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A Novel Translation, Rotation, and Scale-Invariant Shape Description Method for Real-Time Speed-Limit Sign Recognition

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Abstract

Speed-limit sign (SLS) recognition is an important function to realize automatic driving assistance systems (ADAS). This paper presents a novel design of an image-based SLS recognition algorithm, which can efficiently detect and recognize SLS in real-time. To improve the robustness of the proposed SLS algorithm, this paper also proposes a new shape description method to describe the detected SLS using centroid-to-contour (CtC) distances of the sign content. The proposed CtC descriptor is invariant to translation, rotation, and scale variations of the SLS in the image. This advantage increases the recognition rate of a linear support vector machine classifier. The proposed SLS recognition method had been implemented and tested on an ARM-based embedded platform. Experimental results validate the SLS recognition accuracy and real-time performance of the proposed method.

Key words: Speed-limit sign recognition, road-sign detection, shape description, centroid-to-contour descriptor.

Introduction

Implementation of a speed-limit sign (SLS) recognition algorithm is a critical task in the design of automatic traffic sign recognition (TSR) systems. Traditional SLS recognition systems usually work with a global positioning system and a pre-established traffic sign database to determine what speed limits may appear in front of the current location. However, this method may obtain a false alarm when an older version of the database is used in the system. This problem thus motivates us to develop a visual SLS (VSLS) recognition system to efficiently recognize the SLS on the road in real-time.

Current VSLS recognition systems usually consist of SLS detection and SLS recognition processes. Here, we only focus on the issue of SLS recognition, which can be divided into two stages. In the first stage, a sign content extraction process is employed to extract the content of the detected sign. In the second stage, sign content description and classification algorithms are used to recognize the type of the extracted sign content. Several reported works have addressed the issue in the second stage. For instance, Bui-Ninh et al. used image patch of the detected road sign as the sign descriptor to recognize its type using a support vector machine (SVM) classifier [1]. Salhi et al. used feed-forward artificial neural networks to train a scale-invariant sign classifier, which recognizes the detected road sign invariant to scale changes [2]. Jin et al. realized a robust traffic sign classifier based on convolutional neural networks (CNN), which is able to accomplish both feature extracting and classifying tasks simultaneously [3]. However, the training of CNN-based sign classifier is still a challenging task as it usually has a large number of parameters. To reduce the computational complexity of TSR function, some researches have addressed the design of sign description methods to speed up recognition process. In [4], Greenhalgh and Mirmehdi applied the histogram of oriented gradient (HOG) description method [5] to produce HOG features of the candidate sign regions. Zaklouta and Stanciulescu used different-sized HOG features to describe the detected road sign [6]. The authors in [7] reviewed the existing traffic sign recognition methods and found that using HOG features obtains the best detection performance. However, extracting HOG features is also computationally expansive and is difficult to implement on embedded systems.

As the application of embedded systems becomes more and more popular, this paper proposes a novel sign content description method based on centroid-to-contour (CtC) distances of the sign content. The contribution of the proposed CtC descriptor is twofold. First, the proposed CtC descriptor is invariant to translation, rotation and scale variations. This advantage improves the robustness of the SLS recognition process. Second, the computation of the proposed CtC descriptor is simple and efficient. Therefore, the proposed method is very suitable to implement on embedded systems. This advantage increases the applicability of the proposed SLS recognition algorithm. Experimental results show that the proposed method not only provides accurate recognition results robust to translation, rotation and scale variations, but also achieves real-time performance running on an embedded platform equipped with an ARM Cortex-A9 Quad-Core 1.6GHz CPU running Android 4.4 operating system.

System Architecture

Figure 1 shows the block diagram of the proposed SLS detection and recognition system, which consists of four steps: SLS detection, sign content extraction, sign content description, and SLS recognition. In the SLS detection step, an efficient color-based SLS detector was designed to detect the candidate region-of-interest (ROI) in real-time. Each candidate ROI may contain a road sign. To identify the type of the road sign in the ROI, the content of each candidate ROI is extracted using

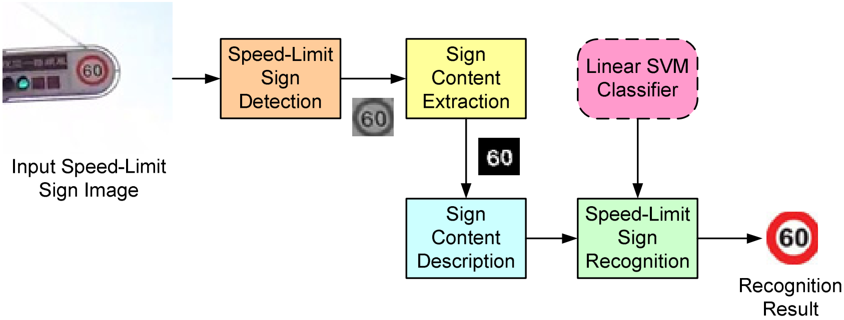

Fig. 1 Block diagram of the proposed SLS detection and recognition system.

image thresholding and connected component analysis operations. Finally, the sign content extraction process results several binary images, each of them records the binarized sign content of the corresponding ROI image.

Before recognizing the type of the candidate ROI image, a shape description process is required to transform the binarized sign content into a shape descriptor to describe shape information of the ROI image. In this paper, a novel CtC-based shape descriptor is proposed. The proposed method is inspired from the existing distance-from-centre (DfC) description method [8], which uses distances from the centre of the blob to the external edge of the blob to describe the detected road sign. By contrast, the proposed method computes distances from the centroid of the binarized sign content to the contour of the content. The technical details of the proposed CtC descriptor are presented in the next section.

Once a CtC descriptor of the candidate ROI image is obtained, a linear support vector machine (SVM) classifier is used to classify traffic signs into ten groups (30, 40, 50, 60, 70, 80, 90, 100, 110, and unknown classes). In this work, the open source LIBSVM library [9] was adopted for the training of the linear SVM classifier based on a training dataset containing about thirty-seven thousand sign content images randomly generated with different translation, rotation and scale variations. Finally, the linear SVM classifier was implemented on an embedded system to realize the proposed SLS recognition system.

The Proposed Method

This section presents the design of the proposed CtC description method, which uses the CtC distances as the shape features to describe a binary sign image. Let $I_b(x, y)$ denote the input binary sign content image of each pixel (x, y). We first compute image moments of the binary sign image

$$M_{pq} = \sum_x \sum_y x^p y^q I_b(x, y), \tag{1}$$

where $p, q = 0,1,2$. Then, the centroid of the binary sign image is then computed by

$$\bar{x} = M_{10} M_{00}^{-1} \text{ and } \bar{y} = M_{01} M_{00}^{-1}, \tag{2}$$

where $\bar{x}$ and $\bar{y}$ are the components of the centroid. Based on Eq. (1) and Eq. (2), the central moments μ_{11}, μ_{20}, and μ_{02} can be determined by

$$\mu_{11} = M_{11} - \bar{x} M_{01},\ \mu_{20} = M_{20} - \bar{x} M_{10}, \text{ and } \mu_{02} = M_{02} - \bar{x} M_{01}. \tag{3}$$

Then, the orientation of the binary sign image is computed using the second-order central moments such that

$$\theta_{sign} = \frac{1}{2} \tan^{-1}\left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right) \text{ for } \mu_{20} - \mu_{02} \neq 0, \tag{4}$$

where θ_{sign} denotes the orientation angle of the sign, which is helpful to produce a rotation-invariant descriptor. Next, a contour detection method is applied on the binary sign image to extract contour paths of the sign content region. Let C_n denote a contour path containing n contour points. Suppose that there are N contour paths extracted from the binary sign image. For the j-th contour path $C_{n_j}^j$, j=1~N, we compute the distance from image centroid to each contour point of $C_{n_j}^j$ such that

$$d_i^j = \left\| \mathbf{p}_i^j - \bar{\mathbf{p}} \right\|_2, \tag{5}$$

where $\|\mathbf{x}\|_2$ denotes 2-norm value of a vector $\mathbf{x}$, $\mathbf{p}_i^j = (x_i^j, y_i^j)$ for $1 \le i \le n_j$ denote the coordinates of a contour point on $C_{n_j}^j$, n_j is the contour point number of $C_{n_j}^j$, and $\bar{\mathbf{p}} = (\bar{x}, \bar{y})$ is the centroid computed by Eq. (2). d_i^j is termed as the CtC distance of each contour point on $C_{n_j}^j$. Moreover, the orientation angle of the contour point (x_i^j, y_i^j) with respect to sign orientation is computed by

$$\theta_i^j = \theta_{\mathbf{p}_i^j - \bar{\mathbf{p}}} - \theta_{sign}, \tag{6}$$

where $\theta_{\mathbf{p}_i^j - \bar{\mathbf{p}}}$ is the direction angle of the vector $\mathbf{p}_i^j - \bar{\mathbf{p}}$, and θ_{sign} is the sign orientation angle given by Eq. (4). Define a positive integer number D that determines the dimension of the proposed CtC descriptor. Then, the elements of the CtC descriptor are defined as the maximum distance value of the CtC distances computed by Eq. (5) within an angular interval such that

$$d_k = \max\left\{ d_i^j : 1 \le i \le n_j, 1 \le j \le N, \theta_{k-1} \le \theta_i^j < \theta_k \right\}, \tag{7}$$

where $\theta_k = 2\pi k / D$ for $1 \le k \le D$ is the k-th fixed angle defined by the descriptor dimension D, and d_k the the k-th element of the CtC descriptor. Finally, the maximum norm of the CtC descriptor is normalized to one to achieve scale-invariant property. In this work, the default dimension number of the CtC descriptor is set as D=36. The robustness of the proposed CtC descriptor is validated in the next section.

Experimental Results

The performance of the proposed CtC-based sign description algorithm has been tested on an Android 4.4 platform equipped

(a)

(b)

Fig. 2 Experimental results obtained from the highway.

with a 1.6GHz ARM Cortex-A9 Quad-Core CPU (Radxa Rock Pro [10]). An Android application program was developed to test the proposed method on android platforms. In the experiments, the image size is set to 640-by-480 pixels. The Android embedded implementation had been tested the system on the highway to evaluate the robustness and real-time performance of the proposed method. Figure 2 shows the experimental results obtained from the highway. It is clear that the proposed method successfully detect and recognize the SLS in real-time.

Table I tabulates the average processing time in each step of the proposed method running on the embedded platforms. From Table I, it is clear that the total processing time of the proposed method is less than 45ms, achieving real-time performance up to 22 fps in processing VGA video streams.

Conclusions and Future Work

A novel CtC-based shape description algorithm is proposed in this paper to achieve real-time robust SLS recognition. The proposed description method uses centroid-to-contour distances as the feature values to describe the detected road sign. The proposed CtC descriptor is robust to translation, rotation and scale variations of the SLS in the image, which improves the recognition accuracy of the SLS recognition process. Moreover, the proposed CtC descriptor is computationally efficient and can run in real-time on an ARM-based embedded system. Experimental results validate the robustness and real-time performance of the proposed method. In future work, more experimental results will be carried out to validate the performance of the proposed method.

TABLE I
AVERAGE PROCESSING TIME OF THE PROPOSED METHOD FOR PROCESSING 640×480 VIDEO STREAMS

SLS Detection	Sign Content Extraction	Sign Content Description	SLS Recognition
42.042 ms	0.749 ms	0.085 ms	1.674 ms
Total Time	44.550 ms		
Frame Rate	22.45 frames per second (fps)		

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References

[1] T. Bui-Ninh, O. Ghita, P. F. Whelan, and T. Hoang, "A robust algorithm for detection and classification of traffic signs in video data," *International Conference on Control, Automation and Information Sciences*, Ho Chi Minh City, Vietnam, pp. 108-113, 2012.

[2] A. Salhi, B. Minaoui, and M. Fakir, "Robust automatic traffic signs recognition using fast polygonal approximation of digital curves and neural network," *International Conference on Multimedia Computing and Systems*, Marrakech, Morocco, pp. 433-437, 2014.

[3] J. Jin, K. Fu, and C. Zhang, "Traffic sign recognition with hinge loss trained convolutional neural networks," *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, No. 4, pp. 1991-2000, 2014.

[4] J. Greenhalgh and M. Mirmehdi, "Real-time detection and recognition of road traffic signs," *IEEE Transactions on Intelligent Transportation Systems*, Vol. 13, No. 4, pp. 1498-1506, 2012.

[5] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Diego, CA, USA, pp. 886-893, 2005.

[6] F. Zaklouta and B. Stanciulescu, "Real-time traffic-sign recognition using tree classifiers," *IEEE Transactions on Intelligent Transportation Systems*, Vol. 13, No. 4, pp. 1507-1514, 2012.

[7] M. Mathias, R. Timofte, R. Benenson, and L. V. Gool, "Traffic sign recognition – How far are we from the solution?" *International Joint Conference on Neural Networks*, Dallas, TX, USA, pp. 1-8, 2013.

[8] C. G. Kiran, L. V. Prabhu, V. A. Rahiman, K. Rajeev, and A. Sreekumar, "Support vector machine learning based traffic sign detection and shape classification using distance to borders and distance from center features," *IEEE Region 10 Conference*, Hyderabad, India, pp. 1-6, 2008.

[9] C.-C. Chang and C.-J. Lin, "LIBSVM: a library for support vector machines," *ACM Transactions on Intelligent Systems and Technology*, Vol. 2, No. 3, pp. 1-27, 2011.

[10] Radxa Rock Pro webpage: http://wiki.radxa.com/Rock

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