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Traffic sign detection and recognition based on random forests

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ABSTRACT

In this paper we present a new traffic sign detection and recognition (TSDR) method, which is achieved in three main steps. The first step segments the image based on thresholding of HSI color space components. The second step detects traffic signs by processing the blobs extracted by the first step. The last one performs the recognition of the detected traffic signs. The main contributions of the paper are as follows. First, we propose, in the second step, to use invariant geometric moments to classify shapes instead of machine learning algorithms. Second, inspired by the existing features, new ones have been proposed for the recognition. The histogram of oriented gradients (HOG) features has been extended to the HSI color space and combined with the local self-similarity (LSS) features to get the descriptor we use in our algorithm. As a classifier, random forest and support vector machine (SVM) classifiers have been tested together with the new descriptor. The proposed method has been tested on both the German Traffic Sign Detection and Recognition Benchmark and the Swedish Traffic Signs Data sets. The results obtained are satisfactory when compared to the state-of-the-art methods.

1. Introduction

Advanced Driver Assistance Systems (ADAS) play an important role in enhancing car safety and driving comfort. One of the most important difficulties that ADAS face is the understanding of the environment and guidance of the vehicles in real outdoor scenes [1]. Humans driving is a task based almost entirely on visual information, and one of the tasks in successful driving involves the identification of traffic signs. Traffic signs provide information about the current state of the road, restrictions, prohibitions, warnings, and other helpful information for navigation. The information provided by the road signs is encoded in their visual traits: shape, color and pictogram.

Road sign recognition has been a challenge problem for many years and is an important task not only for ADAS, but also for other real-world applications including urban scene understanding, automated driving, or even sign monitoring for maintenance. It is a relatively constrained problem in the sense that signs are unique, rigid, intended to be clearly visible for drivers, and have little variability in appearance Fig. 1. However, there are many factors that make the road sign recognition problem difficult such as:

- The colors of road signs, particularly red, may fade after long exposure to the sun Fig. 1(a).
- Air pollution and weather conditions (e.g. rain, snow, fog, shadows, and clouds) may decrease the visibility of road signs Fig. 1(b).
- Outdoor lighting conditions varying from day to night may affect the colors of road signs Fig. 1(c).
- Obstacles, such as vehicles, pedestrians, and other road signs, may partially occlude road signs Fig. 1 (d).
- Video images of road signs will have motion blur if the camcorder is mounted on a moving vehicle due to vehicle vibration as well as motion Fig. 1(e).

In this paper, we present a new traffic sign detection and recognition approach including three stages. The first stage segments the images to extract ROIs. The segmentation is usually performed based on the color information, which is known a priori [2–5]. The second one detects traffic shapes. Given that the geometric form of traffic signs is limited to triangular, circular, rectangular and octagonal forms, the geometric information is used to identify traffic shapes from ROIs provided by the first stage. Most of authors use machine learning algorithms such as SVMs and neural networks (NNs) to classify shapes provided by the segmentation step [5–7]. In this paper, we propose to use the invariant geometric moments with a simple metric to match the ROIs provided by the segmentation process with triangular, circular and rectangular shapes. It gives better results in a lower processing time compared to machine learning algorithms.

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Fig. 1. Examples for difficulties facing the traffic sign recognition (TSR) task.

The third stage recognizes the traffic signs based on the information included in their pictograms. The new method constitutes an improvement of the one presented recently in [8] where grey level-based HOG features have been used instead of HSI-based ones, which are adopted in the current work. Thus, we integrated the color information into the HOG features by using the HSI components to compute the descriptor instead of gray-scale images. Moreover, in this work, we combined the HOG features computed from the HSI color space with the LSS features to form a new descriptor. These features were provided to the Random Forest classifier to perform the recognition.

The rest of the paper is organized as follows. Section 2 presents an overview of past work on traffic sign detection and recognition. Section 3 details the proposed approach to traffic sign detection and recognition. Experimental results are illustrated in Section 4. Section 5 concludes the paper.

2. Related work

Many different approaches to traffic sign recognition have been proposed and it is difficult to compare between those approaches since they are based on different data. Moreover, some articles concentrate on subclasses of signs, for example on speed limit signs and digit recognition. Regarding the detection problem, different approaches have been proposed. In the older studies, e.g. [2,6], as well as in many recent ones, e.g. [9–12], it was common to employ color segmentation [2–4,13,5]. Some authors perform this directly in RGB (Red Green Blue) space, even if it is very sensitive to illumination changes. To overcome this, simple formulas relating red, green and blue components are employed. For example, Escalera et al. in [2] used different relations between the R, G and B components to segment the desired color. In [3] the difference between R and G, and the difference between R and B channels are employed to form two stable features in traffic sign detection. Ruta et al. in [4], used the color enhancement to extract red, blue and yellow blobs. This transform emphasizes the pixels where the given color channel is dominant over the other two in the RGB color space. In addition to RGB space other color spaces such as YUV and HSI are also used. For example, The YUV system is considered in [13] to detect blue rectangular signs. In [9] a segmentation method in both L-a-b and HSI color spaces is used to extract candidate blobs for chromatic signs. At the same time, white signs are detected with the help of an achromatic decomposition. Then a post-processing step is performed in order to discard non-interest regions, to connect fragmented signs, and to separate signs located at the same post.

Another cue used to identify traffic signs is the geometric information. Those shape-based algorithms are generally used directly on scene images, or as a second step after color segmentation. In [2,14,15] a corner detector is used to identify the shape information. Maldonado et al. in [16] used a signature defined as the distance from the mass center to the edge of the blob as a function of the angle to classify blobs as, triangles, squares, or circles. Gavrilla et al. [6] used Distance Transform (DT) and Template Matching (TM) to detect circular and triangular signs. Similarly, Ruta et al. [4] used the Color Distance Transform, where a DT is computed for every color channel separately. Larsson et al. [17] used locally segmented contours combined with an implicit star-shaped object model as prototypes for the different sign classes. The contours are described by Fourier descriptors. Hough transform is another technique employed to detect shapes. In [18] a proprietary and undisclosed algorithm is used to detect rectangles, and Hough Transform for the detection of circles. Loy and Zelinsky [19] proposed a technique similar to Hough transform called fast radial transform, which was successfully used for sign detection in [14,20]. Many recent approaches use gradient orientation information in the detection phase, for example, in [7], Edge Orientation Histograms are computed over shape-specific sub-regions of the image.

After the localisation of region of interests ROIs, classification techniques employed to determine the content of the detected traffic signs. Learning approaches are the most used techniques. Maldonado et al. in [5] utilized different one-vs-all Support Vector Machines (SVMs) with Gaussian kernel for each color and shape classification to recognize signs. In [10] SVMs are used with HOG features to carry out classification on candidate regions provided by the interest region detectors. It withstand great appearance variations thanks to the robustness of local features, which typically occur in outdoor data, especially dramatic illumination and scale changes. In [12], the authors suggest a hinge loss stochastic gradient descent method to train convolutional neural networks (CNNs). The method yields to high accuracy rates. However, a high computing cost is paid to train the data. Lim et al. in [21] used also Neural Networks (NNs), and improved their results by preselecting the color-shape features using Principal Components Analysis (PCA) and Fisher Linear Discriminant. Many other researchers use Nearest Neighbour approaches to classify traffic signs. For example, Kuo et al. in [15] used K-d tree to identify the content of the sign and yields to high accuracy rates. In [13], the identification of signs is carried out by a normalized correlation-based pattern matching using a traffic-sign database.

In general, the quality of the results obtained by any study on TSR varies from one research group to another. It is very difficult to decide which approach gives better overall results, mainly due to the lack of a standard database of road images. It is not possible to know, for example, how well the systems respond to changes in illumination of the images since in the different studies it is usually not specified whether images with low illumination have been used in the experiments. Another disadvantage of the lack of a standardised database of road images is that some studies are based on a small set of images since the compilation of a set of road scene images is a very time-consuming task. The problem with working with such small data sets is that it is difficult to evaluate the reliability of the results.

3. Proposed method

As depicted in Fig. 2, the proposed method is achieved in three main steps. The first one segments the images to extract ROIs. The second one detects the shapes from the ROIs. The last step