Traffic Sign Detection and Pattern Recognition using Support Vector Machine

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***Abstract*—A vision based vehicle guidance system must be able to detect and recognize traffic signs. Traffic sign recognition systems collect information about road signs and helps the driver to make timely decisions, making driving safer and easier. This paper deals with the detection and recognition of traffic signs from image sequences using the colour information. Colour based segmentation techniques are employed for traffic sign detection. In order to improve the performance of segmentation, we used the product of enhanced hue and saturation components. To obtain better shape classification performance, we used linear support vector machine with the Distance to Border features of the segmented blobs. Recognition of traffic signs are implemented using multi-classifier non-linear support vector machine with edge related pixels of interest as the feature.**

I. Introduction

Road safety is always a problem everywhere, especially in developed countries like US, Japan etc. Automated cruise control systems are a potential area of research in these countries. Ultimate aim of such Intelligent Transport Systems (ITS) is to realize fully autonomous vehicle [1]–[3]. Many systems have been proposed and implemented to achieve different features of the ITS. An important field in ITS is driver assistance systems (DAS). Electronic driver assistance systems are used in vehicles to alert driver about the road signs ahead. Computer vision based methods, which have the advantage of high resolution, can be employed to detect road borders and obstacles, and recognize road signs. As the speed of vehicle increases the manual monitoring of road signs become difficult. A vision based road sign detection and recognition system is thus desirable to catch the attention of a driver to avoid traffic hazards [4]. Automatic recognition of traffic signs is therefore important for automated driving or driver assistance systems. The problem of traffic sign recognition has some beneficial characteristics. First, the design of traffic signs is unique, thus, object variations are small. Further, sign colors often contrast very well against the environment. Moreover, signs are rigidly positioned relative to the environment, and are often set up in clear sight to the driver. The traffic sign detection algorithms commonly rely on shape and colour of the traffic signs. Shape based methods detect the signs using a set of predefined templates and hence is sensitive to total or partial occlusion and target rotation. Colour based methods detect signs in a scene using the pixel intensity in RGB or HSI colour spaces. HSI is the most commonly used colour space since it gives different pieces of information in every component [5]. HSI colour space has the added advantage that it is invariant to brightness and shadows. More over HSI colour space is suitable to extract colour features against tough conditions like adverse climate and damaged road signs. This paper describes a general framework for the detection and classification of traffic signs from image sequences using colour information. Colour based segmentation techniques are employed for traffic sign segmentation. Red, blue, yellow and white colours are the most commonly used signs in road traffic. In this work, we have used red, blue and yellow traffic signs for training and testing using SVM classifier. Linear and non-linear support vector machines (SVM) are used for the shape classification and pattern recognition of segmented traffic signs respectively.

This paper is organized as follows: Section II focuses on the system overview for traffic sign detection and recognition. Section III shows the experimental results for traffic sign detection and pattern recognition using distance to border and edge related pixels of interest as the feature vectors to SVM.

II. System Overview

In this paper, we present a system for detection and recognition of traffic signs. The block level representation of the traffic sign detection and recognition system is shown in Figure 1.

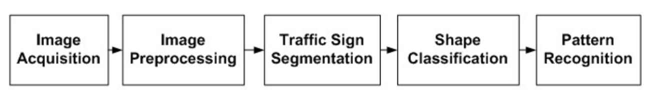

Fig. 1: Block diagram of Traffic Sign Detection and Recognition system

The traffic sign detection and recognition system mainly consists of three stages.

1) Colour Segmentation : Candidate blobs are extracted from the input test image by thresholding the input image. Thresholding in the HSI colour space is used for chromatic signs, meanwhile achromatic signs are segmented using an achromatic decomposition.
2) Shape Classification : In this stage, blobs obtained from the colour segmentation process are classified according to their shape using linear SVM.
3) Pattern Recognition : Here, the shape classified blobs are recognized according to their patterns using non-linear SVM.

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A. Colour Segmentation

In traffic sign recognition, the main task involved in extracting the traffic sign is the segmentation of the traffic sign. The use of colour analysis is basic because road signs are designed in such a way that the chosen colour stand out from the environment. As mentioned in section I, different colour spaces can be employed for segmenting traffic signs. A method for enhancing desired colour in an image, in which a nonlinear transformation for Hue and Saturation is employed using two Look Up Tables (LUT) for every colour that we are looking for. Thus for the Hue component, the sign's red component has very low and very high values [6]. The blue hue LUT has its maximum at a certain value and again decreases for two different values. For the saturation component, the value will be higher as much colour the sign pixel contain. The LUT will follow a ramp until it reaches a saturation value, from that point onwards it will have the maximum value. Once the LUTs are applied the images are multiplied and normalized to the maximum value of 255. This way, pixel classification error through the use of rigid limits as thresholding is avoided. First, the input image in RGB

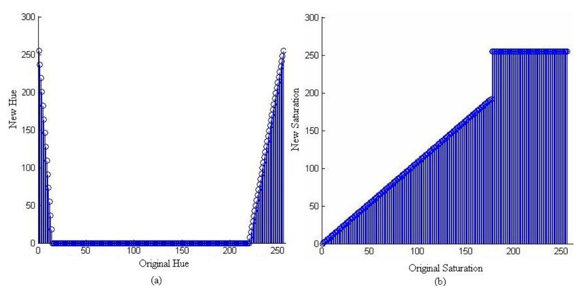


Fig. 2: Hue and Saturation LUT for Red Traffic Sign

colour space is converted to HSI colour space. Then, Look up table (LUT) based enhancement is applied for both hue and saturation values of red, blue and yellow coloured traffic signs. The LUTs used for enhancing Hue and saturation components of red, blue and yellow traffic signs are shown in Figure 2, Figure 3 and Figure 4 respectively. The thresholded binary

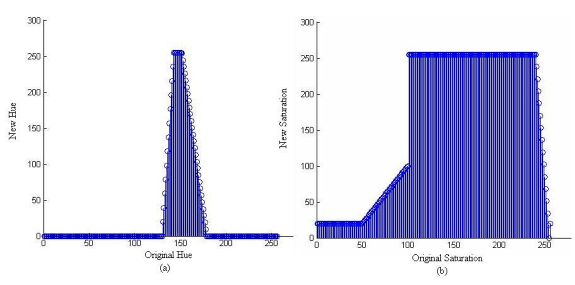


Fig. 3: Hue and Saturation LUT for Blue Traffic Sign

image is obtained from the product of LUT enhanced hue and saturation components using adaptive thresholding. By thresholding the original image in this manner, it is possible to discard more noisy blobs and make segmentation easier for

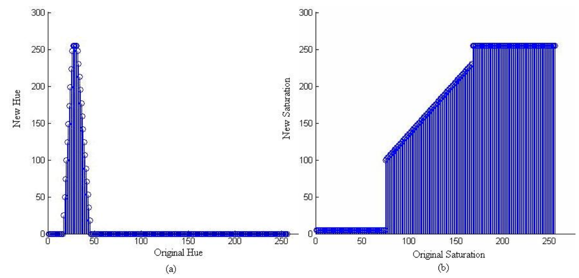


Fig. 4: Hue and Saturation LUT for Yellow Traffic Sign

shape classification. Figure 5 shows the segmentation results for an image containing a red triangular traffic sign.

After segmentation image pixels belongs to any of the three colour categories viz red, blue and yellow. These image pixels are grouped together as connected components. The connected component concept for the segmentation is used since there is a possibility for more than one traffic sign in the image. All candidate blobs are analyzed and some of them are discarded according to their size or aspect ratio. The limits for blob size and aspect ratio were empirically derived using standard road images.

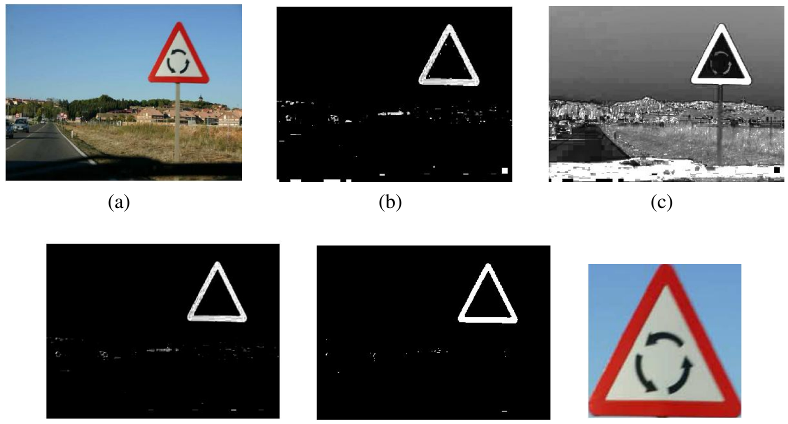
B. Shape Classification

The blobs that are obtained from the segmentation stage are to be classified in this stage according to their shape. In order to perform shape classification, linear SVM is employed. The two major tasks involved in shape classification are discussed in subsection II-B1 and II-B2.

1) Shape Feature Extraction: The first step in shape classification is to make feature vectors for the input to the linear SVM. Many methods have been proposed for obtaining the feature vectors [8], [9]. In this work, we have used distance to border vector (DtB) [9] as the feature vector for training SVM. DtB is the distance from the external edge of the blob to its bounding box. Thus for a segmented blob we have four DtB vectors for left, right, top and bottom.

The main advantage of this method is its robustness to several factors such as translations, rotations and scale. The algorithm is invariant to translation because it does not depend on the position of appearance of the blob in the scene. It is invariant to rotations because all blobs have been previously orientated in a reference position using the DtB vectors. And finally, in order to make the DtBs invariant to changes of scale, they are converted into 20 equally spaced samples. Therefore, for a single instance there are 80 DtB vectors. Figure 6 shows the resampled DtB vectors for a segmented red triangular and circular blob.

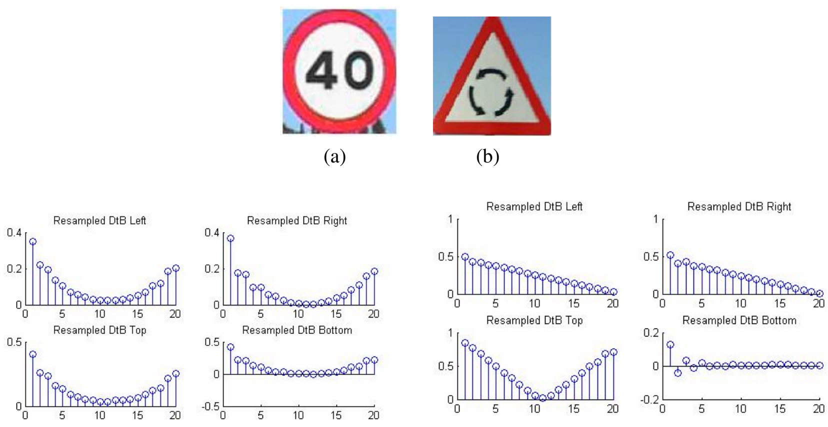
2) Training and Testing using Linear SVM: Once the feature vectors for the candidate blobs are obtained, the shape classification process is initiated. For shape classification, eight linear SVMs are used.Support Vector Machine is a machine learning algorithm which can classify data into several groups. It is based on the concept of decision planes where the training data is mapped to a higher dimensional space and separated



(a) (b) (c)

(d) (e) (f)

Fig. 5: Red traffic sign segmentation results (a) Original Image (b) Enhanced Hue using LUT (c) Enhanced Saturation using LUT (d) Product of Enhanced Hue and Saturation (e) Thresholded Binary Image and (f) Segmented Blob of Interest.



(a) (b)

(c) (d)

Fig. 6: (a) Segmented Circular Blob (b) Segmented Triangular Blob (c) Distance to Border for Circular Blob (d) Distance to Border for Triangular Blob.

by a plane defining the two or more classes of data. The extensive introductions about SVMs can be found in [10], [12]. The formulation of SVMs deals with structural risk minimization (SRM). SRM minimizes an upper bound on the Vapnik Chervonenkis dimension, and it clearly differs from empirical risk minimization, which minimizes the error on the training data. For the training of SVMs, we have used the library LIBSVM [11].

C. Pattern Recognition

Once the shape classification process is completed, the candidate blobs are being sent to the pattern recognition stage. In order to perform pattern recognition, SVMs with radial basis function (RBF) kernels are employed.

1) Pattern Feature Extraction: The shape classified blob is first normalized to a size of 80*80. The normalized image is then converted to gray scale and multiplied using a mask image corresponding to the shape of the blob as classified by the shape classification stage. The masks used for extraction of the POI is shown in the Figure. 7a. The masking operation provides only those pixels that are the part of the sign which is termed as Pixels of Interest (POI). This is used as a feature vector in pattern recognition [5]. In the proposed work, the edge of the masked POI is extracted and used as the feature vector for pattern recognition. The Figures. 7b, 7c, 7d shows the segmented blobs and the positive support vectors used for training the multiclass non-linear SVM for pattern recognition.

2) Training and Testing using Non-Linear SVM: In the recognition stage, different one-versus-all SVM classifiers with a RBF kernel is used. The training and testing are done on the basis of the colour and shape of the candidate blobs. This strategy enables us to compare every candidate blob to those having the same colour and shape, hence reducing the complexity.

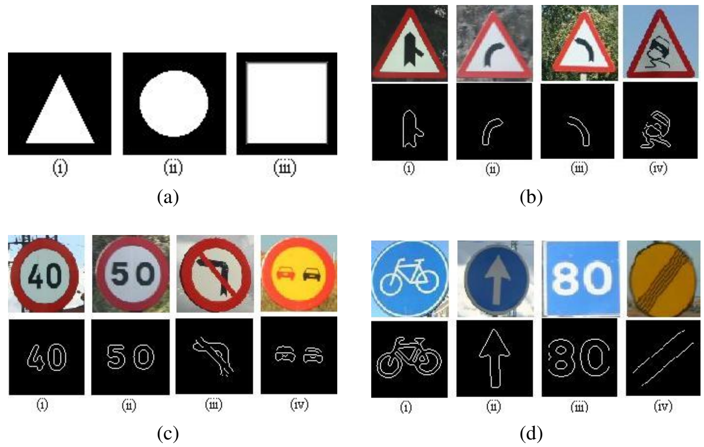


Fig. 7: (a) Masks used for extracting POIs (i)Triangular (ii) Circular (iii) Square, (b) Red Triangular Segmented Blobs and the corresponding edge extracted pattern (i)-(iv), (c) Red Circular Segmented Blobs and the corresponding edge extracted pattern (i)-(iv), (d) Blue and Yellow Segmented Blobs and the corresponding edge extracted pattern ((i)-(iv).

III. Experimental Results

Experimental results obtained for traffic sign detection and pattern recognition are tabulated in Table. I. For the tabulation, we have used three parameters viz. true positive, false positive and false negative to evaluate the performance of shape classification and pattern recognition of traffic signs. True positive indicates the percentage of number of traffic sign images classified correctly to the total number of input images. False positive indicates the percentage of number of traffic sign images classified wrongly to the total number of input images. False negative indicates the percentage of missed classifications.

TABLE I: Pattern recognition results using edge related POI as feature vector

Traffic Signs	Red Circle	Red Triangle	Blue Circle	Blue Square	Yellow Circle
No. of Signs	133	130	60	75	21
True Positive	75.19%	75.38%	81.67%	84%	90.47%
False Positive	4.51%	3.84%	3.33%	4%	NIL
False Negative	20.30%	20.76%	15%	12%	9.52%

IV. Conclusion

This paper proposes a new method for traffic sign shape detection and pattern recognition. Here, a colour based segmentation technique using product of enhanced hue and saturation components is introduced which gives good segmentation results. Also, edge based pixels of interest are extracted from the masked image which is used as a feature vector for pattern classification of the traffic patterns in the detected blobs. The results of the proposed pattern classification method shows better performance as compared to the results cited in the literature.

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