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Traffic sign segmentation and classification using statistical learning methods

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ABSTRACT

Traffic signs are an essential part of any circulation system, and failure detection by the driver may significantly increase the accident risk. Currently, automatic traffic sign detection systems still have some performance limitations, specially for achromatic signs and variable lighting conditions. In this work, we propose an automatic traffic-sign detection method capable of detecting both chromatic and achromatic signs, while taking into account rotations, scale changes, shifts, partial deformations, and shadows. The proposed system is divided into three stages: (1) segmentation of chromatic and achromatic scene elements using $L^*a^*b^*$ and *HSI* spaces, where two machine learning techniques (k-Nearest Neighbors and Support Vector Machines) are benchmarked; (2) post-processing in order to discard non-interest regions, to connect fragmented signs, and to separate signs located at the same post; and (3) sign-shape classification by using Fourier Descriptors, which yield significant advantage in comparison to other contour-based methods, and subsequent shape recognition with machine learning techniques. Experiments with two databases of real-world images captured with different cameras yielded a sign detection rate of about 97% with a false alarm rate between 3% and 4%, depending on the database. Our method can be readily used for maintenance, inventory, or driver support system applications.

1. Introduction

Traffic signs constitute an essential part of any circulation system to control and guide traffic and to favor road safety [1], with a twofold role: conveniently regulating traffic and reporting to pedestrians and drivers on different aspects about road circulation. Nowadays, automatic traffic sign detection and recognition systems are of special interest in many applications, such as intelligent vehicles development and road maintenance. Regarding the first one, on-board automatic traffic sign detection systems aim to help users to detect and interpret traffic signs. Examples of industrial developments in this field are the traffic sign recognition module [2] used in Opel Eye® [3], or the method for detecting and recognizing traffic signs [4] used in Mercedes-Benz Traffic Sign Assist® [5]. Regarding road maintenance, appropriate positioning and maintenance of traffic signs clearly improve road safety, being supervised by authorities with regular inventory campaigns.

However, despite the vast amount of research recently conducted for automatic traffic sign detection and recognition, current traffic sign inventory and monitoring are still mainly carried out manually by an operator visualizing a video recording, and checking the presence, position and status of each traffic sign. This tedious task requires intense concentration during a long time, and errors can be originated by the operator's fatigue or by poor visibility conditions (as shown in Fig. 1). An automatic system can be designed for surpassing these difficulties, as well as for providing a significant cost reduction in the inventory process. The interest of traffic sign automatic identification is further supported by competitive challenges proposed by scientific and technical societies, see e.g. [6,7].

Recent research works usually split the identification process in two stages, namely, detection and classification (recognition), which are designed using a representative set of images or videos (training set). Image segmentation techniques are used for the detection stage, and different approaches have been proposed depending on the type of image, i.e., true-color or gray-level. Regarding true-color images, there are two approaches, either working with the standard *RGB* color space used by digital cameras, or performing a deeper analysis of color information using other spaces for separating color and intensity information (such as *HSI*, *HSV*, *YIQ*, *YUV*, *Luv* or $L^*a^*b^*$) [8]. Many authors have addressed the segmentation by thresholding on *RGB* images, either at pixel level [9], or with more elaborated schemes, such as preprocessing with a Simple Vector Filter Algorithm before thresholding [10].

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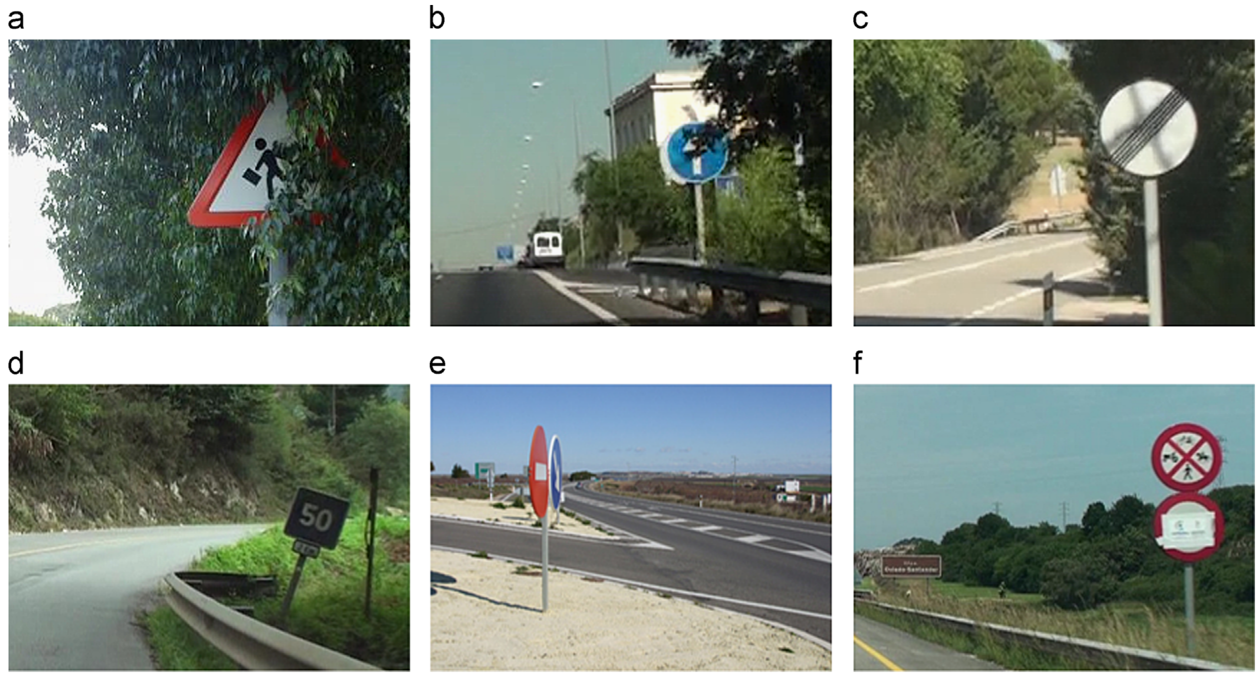

Fig. 1. Examples of challenging images for a traffic sign detection system: (a,b) partial hiding; (c) lighting variation; (d) 2D rotation; (e) 3D rotation; and (f) other factors.

The main drawback of the *RGB* space is its high sensitivity to lighting changes, which hampers segmentation in scenes with excessive or insufficient light. For this reason, many works use color spaces that are theoretically more robust to lighting conditions than *RGB*. In this way, a nonlinear transformation of *H* and *S* components of the *HSI* color space was carried out in [11], with subsequent thresholding segmentation on the transformed components. Segmentation in [12,13] was carried out in two stages: chromatic analysis, where components *H* and *S* were used to segment signs with predominant chromatic colors; and achromatic analysis, where *RGB* thresholding was performed for signs with prevalent achromatic colors. Other works resorted to other color spaces that allow an independent control of chromatic and achromatic information as well. The a^*b^* components of the $L^*a^*b^*$ space were used to extract features by using a Gabor filter in [14], which were subsequently used to detect traffic signs. In [15,16], the *YUV* space was used for thresholding segmentation. Also, the *YCrCb* space has been used for segmentation by using a dynamic thresholding scheme [17]. Whether to use the *RGB* space or other spaces separating chromatic and achromatic information remains controversial. On the one hand, the review in [18] evaluated and benchmarked several thresholding segmentation methods. Authors concluded that the best ones were those using normalization with respect to illumination, such as normalized *RGB* or *Ohta Normalized*, and that the use of *HSI* or *YUV* spaces did not provide a significant advantage. On the other hand, other authors [13,14] proposed the use of *HSI* or *YUV* spaces using more elaborated segmentation schemes, improving the results provided by simpler thresholding-based methods.

Systems dealing with gray-level images are mainly focused on edges detection and their subsequent analysis. A shape-based approach for de-restriction signs detection was presented in [19], which used a black band detector to highlight regions of interest (ROI). A set of histograms of oriented gradients features were used in [20] to design a classifier with a boosting approach to detect pedestrians and traffic signs. A transformation for angle vertex and bisector detection was used in [21] to implement a gradient geometric model to detect triangular signs. In [22], a restricted Hough transform applied on the image contours was proposed as a traffic sign detection method. Nevertheless, detection techniques based on image-gradients and object-edges are very sensitive to noise and computationally expensive, requiring in most cases a complex preprocessing stage. In order to improve the detection stage, several works were proposed to use consecutive video frames to track traffic signs and to reduce false alarm and missing rates by using Kalman filtering [23,24].

Three conclusions arise from the above review: (1) separating chromatic and achromatic segmentation by using *HSI* or $L^*a^*b^*$ color spaces seems to improve segmentation performance; (2) achromatic segmentation is a difficult task, addressed by several works but with limited success; and (3) the potential of $L^*a^*b^*$ and *HSI* spaces to separately segment chromatic and achromatic elements has not been fully exploited yet. These conclusions motivate the search of advanced segmentation techniques based on these spaces.

The problem of traffic sign recognition has been often tackled with matching techniques. As an example, a distortion-invariant Fringe-adjusted joint transform correlation technique was used in [14] to find correlation peaks among segmented regions and a set of patterns extracted from different traffic signs. Also, a dissimilarity measurement was used in [25] to classify the sign by matching its color with a set of patterns. Machine learning techniques have been applied to the traffic sign recognition problem too. In this way, a combination of Convolutional Neural Networks and Multilayer Perceptron was applied in [26] on images normalized by a contrast-limited adaptive histogram equalization, which achieved good performance for German traffic signs recognition. In [17], a hybrid classifier composed of Support Vector Machines (SVM) and Naive Bayes was fed with features provided by a Gabor filter bank. Other works [10,12,13,18,27–29] also used SVM as a classifier, taking into account different features such as shape signature or Pseudo-Zernike moments. Genetic Algorithms (GAs) have been less used, probably due to their high computational cost, and their application has been focused on adapting the use of certain features with other machine learning schemes. A GA was applied in [11], followed by a two-layer neural network, according to the Adaptive Resonance Theory paradigm for classification. In [30], affine transformation coefficients were used as GA