ROAD SIGN DETECTION BASED ON VISUAL SALIENCY AND SHAPE ANALYSIS

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ABSTRACT

Road sign detection plays an important role in driver assistance system. However, it faces problems of high computational cost and low contrast in video sequences. In this paper, we propose a two-level hierarchical algorithm which addresses these problems by making better use of the color and shape information of road signs. In order to solve the problem of low image contrast, we propose to improve the color contrast using our algorithm based on visual saliency. In order to reduce the high computational cost, an improved radial symmetry transform (IRST) is developed for grouping feature points on the basis of their underlying symmetry in an image. Experimental results show that our methods are robust to a broad range of lighting conditions and efficient enough for real-time applications.

Index Terms— Road sign detection, Shape analysis, Visual saliency, Improved radial symmetry transform (IRST)

1. INTRODUCTION

Recently, Ministry of Transport of the People's Republic of China reported that the 65-75% of the traffic accidents that have resulted in over 100,000 deaths per year in China were resulted from driver inattention and distraction [1]. Furthermore, there is an increasing number of in-vehicle systems information, communication and entertainment systems which dramatically increase car accidents as resulting by driver distraction. Thus, the advanced driver assistance systems have received more attention. For implementing such a system, the road sign detection technology has been important issues for researchers.

Automatic detection of road sign is an essential task for regulating traffic, guiding and warning drivers and pedestrians. However, there exist a number of difficulties which make it a challenging task, such as complex background and illumination, shape variations caused by translation and rotation, low resolution, noisy and obscured signs caused by different geographic and weather conditions, differences of the same signs, other objects with the same color and texture, etc. On the other hand, road signs have well defined color, shape, and size, which can aid in detection. This paper describes a fast method for locating road signs in a sequence of images.

Most existing algorithms for road sign detection focus on the color and shape information of road signs [2, 3, 4, 5]. So, several color-based sign detection algorithms and shape-based sign detection algorithms have been proposed by taking use these beneficial characteristics [8, 9]. Although these methods have achieved a reasonably good performance for detecting specific road traffic signs, there remain a number of challenges for successful detection of road signs with large variance in their appearance.

In this paper, we aim to develop a more effective algorithm that can handle the large variety of road signs. The approach proposed in this paper follows a two-level hierarchical structure, as illustrated in Fig. 1. In our algorithm, the input image sequences firstly go through a segmentation module to obtain candidate regions which may contain road signs. These candidate regions are then identified as either a road sign or non-road sign by a recognition module.

In the context of this framework, our main contributions in this paper are two-fold: 1) When generating candidate regions, we propose a novel color enhancement scheme based on visual saliency and shape features; 2) For sign recognition, instead of using the conventional shape-based features, we modify the radial symmetry transform and propose an improved radial symmetry transform, named as IRST, which can recognize road signs more efficiently.

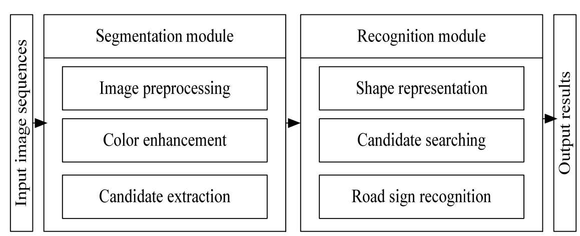

Fig. 1. The framework of the proposed method.

The rest of the paper is organized as follows. Sections 2 and 3 detail the two above mentioned modules of our proposed algorithm. Section 4 presents experimental results where performance is compared with the state-of-the-art approaches. We conclude the paper in Section 5.

2. SEGMENTATION

Image segmentation is the procedure of dividing an image into its constituent regions, where the regions generally correspond to objects or parts of objects. Obtaining candidate road sign regions is the key goal in this section.

As the camera installed on a vehicle is moving, additional image distortions, such as motion blur and abrupt contrast changes, can occur frequently. Moreover, because of variation in the ambient illumination, it is very hard to search for regions with specific red, green, and blue values. To solve this problem, a segmentation algorithm based on visual saliency is proposed.

Several authors suggested using the HSV and YCbCr color space instead of RGB [3,4], but we found that our color enhancement algorithm based on normalized RGB colors worked better and did not require color space conversion.

After extracting the red (R), green (G), blue (B) color feature from an input color image, the normalized r, g, b, and y color features are defined as：

$$
\begin{aligned}
r &= \max(0, R - \frac{G+B}{2}) \\
g &= \max(0, G - \frac{R+B}{2}) \\
b &= \max(0, B - \frac{R+G}{2}) \\
y &= \max(0, \frac{R+G}{2} - B).
\end{aligned}
\tag{1}
$$

where the operation $\max(X,Y)$ returns the larger value between X and Y.

Then, in order to depict the characteristics of road signs, for warning signs, we require that the r, g, b, and y values conform to the following constraints:

$$y/(y+g) > \alpha_{warn} \;\&\; y/(y+b) > \beta_{warn} \;\&\; y - r > \lambda_{warn} \tag{2}$$

Whereas for prohibitory signs (generally with red color), we require:

$$r/(r+g) > \alpha_{red} \;\&\; r/(r+b) > \beta_{red} \;\&\; r - y > \lambda_{red}, \tag{3}$$

where $\alpha_{warn}, \alpha_{red}, \beta_{warn}, \beta_{red}, \lambda_{warn}$ and λ_{red} are constants, which values are determined by sampling the red, green, and blue values of images of typical signs. For these guiding signs on highways (white letters green background), we define a similar set of constraints, making it very easy to increase the range of signs detected by the algorithm.

Finally, a segmentation algorithm based on visual saliency is shown as follows:

Segmentation algorithm based on visual saliency

Input: Image sequences.
Output: Final segmentation results.
While there exists an input image in the last loop
Step 1. The Equation (1) is applied pixel by pixel to the input image to obtain normalized color features.
Step 2. The Equations (2) and (3) are calculated using the normalized color features, As a result, a binary image is generated, which non-zero pixels indicate candidates for belonging to a road sign.
Step 3. Perform morphological erosion, area filling and image denoising on the binary image obtained in **Step 2**.
Step 4. For each connected area (a.k.a, blobs), compute its centroid and compactness (i.e., the ratio of the area of the blob to the area of its bounding box). Blobs that conform to the rules of road signs are considered to be road sign candidates.
End

3. SHAPE ANALYSIS

The blobs that are obtained from the segmentation stage are verified in this section according to their shape symmetry feature. Radial symmetry transform (RST) was used to detect regular polygons in [6, 7, 10]. The method uses the symmetric nature of these shapes, together with the pattern of edge orientations exhibited by equiangular polygons with a known number of sides, to establish possible shape centroid locations in the image [6]. This method operates on the gradient of a gray-scale image and can efficiently detect points of high radial symmetry. Unlike previous techniques, RST evaluates the contribution that each pixel makes to the symmetry of pixels around it, rather than considering the contribution of a local neighborhood to a central pixel.

In the traditional RST algorithm, sometimes the search of certain regions is unnecessary, and hence the detection method is not most efficient. In order to decrease the computational complexity and improve the accuracy of detection, we propose an IRST, which improves the original RST mainly from the following two aspects: limiting the scope of the search, and changing the voting rule.

In order to illustrate our improvement more clearly, some concepts will be introduced in advance.

1) The area S of each blob (in Section 2) is defined as:

$$S = \sum_{(x,y)\in R} f(x,y), \tag{4}$$

where $f(x,y)=1$. It can be easily verified that area S is rotation and translation invariant.

2) Roughness of shape, denoted as P, is defined as:

$$P = 4\pi S / L^2, \tag{5}$$

where L denotes the length of the outer boundary of the blob. Different P values denote different shapes, for example, P=1 (circular) and P=0.6046 (triangular).

3) Color enhancement image, denoted as ei, is obtained as follows:

$$ei = \left|(r-g)-(b-y)\right|, \tag{6}$$

where r, g, b, and y are defined in Equation (1).

4) Edge image e is defined as follows:

$$e = \sqrt{(ei \cdot R_x)^2 + (ei \cdot R_y)^2}, \qquad (7)$$

where R_x and R_y are horizontal and vertical Sobel operators.

In Section 2, we have obtained candidate regions. Here we retain the segmented regions above in the edge image e, and remove other regions that do not belong to candidate regions, then we can get a new image, denoted by $\bar{e}$. Our IRST algorithm operates on the image $\bar{e}$. Hence, it reduces the scope of the search to the utmost extent and improves the computation efficiency.

On the other hand, the traditional voting rule increases the computational complexity due to not determining the shapes and centers of targets in advance. In our algorithm, the points voted for are called *affected pixels* and are defined as:

$$A \pm ve(A) = A \pm round\left(r \frac{g(A)}{\|g(A)\|}\right), \qquad (8)$$

where $g(A)$ denotes a unit gradient vector starting at point A and passing by the centroid of the blob (Section 2), and is perpendicular to the edge at point A, r is the searching radius, $\|\cdot\|$ is the norm of a vector, and "round" rounds each vector element to the nearest integer. There are positive $A + ve(A)$ and negative $A - ve(A)$ affected pixels corresponding to points that the gradient points to, at a distance of r, and away from A respectively. In our experiments, $r \in \{8, 10, ..., 18\}$.

Thus, the line on which the affected pixels lie can be approximated by:

$$L(A) = \begin{cases} A \pm ve(A) + r \tan\frac{\pi}{8} \frac{g(A)}{\|g(A)\|}, & 0.8511 < P < 0.9566 \\ A \pm ve(A), & 0.9566 < P \le 1 \\ A \pm ve(A) + r \tan\frac{\pi}{3} \frac{g(A)}{\|g(A)\|}, & 0.5566 < P \le 0.6046 \end{cases} \qquad (9)$$

For other P values, we do not do the operation of voting rule. Whether targeting circles or regular polygons, all votes are accumulated into a voting image, calculate the output image at radius r, and accommodate for scale. The result is a vector field B_r, whose magnitude indicates how well the gradient elements voting on each point match the target angular spacing. Based on our voting rule idea, rotational symmetry centers can be detected, as shown in Fig. 2.

Fig. 2. Input images and their voting results.

To detect the signs, we search the voting image, for values above a threshold defined as the required number of pixels for the smallest radius. We then check all the individual radii to find if any are above the threshold of edge pixels for that radius. It could be that a high vote in Equation (9) results only from a collection of accidental votes from several contributing radii. If a particular radius is above the threshold, then this is a possible road sign region.

Other details of the IRST algorithm are similar to those in [6], with some modifications to suit the above equations.

Thus, the IRST algorithm examines each candidate region in the segmented images and classifies them as either known road signs for output or not.

4. EXPERIMENTAL RESULTS

To demonstrate the efficiency of our proposed algorithm, we performed experiments on a large collection of images, which are collected and captured by us using cameras installed on moving vehicles. In the data set, there are 500 images containing in total 726 road signs of 42 different types. Fig. 3 shows the segmentation results based on visual saliency (Section2). It can be seen that some small blobs and big blobs have been removed and blobs not meeting these rules have also been deleted from further processing.

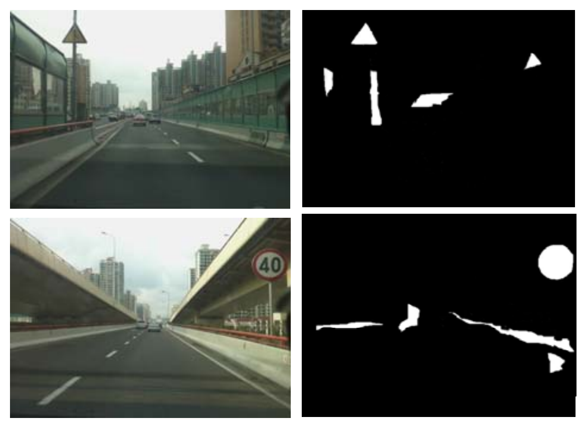

Fig. 3. Examples of detection results. Left: original images; right: the segmented images.

Now the IRST algorithm takes the candidate regions as input and processes all these regions in order to classify them as known road signs or to reject them. Examples of the detection are shown in Fig. 4 and Fig. 5.

The algorithm only fails in two instances and these are shown in Fig. 6. In one case this is due to occlusion (left), while the other one (right) is caused by the lack of contrast and the indistinct edge between the sign and the background.

In order to demonstrate the superior performance of our proposed algorithm, we compared the performance of our algorithm with those of the state-of-the-art approaches implemented by us, including the SVM approach proposed in [2] and the RST approach of [6]. Detection rate (Hits), missing rate (Misses), false alarm rate (FA) and average processing time are compared, as shown in Table 1. All experiments were conducted using a computer with 2.19GHz CPU of 1GB RAM.

Fig. 4. Results of searching for road signs, where the localized road signs are marked in white circles.

Fig. 5. Some images where candidate detection was difficult.

Fig. 6. Instances where our sign detection algorithm failed. Left: occlusion. Right: low contrast.

Table 1. Performance comparison of our algorithm with the state-of-the-art.

Algorithms	Hits	Misses	FA	Time
SVM [2]	93.29%	6.71%	2.59%	621ms
RST [6]	96.21%	3.79%	1.16%	408ms
Ours	**97.66%**	**2.34%**	**0.96%**	**293ms**

By verifying the obtained results, we can find that the visual saliency and shape analysis based on our proposed system is effective and robust for correct detection of road signs.

5. CONCLUSION

In this paper, a novel algorithm for road sign detection based on visual saliency and shape analysis has been proposed. The segmentation-based detection algorithm is found to be robust for its ability to mark a road sign as a candidate region. Then, the shape classification algorithm improves the computation time in the next stage of recognition. In general, in this paper we mainly do the following work: in order to solve low contrast problem, segmentation algorithm based on visual saliency is proposed; in order to effectively recognize road signs, an IRST algorithm is proposed. Experimental results have shown a high detection rate, and the choice of the visual saliency has a profound impact on the performance of detection and recognition.

The vision-based road sign detection is a relatively independent subject that touches wider areas, and there exist many problems that have not been solved perfectly. In future work, we are planning to focus on the following issues: 1) To develop other detectors that are capable of finding signs with other shapes, such as give-way signs. 2) To utilize the developed system for tracking the road signs in a continuous mode from a video sequence. 3) To do some improvements so that the algorithm will not fail to detect road signs in the case of insufficient contrast with background and considerable occlusion.

6. ACKNOWLEDGMENT

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