Road Sign Detection and Recognition by Using Local Energy based Shape Histogram (LESH)

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Abstract

This paper describes an efficient approach towards road sign detection and recognition. The proposed system is divided into three sections namely; Colour Segmentation of the road traffic signs using the HSV colour space considering varying lighting conditions, Shape Classification using the Contourlet Transform considering occlusion and rotation of the candidate signs and the Recognition of the road traffic signs using features of a Local Energy based Shape Histogram (LESH). We have provided experimental results and a detailed analysis to justify that the algorithm described in this paper is robust enough to detect and recognize road signs under varying weather, occlusion, rotation and scaling conditions.

Keywords: Road Signs, HSV, Contourlet Transform, LESH, Autonomous Vehicles

1. INTRODUCTION

Road sign detection and recognition has drawn considerable research attention in recent years due to its challenging nature as a computer vision problem. Road signs have a direct impact on ones daily life be it as a driver, cyclist or as a pedestrian as possible life threats can be easily formed due to their ignorance. In recent years a number of Driver Assistance Systems have been implemented including vision based algorithms claiming to be efficient towards road sign detection and recognition. Generally road signs consist of three properties; firstly they are represented by colours such as Red, Green, Blue, and Brown etc. Secondly they consist of a particular shape such as Circular, Triangular, Octagonal, Square etc. The inner contents of the road signs represent the third property, which may vary depending on the application of the road sign. In this paper we have highlighted the importance of using these properties separately by considering different problems including various lighting conditions, scaling, angular rotation and occlusion.

The perceptual colour of a road sign appears to be different due to varying lighting conditions. This makes it difficult to extract the accurate colour information of a sign. The weather defined by rain, fog, snow etc., and time of the day defined by day, dusk, night etc., play an important role in creating the above mentioned variations of illumination.

The size of a road sign as appearing in the scene has an impact on its detection and identification accuracies. Signs that appear small will not be even detected as picking up the colour or shape will be a challenging issue for even the best computer vision algorithms. Therefore it is important to include a system functionality, which keeps track of the candidate sign from the point it first become visible in the scene until a reasonable size that will enable its recognition.

Further the detection and recognition in the presence of likely angular rotation of a road sign is also a further challenging computer vision problem which needs to be addressed and resolved. The detection and recognition of a road sign can also be affected by occlusion, i.e., due to the presence of objects in the field of view. In the proposed approach the verification of the road sign is completed at multiple stages. This helps to overcome partial occlusion at a high success rate.

To accommodate the recognition ability of all categories of road signs it is important to distinguish road signs not only by their content but also by their colour and shape information. Table 1 below shows different categorical divisions of road signs according to their colour and shape information.

TABLE 1: Different road signs categorized according to colour and shape information

For clarity of presentation the paper is organized into the following sections: Section 2 focuses on a literature review in the area of road sign detection and recognition. Section 3 presents the proposed road sign detection and recognition system. It is further categorized into three important sections A: Colour based segmentation of a road sign using the HSV colour space, B: Shape Classification using Contourlet Transform (CT) and C: Recognition using features from the Local Energy based Shape Histogram (LESH) and Support Vector Machine (SVM) based classification. Section 4 illustrates the experimental setup and results. The conclusion and future work are presented in Section 5.

2. STATE OF THE ART

Generally road sign detection and recognition literature can be divided into two groups that concentrate on 1: Road Sign Detection and 2: Road Sign Recognition. The Road Sign Detection consists of the procedure of extracting the candidate road sign from a scene. Majority of the work in detection is initiated using colour information of the road sign. The segmentation of the candidate sign from the scene is carried out by employing a colour space. The most popular colour spaces used for this purpose are HSI, RGB, CIElab, YCbCr, CYMK and HSV. In the colour based segmentation approaches images are first converted to a designated colour space and then a segmentation algorithm e.g. thresholding, is applied [2]. In [1], [3], [4], colour based segmentation of road signs have been achieved by first transforming the original image to the HSI colour space and subsequently marking the desired colour pixels (such as Red, Green, Blue etc.) by a white pixel. Pixels that are outside the threshold values are treated as background or noise. Thus a binary image is formed in which white pixels represents the desired coloured area and black pixels represent noise or background. In [5], [6], segmentation has been achieved using RGB (Red, Green, Blue) colour space and the desired pixels are extracted by using threshold values for each colour. These threshold values are obtained on the basis of changing illumination conditions during different times of the day [3]. In [2], [8], [9], segmentation is performed by transforming the images to HSV (Hue, Saturation and Value) colour space to obtain thresholds using Otsu's algorithm [10]. In [11], though the segmentation is performed in the HSV colour space, pixels of interest are obtained by employing a set of fuzzy rules. In [12], CIElab colour space is employed with a Gaussian model to target the colour information and in [13] chromatic channels are transformed to binary images using Otsu's algorithm. YCbCr colour space is employed in [14] and adaptive thresholding has been performed to obtain the pixel of interest. In [15] CIECAM97 colour space is employed to segment out the road signs and results are compared with HSI, RGB and CIELUV colour space segmentation. Recently a number of attempts have been made to use combined colour spaces and combined colour space models in road sign colour detection. In [16] a joint colour space segmentation approach has been adopted. The Hue of the HSV colour space and image chrominance (U, V) values from YUV space have been jointly used. The results of the two colour spaces are combined by a logical AND operation. 256 RGB and HSL transforms are used in [17] to construct colour distinctions of the image by following simple thresholding. RGB and HSI colour spaces are jointly used to threshold the image in [18]. HSI threshold values for Blue and Red colours are tabulated. Joint colour space has been employed [19] in which HSI is used to extract the chromatic information and RGB is used to extract the achromatic information. Adaptive chrominance and luminance thresholding has been achieved in [20] by employing joint colour space i.e. CIElab and HSI. In [21] a four colour space based colour classifier has been introduced to segment road signs captured under various weathers and lighting conditions.

In conjunction with colour based approaches, shape based approaches are also seldom used in the segmentation of road signs. In this case the colour information is either used as a pre processor or never used at all. Two shape measures are used for circular and triangular road signs by using a fuzzy shape recognizer in [22]. Distance to Border (DtB) vectors are obtained of the segmented road sign from four different views and shape has been classified by using a linear Support Vector Machine (SVM) [4].For shape determination Hough Transform [18] and median filter are applied to detect the triangle and circular road sign shapes [23].The circular shapes are identified through Fast Radial symmetry detection method (FRS) and the triangular and square shapes are identified by using Harris corner detection algorithm [10].Difference of candidate background histogram and template histogram is used to obtain the shape information of the candidate sign [24].Fast Fourier Transform (FFT) is employed to retrieve shape signatures by comparing it with shape references in [25] and [26]. The 2D correlation coefficient is derived to represent the shape similarity by correlating the candidate ROI with 2D binary template in [27]. A coarse-to-fine scheme is proposed for candidate shape verification in [28]. Hopfield neural networks are used to determine triangular and rectangular shapes by obtaining information related to angle, gradient and distance between edges [29]. The RANdom Sampling and Consensus (RANSAC) algorithm is used to examine and determine the circular shapes in [30]. The shape context and its invariance to rotation and scale are determined by employing corners as salient points in [31]. Geometric properties of different road sign shapes are computed by using the Affine Moment Invariants in [11].

Both the recognition and classification of road signs has been carried out by employing series of approaches which include Multi Layer Perceptrons (MLP), Neural Networks [32] with feed forward topology in [33]. To recognize road signs a template matching technique was proposed in [22]. Different types of Neural Networks are employed in the recognition and classification of road signs such as LWN++ in [34], 3-layered [35], Hopfield [36], back propagation [37] and ART1 [38]. Scale Invariant Feature Transform (SIFT) is used in the recognition of road signs [39] and similarity measures among features are obtained through objective functions [40]. SVM Gaussian kernel is used for content recognition in [41]. A two class SVM classifier is used in [42], one versus all SVM classifier in conjunction with RBF kernel is proposed in [43] and SVM polynomial kernel is used with regards to AdaBoost naive Bayes in [44]. The classification of road signs has been performed by Normalized Correlations in [45] and Normalized Cross Correlation is introduced in [46]. Other recognition methods such as, Fuzzy Shape recognizers [11], Adaptive Hausdorff distance based on similarity weights [47] and Gabour Wavelets [18] filters have also been used. The next section aims to address the above research gaps in designing a robust road sign detection and recognition system capable of performing under wide variations of illumination and environmental conditions.

3. SYSTEM OVERVIEW

The proposed road sign detection and recognition system comprises of three stages, which are detailed in this section. Figure 1 gives an overview of the framework.

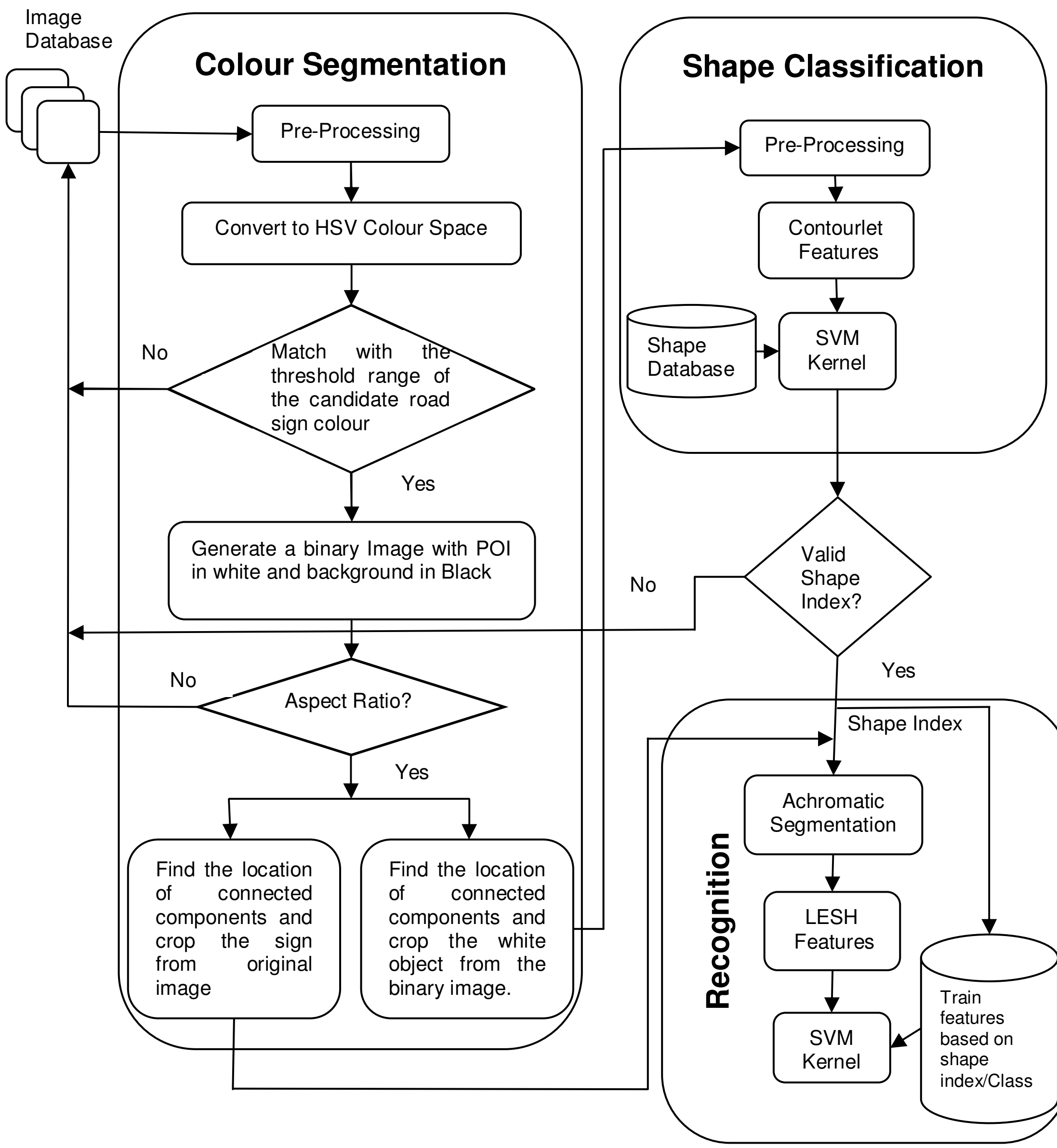


FIGURE 1: Overview of proposed road sign Detection and Recognition framework

A. *Colour Segmentation*: The road sign detection and recognition system is initiated by the colour segmentation process. This process involve the use of a colour constancy algorithm followed by a HSV colour space based segmentation of road signs using threshold values described in [2].

B. *Shape Classification*: The segmented Region of Interest (ROI) is further processed to remove the false detections and to identify those geometric features which truly represent road signs. Contourlet Transforms with Support Vector Machine (SVM) kernel are applied to measure the shape properties at this stage.

C. *Recognition*: The road signs have different meanings according to their contents. The recognition stage comprises of the use of Local Energy based Shape Histogram features with SVM kernel to recognize various contents of road signs at this stage.

3.1 Colour Segmentation

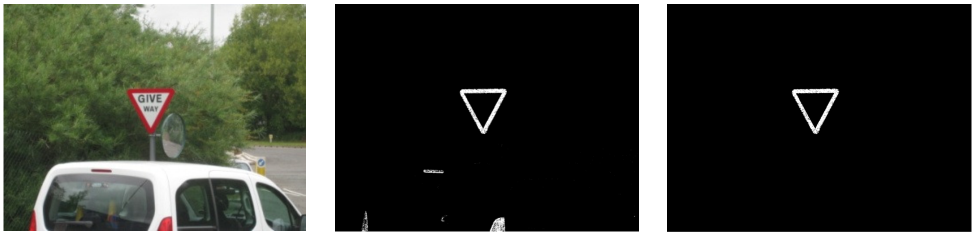
As mentioned in section 2 the segmentation process of the road sign is initiated by employing a colour space. The possible challenges such as variation in illumination and exposure to rain/sun light may affect the colour definition of the road signs. We have employed HSV colour space to segment the colour of the road sign due to its ability to enhance segmentation results [2] as compared to other available colour spaces, specifically in the outdoor environments. RGB images taken from the camera are first passed through a pre-processing stage which helps to maintain the colour constancy in different illumination conditions [49]. It is then transformed to HSV colour space using the following equation [48].

$$H = \cos^{-1}\left(\frac{0.5(R-G)+(R-B)}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right) \tag{1}$$

$$S = 1-\left(\frac{3}{R+G+B}\right)\min(R,G,B) \tag{2}$$

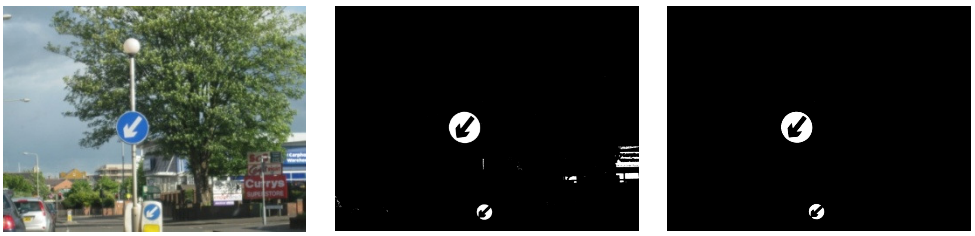
$$V = \max(R,G,B) \tag{3}$$

Where R,G and B are representing the three channels of a RGB image. Pixels of interest (POI) can be segmented by using all three of the above components as shown in equation 1-3 i.e. H, S and V. The Hue (H) component contains the colour information while Saturation(S) generates different shades of a particular colour and Value (V) indicates the brightness or darkness of the colour components respectively. Every colour in H component of HSV colour gamut has an angular value which varies according to change appears in S and V components. If S and V components remain constant i.e. S = 100% and I = 100% then Red, Green and Blue colours can be found at $0^o, 120^o$ and 240^o anti clock wise respectively. These values are determined by taking the histogram of H, S and V components. In the segmentation process a desired pixel which belongs to Red, Blue or Green colours are represented by 1 or white colour and rest of the pixels are treated as background or 0 as shown in the Figures 2(b) and 3(b). At this stage we have to utilize a rule based approach to keep the segmentation process as fine as possible. At first instance median filtering and thinning are utilized for improving the segmentation consistency. Further to this, objects are selected as road sign candidate and discarded as noise according to their aspect ratio. A priority definition of the colours is embedded with the aspect ratio of the candidate sign to help in selection and rejection process which is shown in Table 2. Red colour has high priority and it can appear to be Triangle, Hexagon or Circular shape in the scene. Blue colour can appear as rectangle and circle where as Green coloured signs can appear as Rectangular shape in the image. The corresponding bounding box of the segmented object is analyzed according to its centre and corner points as illustrated in the Figure 4. The segmented objects within the aspect ratio should meet this sign criteria definition. The Figure 2(c) and 3(c) are the results after removing objects with unsuitable aspect ratio and sign criteria.



(a) (b) (c)

FIGURE 2: Red Colour Segmentation



(a) (b) (c)

FIGURE 3: Blue Colour Segmentation

Colour	Priority	Shape
Red	1	Triangle, Hexagon, Circle
Blue	2	Rectangle, Circle
Green	3	Rectangle

TABLE 2: Colours with their shapes and priority

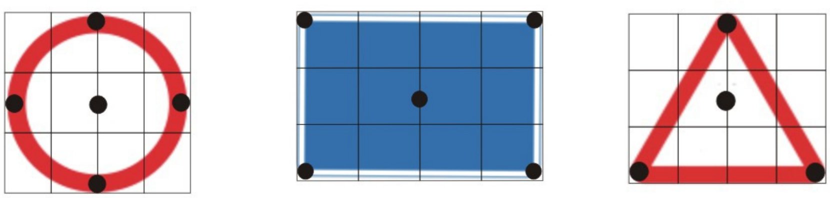


FIGURE 4: The Sign Criteria

3.2 Shape Classification

Road Signs are represented by basic geometric shapes i.e. Triangular, Circular, Hexagonal and Square/Rectangle. This analysis of the road sign, consisting of one of the shapes mentioned earlier is carried out after Colour Segmentation of the road signs. It not only helps to remove non-sign objects but also lessen the burden at recognition stage.

The segmented objects resulting from Colour Segmentation stage are pre-processed at the first stage of the Shape Classification. The pre-processing involves edge sharpening and filling the holes inside the objects. Figure 5 shows the procedure of pre-processing stage in the Shape Classification where as Figure 5(b) shows processed objects which is the output of the pre-processing stage. The Contourlet Transform [50] that is successfully used in image compression and enhancement domains has been employed here to extract the shape features of the pre-processed objects. The shape features comprises of contour edges of an object along 2 dimensional (2D) spaces. These contours are stored for training or testing purposes in the later

Shape Classification stage. The 3 level frequency decomposition is used due to its capability of producing diagonal direction edges. It is a very helpful technique for distinguishing circular shapes with hexagonal shapes. The comparison of 3-level frequency decomposition with 2-level frequency decomposition is presented in Section 4. The proposed frequency decomposition contains 'Haar' attributes of Laplacian pyramid filter and a Directional filter bank, as illustrated in Figure 6.

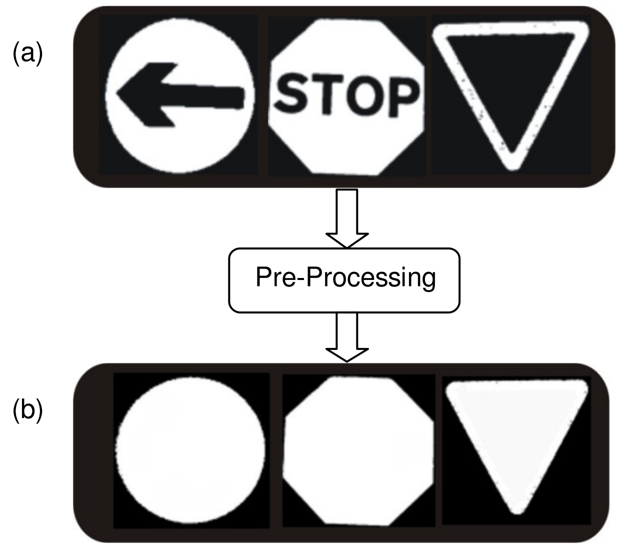


FIGURE 5: Shape Classification Pre-processing procedure (a) Binary Objects (b) Processed Objects

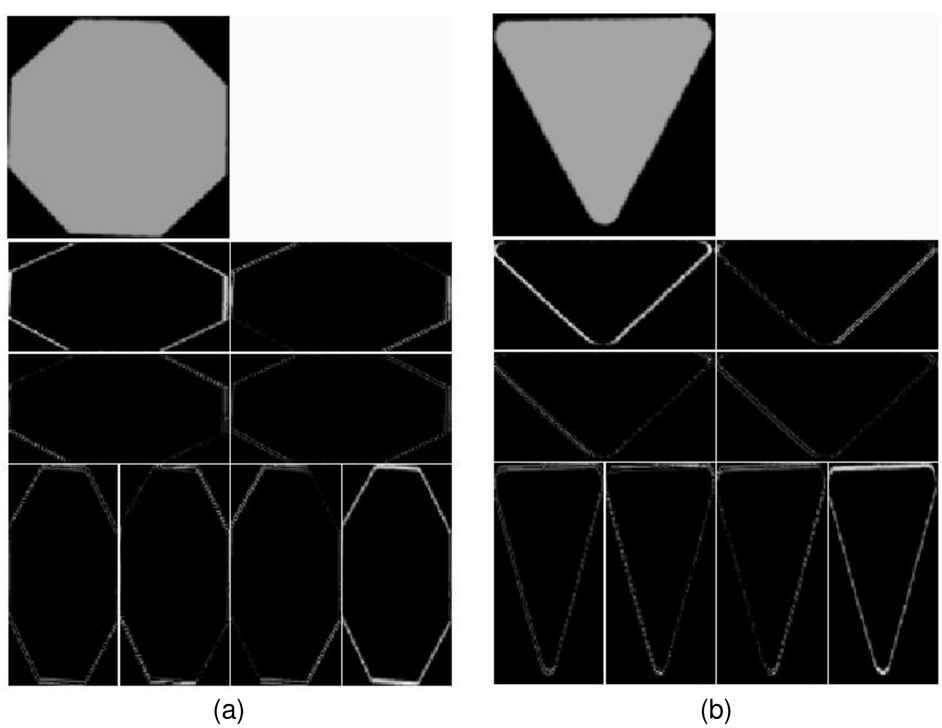


FIGURE 6: Contourlet Transform 3-level frequency decomposition (a) Hexagonal Shape (b) Triangular Shape

The extracted Contourlet features of different shapes are fed in to Support Vector Machine (SVM) which helps to classify the exact shape of the candidate sign. The SVM classifier first proposed in [51] is an effective and powerful method for general purpose pattern recognition and classification. SVM based kernels are used to map the input data to the high dimensional feature space and process it in linear form. In our experiments we have tested few popular kernels functions, $k(u,v)$ defined as follows:

$$k(u,v) = \langle u,v \rangle \tag{4}$$

$$k(u,v) = (u.v+1)^d \tag{5}$$

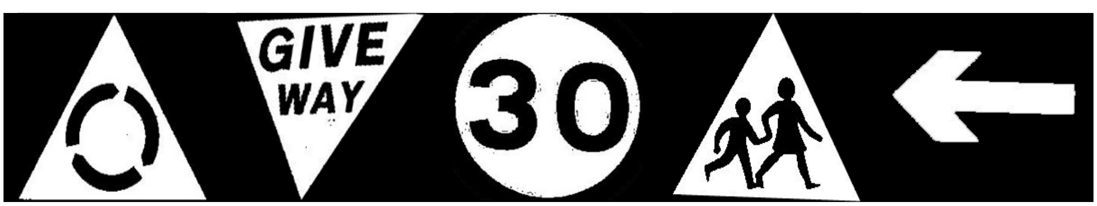
$$k(u,v) = e^{\frac{|u-v|^2}{\sigma^2}} \tag{6}$$

In most applications it has been generally concluded that, a low degree polynomial kernel shown in equation (5) or a Radial Basis Function (RBF) as kernel shown in equation (6) works quite well. In our case, a polynomial kernel with degree 1 and 2 provides the best results for shape classification. The method described here for shape classification is invariant to scale, rotation and partial occlusion problems. The method has the capability to classify any geometric shape due to its distinguishing multi channels feature analysis.

3.3 Recognition

Once the candidate shape is classified, it initiates the process of Recognition and classification of the road sign contents. The Recognition process comprises of the LESH features extraction of the road sign contents and training/testing of these features is carried out by employing SVM kernel classifier. The candidate road signs which are extracted through Colour Segmentation and hence validated as the road sign shape by Shape Classification are further processed to obtain the valid road sign contents for feature extraction.

The road sign contents are normally represented with black and white colours. In this context achromatic segmentation is introduced to extract the black and white areas of the candidate road sign from rest of the image. The objects which are meeting the criteria of aspect ratio are considered as valid road sign contents and vice versa. The black and white objects after achromatic segmentation and in accordance to aspect ratio are shown in Figure 7.



(a) (b) (c) (d) (e)

FIGURE 7: Road signs after achromatic segmentation

The Local Energy Model was first introduced in [52] proving that features can be extracted at those points from an image where local frequency components represent maximum uniformity. The extended framework of local energy model is given in Equation (8) and is normalized by the summation of noise cancellation factor T, Sine of phase deviation and factor W, which is the weighting of the frequency spread. Further details of this extended framework can be found in [53].

$$E = \frac{\sum_n W(x) \lfloor A_n(x) \left(\cos\left(\phi_n(x) - \bar{\phi}(x)\right) - \left|\sin\left(\phi_n(x) - \bar{\phi}(x)\right)\right| \right) - T \rfloor}{\sum_n A_n(x) + \varepsilon} \tag{8}$$

The Local Energy gives reliable information to extract the interest points from an image in an invariant manner to illumination and noise. This raw energy indicates the corners, contours or edges of underlying shape in an image. LESH [54] features are obtained firstly by dividing the candidate image into 16 sub-regions and then the local energy information is calculated for each sub-region along 8 different orientations with the help of Gabor Wavelets kernels [55].

$$G_{u,v}(z) = I(z) * \Psi_{u,v}(z) \tag{9}$$

Where $z = (x, y)$ represents the image position, the symbol "$*$" is convolution operator and $\Psi_{u,v}(z)$ can be calculated as equation (10).

$$\Psi_{u,v}(z) = \frac{\left\|k_{u,v}\right\|^2}{\sigma^2} e^{\left(\frac{-\left\|k_{u,v}\right\|^2 \|z\|^2}{2\sigma^2}\right)} \left[e^{ik_{u,v}z} - e^{-\sigma^2/2} \right] \tag{10}$$

The orientation label map is produced representing labels of orientation of pixels containing largest energy across all scales in an image. The local histogram h is calculated in equation (12) as follows:

$$w_r = \frac{1}{\sqrt{2\pi\sigma}} e^{\left[(x-r_{xo})^2+(y-r_{yo})^2\right]/\sigma^2} \tag{11}$$

$$h_{r,b} = \sum w_r \times E \times \delta_{Lb} \tag{12}$$

Where w is the Gaussian weighting function of region r calculated as in equation (11), E represents the local energy computed as equation (8), δ_{Lb} represents Kronecker's delta, L orientation label map and b current bin. From the above description it can be seen that the LESH descriptor of a shape is 8x16=128 dimensional feature vector.

Each object shown in Figure 7(a-e) is representing a separate class of objects. These objects are normalized into fixed size dimensions and converted to gray level images. The next stage is to extract the LESH features of these normalized images. LESH features are obtained by computing the local energy along each filter orientation of image sub-region and its histogram is generated. The overall histogram represents the concatenated histograms computed along each sub-region of the image. Figure 8 shows the LESH features representation of 30 speed limit and round about signs respectively. These features from different classes are classified with the help of multiclass SVM polynomial kernel which is explained earlier in section 3.2.

4. EXPERIMENTAL SETUP AND RESULTS

Using a standard photographic camera, mounted of a car, we have obtained 1200 images of different road signs. These signs were captured during various ambient and lit-up levels of illumination and weather conditions. The road signs collected were limited to ones with basic colours i.e. Red, Green and Blue. Figure 9 illustrates some samples of images taken from a Canon IXUS80IS digital camera at a resolution of 2592 x 1944. The images are pre-processed before converting them to the HSV colour space. This involves the stabilization process of colour

(a)

(b)

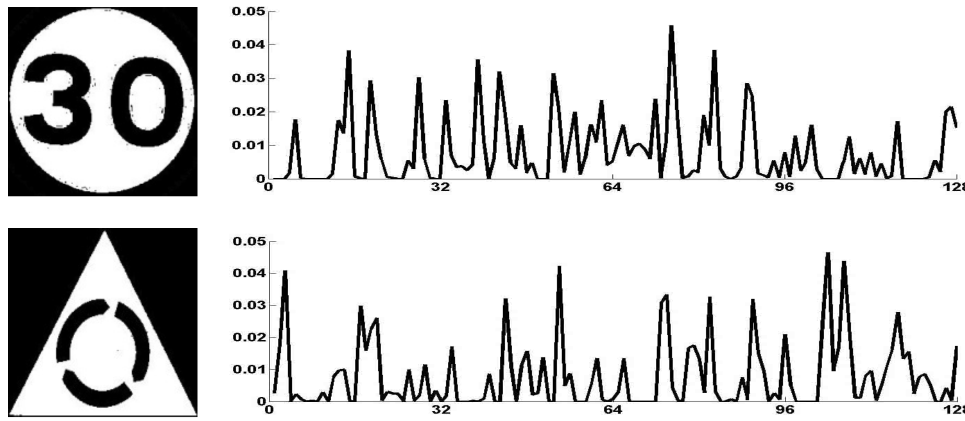


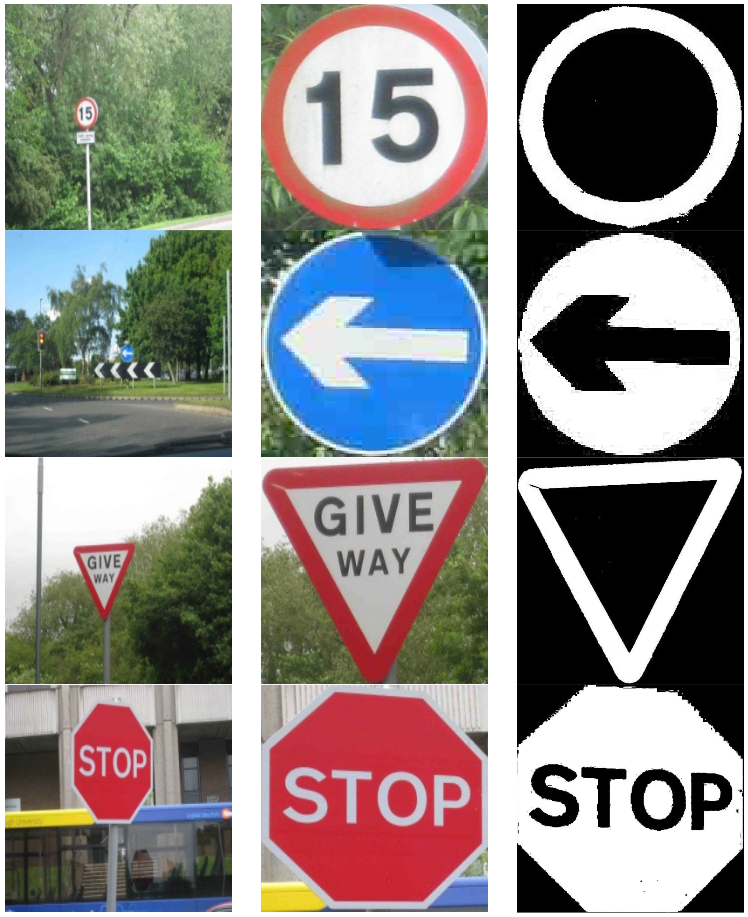
FIGURE 8: LESH feature representation for (a) 30 speed limit sign (b) round about road sign

FIGURE 9: Original coloured images contain red, blue and green colour road signs captured under different environmental conditions

constancy at a particular illumination level. As shown in Figure 1 from section 3.1 the processed images are then transform to HSV colour space and POI are obtained using the threshold values [2] for Red, Blue and Green coloured road signs. The output image is then later converted to binary image in which the white pixels represents the POI and vice versa. The bounding boxes of the white region are analyzed according to their aspect ratios and the sign criteria.

The objects which meet the criteria of being a candidate sign are cropped from both the original image and the binary image. The location information of these cropped signs is also noted for later usage. Figure 10 shows some results after Colour Segmentation. The objects segmented as candidate sign are passed through the Shape Classification module where experiments are carried out on 5 different shape classes. The inputs of the Shape Classification module are the cropped objects from the binary image as shown in the Figure 10(c). These objects are pre processed at first instance in this module which consists of normalization of the object in terms of size and removal of the contents.

The objects are resized to 100x100 fixed size dimensions then algorithms for edge sharpening and to fill the necessary holes are applied as shown in Figure 5. The shape feature selection is done by using Contourlet Transform, which represents the object shape with respect to its



(a) (b) (c)

FIGURE 10: Colour Segmentation using HSV colour space (a) Road Signs in the natural environment (b) Cropped Road Signs from the original Image (c) Cropped Road Signs from the Binary Image

Index	Shape	Level*	Pyramidal and Directional Filters	Trained Instances
1		3	Haar	50
2		3	Haar	50
3		3	Haar	50
4		3	Haar	50
5		3	Haar	50

TABLE 3: Shapes considered for obtaining Contourlet features, Level* = Sub band Decomposition

Shape Index	Classified Shapes with Level			
	Level	*Success*	*Level*	*Success*
1	2	75%	3	100%
2	2	0%	3	100%
3	2	75%	3	100%
4	2	100%	3	100%
5	2	100%	3	100%

TABLE 4: Success percentage at different decomposition Levels

relevant class. Table-3 shows the details about the shape classes we have considered for our training and testing purposes. Table-4 shows the success percentage while using different decomposition levels on each class. It is observed that as Hexagonal shapes require more sides to represent the shape, when using the Level 2 decomposition which only uses the horizontal and vertical edges of the shape, the shape classifier gives the wrong interpretation of Hexagons, i.e. they are classified as of having circular shape. The Level 3 decomposition gives directional edges at angle 2π by considering all sides of hexagon shape. The classification of shape involves the comparison between testing object instances having unknown class with the offline trained object instances named by defined classes. We have performed offline training of 50 instances as per shape class which was proven experimentally to classify any geometrical shape at significantly high accuracy. Figure 11 and Table-4 are showing the results of Shape Classification in which it can be observed that by using the Level 3 decomposition of Contourlet Transform the classifier produces 100% success rate.

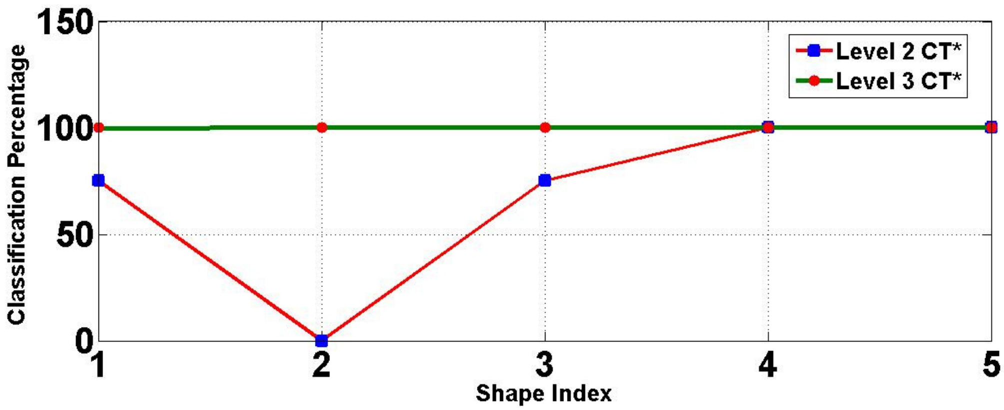
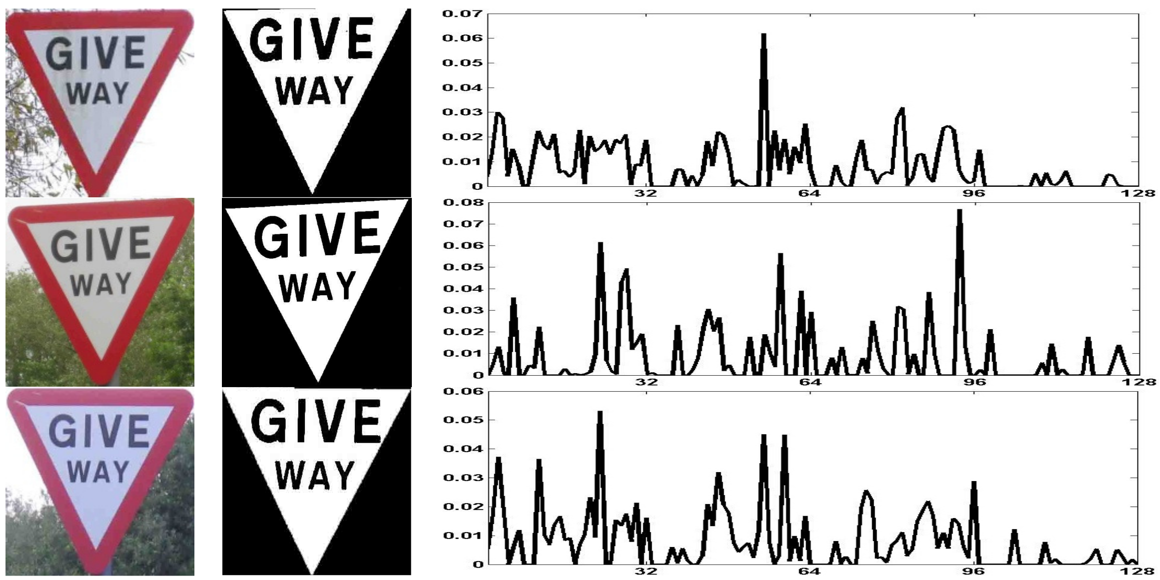


FIGURE 11: SVM classification results, CT = Contourlet Transform

The recognition module takes the input which is the combination of shape index and the cropped road sign from the original image as shown in figure 1. At first stage of recognition the contents of the road sign are captured by applying achromatic segmentation. This segmentation uses the V component of the HSV colour space to obtain the intensities of the pixels in the image. The image is then converted to binary image by using suitable threshold parameters and in accordance to its pixel intensities results. The images used in our experiments are resized to 128x128 fixed sized dimensions and later converted as gray level image. Figure 12 and 13 show LESH feature representation of '*Give Way*' and '*15 Speed Limit*' road sign contents respectively. Figure 12(a-b) and 13(a-b) are representing the original images with colour information and their corresponding pre processed images respectively. The extracted LESH features of these images are presented in Figure 12(c) and 13(c) respectively. The SVM classifier is trained offline on the LESH features of 25 classes containing 25 instances of each class.

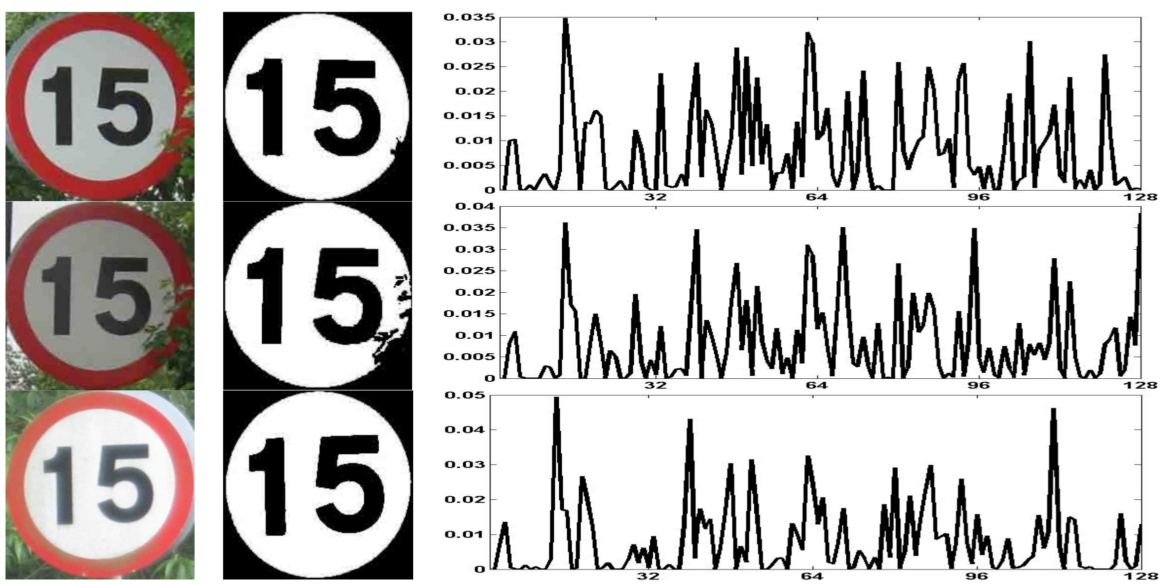
The shape index information is fed in to the trained feature database of 25 classes. This helps to retrieve only the specific road sign content which matches with the shape index. The SVM kernel testing set is compared with the retrieved query results from feature database. This makes the functionally of the recognition task more robust, accurate and efficient.

Table 5 shows the recognition accuracy results during various illumination conditions. The results show that the best accuracy figures are indicated during daylight conditions and the worst during fogy situations. Rainy conditions do not appear to have affected the performance of the algorithm significantly.



(a) (b) (c)

FIGURE 12: LESH feature representation for '*Give Way'* road sign



(a) (b) (c)

FIGURE 13: LESH feature representation for '15 speed limit' road sign

	Ambient Illumination			
	Day light	**Raining**	**Fog**	**Night**
Traffic Signs	560	430	70	110
Correct Recognition	552	426	61	103
False Recognition	8	4	9	7

TABLE 5: Recognition results during various levels of ambient illumination

5. CONSLUSION & FUTURE WORK

In this paper we have presented a novel approach towards road sign detection and recognition. The system utilizes a robust method of *Colour Segmentation* by employing the HSV colour space and using empirically determined threshold values suitable for various illumination conditions. A novel *Shape Classification* methodology is proposed in which all possible road sign shapes are classified by introducing the use of Contourlet Transform with SVM classifier. The *Recognition* stage introduces the SVM classifier with the Local Energy based Shape Histogram (LESH) features. We have provided experimental results to prove the effectiveness of this approach under varying levels of illumination and environmental conditions. Overall accuracy figures of 96-98% have been reported. We are currently working on real time application of the algorithm within an in-car navigation system.

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