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ROAD SIGN DETECTION AND SHAPE RECONSTRUCTION USING GIELIS CURVES

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Abstract: Road signs are among the most important navigation tools in transportation systems. The identification of road signs in images is usually based on first detecting road signs location using color and shape information. In this paper, we introduce such a two-stage detection method. Road signs are located in images based on color segmentation, and their corresponding shape is retrieved using a unified shape representation based on Gielis curves. The contribution of our approach is the shape reconstruction method which permits to detect any common road sign shape, i.e. circle, triangle, rectangle and octagon, by a single algorithm without any training phase. Experimental results with a dataset of 130 images containing 174 road signs of various shapes, show an accurate detection and a correct shape retrieval rate of 81.01% and 80.85% respectively.

1 INTRODUCTION

Intelligent Transportation System (ITS) has been a rapidly growing topic of research over the last years. One important component of any ITS is the capability of automatic road sign recognition. The detection and identification of road sign is useful in highway maintenance, sign inventory or driver support systems.

A road sign recognition system is composed of two main stages: the detection and the recognition (Bascon et al., 2007). Detection is performed to obtain an initial candidate of road sign, *i.e.* the possible region that represents road sign characteristics, using either color or shape information. Consequently, it requires a *recognizer* equipped with a set of features or patterns (Bascon et al., 2007; Escalera et al., 2003). Commonly used classifiers include neural network (Bascon et al., 2007), clustering (Escalera et al., 2003), nearest neighbor (Escalera et al., 2004), Laplace kernel (Fang et al., 2003), and support vector machines (Nguwi and Kouzani, 2008).

In this paper we focus on the detection stage of road signs in still images or videos. Several problems on detecting road signs in natural scene images include misdetection, occlusions, motions blur issues and scale variations.

The two main features used to detect and recognize road signs are the color and the shape. Color is a powerful cue for object detection, but is sensitive to image acquisition conditions. On the other hand, the shape is invariant to illumination, but sensitive to occlusions and perspective distortions. Color based detection methods are based on color segmentation. For example, (Varun et al., 2007) use a simple threshold formula applied to the red color channel to detect red road signs. Several color spaces can be used, including HSV (Paclik et al., 2000), HSI (Escalera et al., 2003; Fang et al., 2003), CIECAM97 (Gao et al., 2006) and IHSI (Fleyeh, 2004).

Shape based methods have strong robustness to changing illumination as they detect shapes based on edges. The most recurrent method is certainly the generalized Hough transform (Ballard, 1981). Recently, (Loy and Zelinsky, 2002) propose the fast radial symmetry transform which is a technique similar to Hough transform. The method was extended and successfully used to detect regular polygons by (Loy and Barnes, 2004). (Gavrila, 1999) uses a template matching approach for shape detection. First, edges in the original image are found. Then, a distance transform image is created and match against a reference template (for instance, a triangle).

In this paper, we propose a robust road sign detection method which uses the color information to localize potential road signs and then, based on shape representation using Gielis curves (Gielis, 2003), identifies the shape of the detected signs. The major advantage of our approach is that it does not need

a multi-layer architecture as used in machine learning approaches (neural network or support vector machines). Furthermore, no initial training is needed. Hence, the method is simple, fast, and is able to identify any common road sign shape (triangle, rectangle, octagon and circle). Additionally, the proposed method is scale invariant and accurately detects road signs of different sizes.

The paper is organized as follows: The color segmentation method adopted in our work is then described in Section 2. Section **??** introduces Gielis curves and the road sign shape identification algorithm. Experimental results are shown in Section 3 before our conclusions in the last section.

2 ROAD SIGN DETECTION AND SHAPE RECONSTRUCTION

The first step of the proposed method is the localization of potential road signs in the image through color segmentation. For robustness against lighting variations, the Improved Hue, Luminance and Saturation (IHLS) color space is selected. Once an image is converted to IHLS color space, potential road signs are detected using the segmentation method first introduced by (Escalera et al., 2003) and also used by (Fleyeh, 2004).

Figure 1 shows some segmentation results. As can be seen, road signs are correctly localized with the segmentation method in most cases. However, in some situations, because of lighting changes or occlusion, road signs are not entirely detected. Thus, some post-processing steps are necessary to help the shape reconstruction algorithm.

Introduced by (Gielis, 2003), the superformula extends the superellipses by introducing variable rotational symmetry and asymmetric shape coefficients. The angle ϕ is replaced by $\frac{m\phi}{4}$ to obtain m rotational symmetries, and the unique shape coefficient n for superellipses is replaced by a triplet (n_1, n_2, n_3), leading to the following radial polar parameterization:

$$r(\phi) = \frac{1}{\sqrt[n_1]{\left|\frac{1}{a}\cos\left(\frac{m\phi}{4}\right)\right|^{n_2} + \left|\frac{1}{b}\sin\left(\frac{m\phi}{4}\right)\right|^{n_3}}}. \quad (1)$$

a, b, and n_i are positive real numbers ($a, b, n_i \in \mathbb{R}^+$). a and b control the scale while n_1, n_2, and n_3 control the shape. $m \in \mathbb{R}_*^+$ represents the number of rotational symmetries. By modifying the shape parameters, the set of the regular polygons can be generated. Three additional coefficients T_x, T_y and ϕ_0, corresponding to the position of the shape in the image and its angular offset are added to represent Gielis curves in the general case. Consequently, the parameters set Λ of a Gielis curve is defined as $\Lambda = \{a, b, n_1, n_2, n_3, m, T_x, T_y, \phi_0\}$.

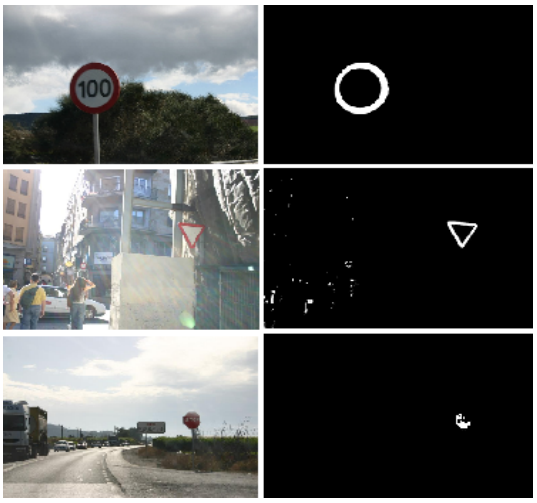


Figure 1: Example of segmentation results.

The process of 2D data representation by Gielis curves starts by building a signed potential field (Fougerolle et al., 2005). A potential field is a signed function F which characterizes the inside and outside of a closed object, such that $F(x)$ is positive if a point x lies within the object, $F(x)$ is negative if x lies on the outside, and $F(x) = 0$ if x lies on the curve.

The potential field is used to build a cost function to be minimized in the least-squared sense using Levenberg-Marquardt (LM) algorithm as illustrated in Figure 2.

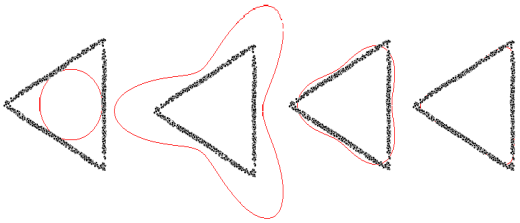


Figure 2: Levenberg-Marquardt: evolution of the curve.

3 EXPERIMENTS

We evaluate the performance of the proposed approach on a dataset of 130 images containing 174 signs of various shapes and types. The dataset is a subset of the one used by (Bascon et al., 2007).

Figures 3, 4, 5, and 6 show some detection results for circular, octogonal, rectangular and triangu-



Figure 3: Detection for circular road signs



Figure 4: Detection for octogonal road signs



Figure 5: Detection for rectangular road signs

lar signs, respectively. As can be seen in these images, the shape reconstruction method can successfully identify different road sign types. It is important to note that the algorithm accurately detects road sign of different sizes in the image. This is a clear advantage over the method developped by (Loy and Barnes, 2004) where different radii are tried in order to find the correct size of road signs.

Detection results using the entire dataset are summarized in Table 1. From the 174 road signs, 141 are correctly detected and 114 road sign shapes are successfully reconstructed. Undesired detection occurs for 23 objects having similar color with road signs, while 27 road signs are incorrectly reconstructed. The percentage of road sign detection and shape reconstruction results are listed in Table 1. For each reference color, we calculate the percentage from the number of detected (reconstructed) road signs divided by the total number of road signs of that particular color. The total percentage is calculated from the number of detected (reconstructed) road signs in both colors divided by the total number of road signs in the images.

Note that the performance of the shape reconstruction method (identification of road sign shape) is directly related to the performance of the detection step (color segmentation). Indeed, the shape of a road sign which is not detected in the segmentation step will obviously not be reconstructed. Several road signs in the dataset appear at a far distance from the camera, and can be eliminated in the post-processing stage, lowering detection rate.

Incorrect reconstructions are due to different causes including incorrect segmentation, wrong initialization of the fitting algorithm and perspective distortion as illustrated in Figure 7.

4 CONCLUSION

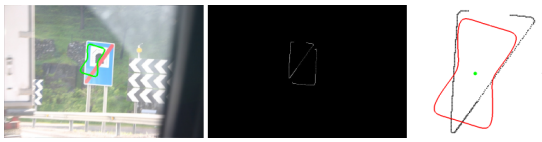
In this paper, a novel road sign detection method is proposed. The method first uses color information to localize potential road signs and then, identifies the correct shape of the detected signs. Shape detection is based on shape representation using Gielis curves which provides an elegant way to handle all common road sign types, *i.e.* triangles, rectangles, octagons, and ellipses. Experimental results show the robustness of the approach in detecting traffic signs of various shapes. The method is invariant to in-plane rotation and to small perspective distortion due to the introduction of a rotational offset as a parameter in the fitting algorithm. It is also able to detect signs of different sizes in the image. The different causes of failure can be considered by improving the color segmentation method robustness to illumination effect. We could for example apply a color constancy algorithm prior to segmentation. Another improvement would be the introduction of a parameter in the fitting algorithm to account for strong perspective distortions. Eventually, the general least square formulation of the problem could be replaced by a more robust version, using M-estimators for instance, in or-



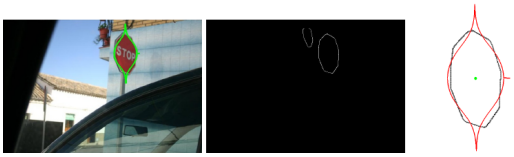
Figure 6: Detection for triangular road signs

Table 1: Summary of detection and reconstruction results

	Detection (%)		**Reconstruction (%)**	
	detected	not detected	correct	incorrect
Red Signs	81.43	18.57	81.58	18.42
Blue Signs	79.41	20.59	77.78	22.22
TOTAL	**81.03**	**18.97**	**80.85**	**19.15**



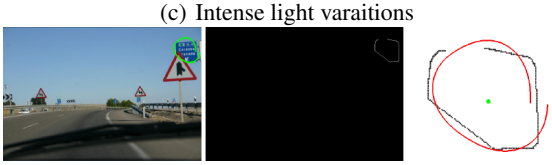
(a) Multiple parts extraction



(b) High perspective distorsions



(c) Intense light varaitions



(d) Occlusions

Figure 7: Examples of wrong reconstruction.

der to better handle outliers to improve the results in presence of degenerate contours due to occlusions or strong light variations.

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