated by a linear function. A solution is to map the input data into a different space \( \Phi(x) \). This paper uses RBF kernel function \( K(x_i, x_j) \) as follows:

\[
K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0
\]

The recognition state input is the features of ROI. In the classification system design, features extraction of traffic signs is the foundation of well realization of road signs recognition. In this paper, the HOG features are extracted from the image, which represent the occurrence of gradient orientations in the image. The HOG descriptor provides excellent performance compared to other existing feature descriptors, due to its fine-scale gradients, fine orientation binning and high-quality local contrast normalization in overlapping descriptor blocks [21].

The HOG features are computed on a dense grid of cells using local contrast normalization. A nine-bin histogram of unsigned pixel orientations weighted by magnitude is created for each cell. These histograms are normalized over each overlapping block. The components of the feature vector are the values from the histogram of each normalized cell. Although this intensive normalization produces large feature vectors, it provides high accuracy. The dimensions \( D \) of the HOG feature vector is computed using

\[
D = \left( \frac{R_{\text{width}}}{M_{\text{width}}} - 1 \right) \times \left( \frac{R_{\text{heigh}}}{M_{\text{heigh}}} - 1 \right) \times B \times H,
\]

where \( R \) is the region, \( M \) is the cell size, \( B \) is the number of cells per block, and \( H \) is the number of histograms per cell. Road sign examples and related HOG features are shown as Fig. 5.

The road sign detection and recognition results are displayed in Fig. 6. Different experiments including sunny, cloudy and rainy conditions are done. And the results are apparent and efficient.

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Fig. 5. Road signs and related histograms of oriented gradients (HOG features).

Fig. 6. Some results of road sign detection and recognition on the images from [22].
3. Experimental Results

To prove the effectiveness of our framework, we test the proposed method on the database from [22]. Each image is segmented using the hue component of a HSI image. Histograms of hue are built for red, blue, and yellow sign colors. Geometry symmetry is applied to discard non road sign objects and speed up the process. And shape symmetry and area are further used to classify the different sign shapes initially. SVMs with RBF kernel is then used to recognize each sign type based on a training set of between 50~100 images per class on an unspecific number of classes. A model is obtained after SVM training and it is used to recognize candidate regions directly. Recognizing road signs without training the database every time saves a lot of processing time.

To assess the performance of the system, a test data set is collected and road sign images are obtained from the Internet. Images are all scaled to 640×480 pixels. The implementation is running on a 1.5 GHz Intel Core T5250 central processing unit under Visual Studio 2008. There are two important criteria that defined for evaluating the system as below:

- Processing time: the time of recognizing road signs from an image. This criterion is calculated based on the average processing time of detection and recognition.
- Accuracy rate: the accuracy of recognizing the exact road sign types in the images. This measure is calculated as follows: ratio of the number of signs that have been correctly recognized to the total number of road signs.

According to the experiments, the average processing time is 1.23 second, and the accuracy rate of different conditions can be seen in Table 2.

<table>
<thead>
<tr>
<th>Situation</th>
<th>Image samples</th>
<th>Correct recognition</th>
<th>Accuracy rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sunny</td>
<td>33</td>
<td>30</td>
<td>90.90 %</td>
</tr>
<tr>
<td>Cloudy</td>
<td>28</td>
<td>26</td>
<td>92.85 %</td>
</tr>
<tr>
<td>Rainy</td>
<td>17</td>
<td>16</td>
<td>94.12 %</td>
</tr>
</tbody>
</table>

According to the experiments, the average processing time is 1.23 second, and the accuracy rate of different conditions can be seen in Table 2.

4. Conclusions

In this paper, a new method is provided for road sign detection and recognition. The method depends mainly on color segmentation, shape detection and classifications and SVM recognition exactly. In the system, the especially novel point is the detection and classification based on the geometry symmetry and shape area, as all the road signs shape like circle, rectangle, triangle, octagonal are symmetrical.

Currently, collecting numerous road sign images in real environment and improving the system is ongoing to enhance the system performance. For future work, more samples need to be tested in order to get a better evaluation of the system and more methods will be proposed to keep the road sign detection and recognition system more efficient. Furthermore, the approach based on symmetry, the property of some shapes, will also be considered to apply to other fields.

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