Unconstrained Road Sign Recognition

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Dedication

This effort is dedicated to

My Family

My beloved wife Taghreed Turky

My Sons and My Daughters

Acknowledgment

First, I would like to express my appreciation to my supervisor Professor Raouf Hamzaoui for his support during my PhD research and for his helpful guidance. Also, the fruitful discussions during the research and the writing period with my second supervisors Professor Marwan Al-Akaidi and Dr Khaled Walid should be acknowledged.

Many thanks also go to Dr Hasan Fleyeh for his cooperation and helpful comments. Finally, the greatest appreciation goes to Al-Zaytoonah University for allowing me to use the university resources for testing the proposed algorithms.

Abstract

There are many types of road signs, each of which carries a different meaning and function: some signs regulate traffic, others indicate the state of the road or guide and warn drivers and pedestrians. Existent image-based road sign recognition systems work well under ideal conditions, but experience problems when the lighting conditions are poor or the signs are partially occluded.

The aim of this research is to propose techniques to recognize road signs in a real outdoor environment, especially to deal with poor lighting and partially occluded road signs. To achieve this, hybrid segmentation and classification algorithms are proposed. In the first part of the thesis, we propose a hybrid dynamic threshold colour segmentation algorithm based on histogram analysis. A dynamic threshold is very important in road sign segmentation, since road sign colours may change throughout the day due to environmental conditions. In the second part, we propose a geometrical shape symmetry detection and reconstruction algorithm to detect and reconstruct the shape of the sign when it is partially occluded. This algorithm is robust to scale changes and rotations. The last part of this thesis deals with feature extraction and classification. We propose a hybrid feature vector based on histograms of oriented gradients, local binary patterns, and the scale-invariant feature transform. This vector is fed into a classifier that

combines a Support Vector Machine (SVM) using a Random Forest and a hybrid SVM k-Nearest Neighbours (kNN) classifier.

The overall method proposed in this thesis shows a high accuracy rate of 99.4% in ideal conditions, 98.6% in noisy and fading conditions, 98.4% in poor lighting conditions, and 92.5% for partially occluded road signs on the GRAMUAH traffic signs dataset.

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List of Abbreviations

HOG	Histograms of Oriented Gradients
LBP	Local Binary Pattern
SIFT	Scale Invariant Feature Transform
SVM	Support Vector Machines
KNN	K-Nearest Neighbours
RF	Random Forest
RGB	Red Green and Blue
HSV	Hue Saturation and Value
ADAS	Advanced Driver Assistance Systems
TSR	Traffic Sign Recognition
HSI	Hue Saturation Intensity
HSL	Hue Saturation Lightness
WHO	World Health Organization
AHE	Adaptive Histogram Equalization

Chapter 1 Introduction

1.1 Motivation

Due to a growing population and a greater number of cars, threats to road users have increased in recent decades. For example, according to the department of transportation [3], UK road traffic has increased by 70% since 1970. Injury assessment data [8] from the World Health Organization (WHO) show that in 2000, 25% of all injuries resulted from road traffic accidents (Figure 1.3).

Recently, many car manufacturers have started to add road sign recognition as part of their Advanced Driver Assistance Systems (ADAS) [1,2]. For example, new Ford vehicles use a Traffic Sign Recognition (TSR) system to identify and display the traffic signs on a flashed panel to warn drivers when exceeding the speed limit (Figure 1.1 [9]). Figure 1.2 shows a TSR in new Range Rover models [4].

However, most of these systems have limited functionality in adverse weather conditions and for partially occluded signs. For example, Google's self-driving cars [172, 173, and 174] still need many years to be fully applied in real roads.

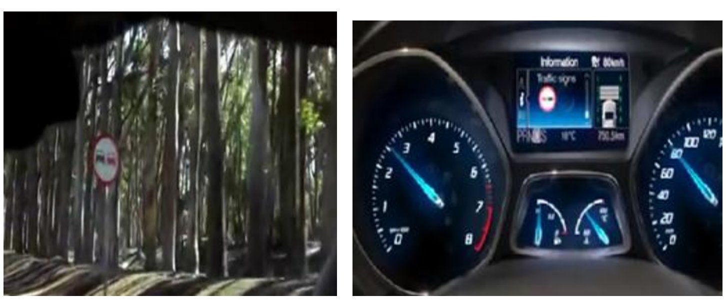


Figure 1.1 Ford cars using TSR technology to identify traffic signs [9]

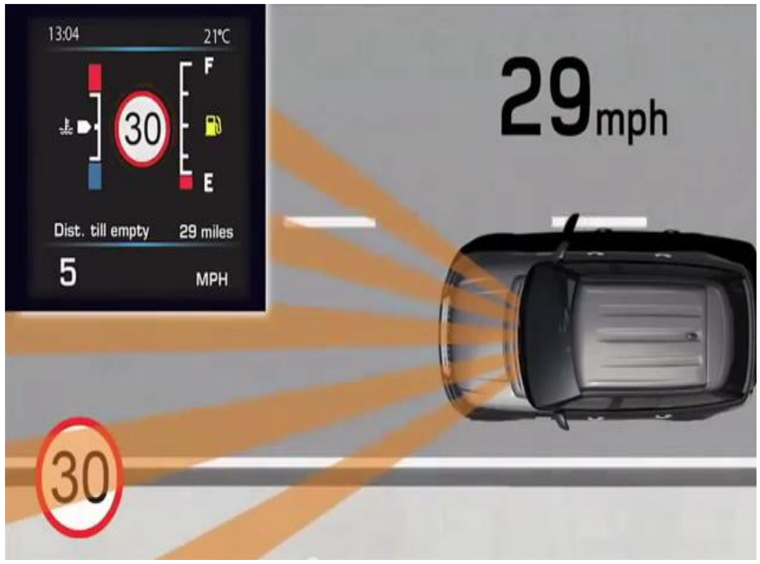


Figure 1.2 Range Rover cars use TSR technology [4]

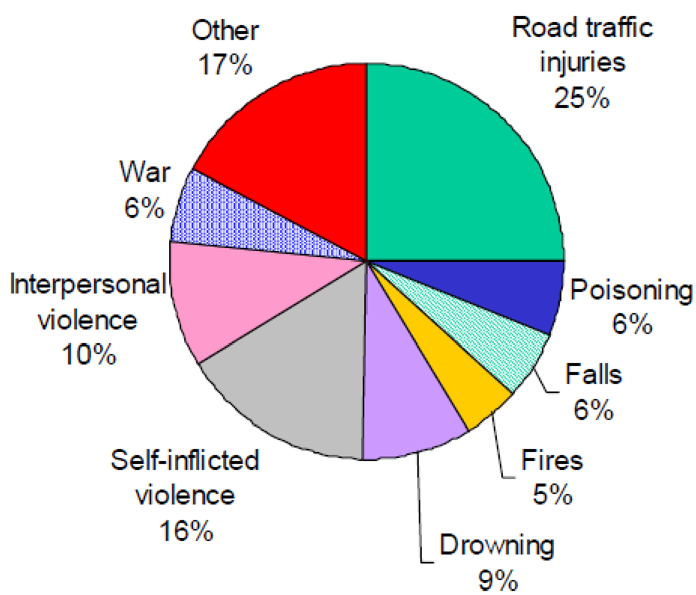


Figure 1.3: Global mortality distribution of injury [8].

This has motivated researchers to improve road sign recognition technology.

Generally, road sign recognition systems include two main steps: 1) segmentation and detection and; 2) recognition. The detection phase is used to extract the candidate road sign shape from the scene. In segmentation, most research focuses on the road signs colour features where the candidate road sign is extracted by colour segmentation from the scene using one colour space as in [11], [15], [26], and [33], or by combining more than one colour space [63] [64] and [65]. Colour segmentation was done by a thresholding value as in [11], [15], [26], [33], [73], [88], [90], [107], and [111]. Other segmentation methods were proposed in [74], [108], [27] and [109]. Besides that, many methods use shape detection such as a fuzzy shape recognizer [54], distance to border (DtB) [26], [36], pattern matching shape detection [93], and the Hough transform [34], [107].

In classification and recognition of road signs, many approaches have been proposed such as Multi-Layer Perceptron (MLP) and Neural Networks in [55] and [68], trained back-propagation neural network [11] and [138], genetic algorithms (GA) and three-layer structure neural networks [84], Adaptive Resonance Theory (ART) architecture neural networks [94], and template matching [34] and [79], matching pursuit [87], Normalized Cross-Correlation rules-based on template matching as a shape detector [139], and different types of Support Vector Machine (SVM) methods [13], [26], [33], [36], [48], [51], [56], [58] and [106]. Other recognition methods such as Gabor Wavelet filters [65] and Fuzzy Shape recognizers [54] have been used.

Current image-based road sign recognition systems achieve good results under ideal conditions, but they face challenges if the image capturing conditions are impaired. For example, during daylight, shadows and weather conditions may affect the road sign appearance. Furthermore, some road signs may be occluded or partially occluded by other objects such as other signs or trees. In other situations, the road signs may have the same colour as objects in the surrounding environment.

1.2 Limitations of Previous Research

Road signs have unique properties that may be exploited by numerous approaches for road sign segmentation, detection and recognition. Many road sign recognition systems start with colour segmentation as the first step in order to reduce the search space in classification step. Many segmentation methods were based on colour thresholding [93], [11], [26], [73], [74], [76], [77], [18] or Bayesian classification of the colour [85]. Many colour spaces have been used to be more or less dependent on lighting conditions as in [74], [85] [93], and [98]. Most studies use a single colour space that deals with lighting illuminations within the colour space properties and in general some problems such as poor lighting have not been solved yet, [11], [18], [26], [73], [74], [76], [77], and [93]. In [27], colour and shape features are combined in order to increase the accuracy. Therefore we can decide to put more research effort into the pre-processing phase including the segmentation process and features handling. While these methods improve the accuracy of the road sign recognition systems, they still have segmentation problems.

Another traffic signs detection approach is the searching for distinctive shapes, which can be easily distinguishable from other surrounding objects because of their artificial appearance [26], [34], [36], [50], [54], [62], [63], and [107]. Most shape detection studies can detect a road sign in ideal situations. But when the road sign is partially occluded, it cannot be extracted from the scene. Because of this limitation, many partially occluded road signs will not be passed to the next step in the recognition system.

Under poor lighting conditions and for partially occluded signs, the recognition accuracy can be as low relative to the occlusion size as 67.85% for medium-size, and 44.90% for large size [26]. In addition, the size of the feature space dimension is very large [26], [73] and [48]. Other approaches were tested in ideal sign conditions [11] and [77]. Besides the above limitations, there is a major problem in [74] in colour detectors such as shadows and light changes. Another problem is the stability of the Hue caused by the effect of reflections, where the colour space is a very important issue relative to the outdoor environment such as [74], [85], and [98].

However, road sign detection and recognition is still an open problem for research, depending on road sign location, orientation and environmental constraints such as lighting problems, shadow, partially occluded signs, and poor lighting conditions.

1.2 Aims and Objectives

This research aims at developing an automated image-based road sign recognition system that is robust against poor lighting and partially occluded road signs. We do this by developing road sign algorithms for segmentation, shape detection, and classification.

The main objectives of this research are as follows:

- To explore the effectiveness of RGB, HSV, and YCbCr colour spaces during varying lighting conditions.
- To propose a road sign recognition system that is suitable for different road sign categories.
- To propose a system that is robust under different environmental conditions, poor lighting, and partially occluded signs.
- To implement a complete road sign recognition system.

Our research will introduce a robust road sign recognition system that deals with the mentioned limitations, especially poor lighting and partially occluded signs.

1.3 Contributions

The main contributions of our thesis are as follows.

- A new dynamic colour space selection algorithm based on pre-processing is presented to identify the noise factors affecting the input image. This algorithm is illumination invariant based on a Hybrid Colour Model (HCM) to be used in colour image segmentation by selecting the colour space (RGB, HSV, or YCbCr). This algorithm shows good results in different environmental conditions, including poor lighting.
- A new hybrid dynamic threshold segmentation algorithm is presented. This algorithm is based on the colour space selection pre-processing step and can be

applied to different road sign colours (red, blue, and yellow) and shapes (triangles, circles, octagons, and rectangles). This algorithm is suitable for road sign recognition applications in different environmental conditions. The algorithm automatically generates a dynamic threshold based on the selected colour space.

- A novel geometrical shape symmetry detection and reconstructive algorithm is presented to detect and reconstruct the road sign shape when it is partially occluded. This algorithm is invariant to translation, rotation, scaling and partial occlusion. The algorithm resets the outer road sign shape if it is partially occluded.
- A robust local feature extractor based on combining HOG, SIFT, and LBP features is presented. This method is invariant to translation, scaling and rotation.
- A dynamic hybrid classification method is presented based on two hybrid classifiers: the first one is RF and SVM and the second is based on kNN and SVM.

1.4 Thesis outline

The thesis is organized as follows:

Chapter 1 gives the motivation for this work, the aims and objectives, summary of the limitations of previous research, and the main contributions.

Chapter 2 presents background information, including a description of road sign categories and environmental conditions related to road signs.

Chapter 3 introduces a literature review of image-based road sign recognition research; including colour segmentation, feature extraction and classification methods. Also, an overview of some road image databases is presented.

Chapter 4 describes the proposed hybrid dynamic threshold segmentation algorithm. An analysis of results and comparisons with state-of-the-art techniques are presented.

Chapter 5 describes the proposed geometrical shape symmetry detector algorithm. It also describes a new method to deal with rotated and partially occluded road signs.

Chapter 6 introduces the proposed hybrid features and hybrid classifier algorithm. The complete road sign recognition framework is validated with experimental results and comparisons.

Chapter 7 contains the conclusions and the proposed future work.

Chapter 2 Background

2.1 Introduction

Road signs are used to guide, warn, regulate and inform people of road regulations. Also, road signs improve the safety for pedestrians, drivers, and vehicles. Road signs are recognized and distinguishable by drivers and pedestrians because they have well-known colours and shapes [28]. In all countries worldwide, there are traffic engineering departments to regulate and define the appearance of all signs on the road. The placement of road signs must be accommodated to the road design and relative to the locations and positioning of other signs on the road. Because of this, the location and size of the road signs vary from road to road and in different locations. These variations impact the traffic signs to be of a sufficient size to enable drivers to recognize them. In addition, the road sign size must be appropriate to the traffic speed on the road. All sign sizes, are generally based on the visibility of the sign relative to the speed; table 2.1 [29] shows minimum clear visibility distances measured from the centre of the disadvantaged driving lane. Because of this, sign visibility should be checked from the appropriate viewing distance.

Table 2.1 minimum clear visibility distances [29]

Speed (Mile per Hour)	Minimum distance in meters for clear visibility
0 - 20	45
21 - 30	60
31 - 40	60
41 - 50	75
51 - 60	90
more than 60	105 (120)

In general, road signs are located about two meters from the road and the average height of signs from the base to top is between 0.6 to 2.0 meters for roads used by motor vehicles [29]. In addition, as many as three signs may be found on one pole placed the most important sign at the bottom [29].

2.2 Proprieties of Road Signs

The main requirements of road signs are that they simplify the driving and optimize road safety. The road sign characteristics such as road sign colours, the outer shape of the road sign, the inner contents (text, pictograms) are the most important features in any road sign recognition system. In addition, road signs are prepared carefully relative to strict regulations [30] to be suitable for the environmental conditions. The general road signs properties are listed below:

- They are represented by colours to contrast with the surroundings such as red, green, blue, or yellow, etc. [28, 31], these colours will differentiate the road sign from other surrounding colours.
- They are designed in certain shapes such as triangular, rectangular, octagonal, circular, square, etc. [28, 32], these shapes will be very helpful in the road sign detection process.
- The sizes of road signs vary depending on the road constraints [29].
- Road signs are relegated to colour categories and placed in suitable locations according to the road [28].

- They may contain a set of meaningful characters, pictogram, or both [29, 30] to clarify the meaning of the road sign to the drivers.
- They can appear in different weather conditions, including partially occluded, and distorted.
- More than one sign may be clustered in a one-pole base-sign [32].
- A road sign contains information represented by single colour and the rest of the sign has another colour.
- Road sign contents vary according to location. For example, road signs used in city areas have a different appearance than those of highway roads.

In general road signs can be categorized into the following groups; with each group have a different meaning:

- Warning signs: they are a triangle with equal thick red border, and the interior colour is white or yellow and many pictograms are used to specify different warnings such as (Children Crossing, Steep hill, etc.…) Figure 2.1.

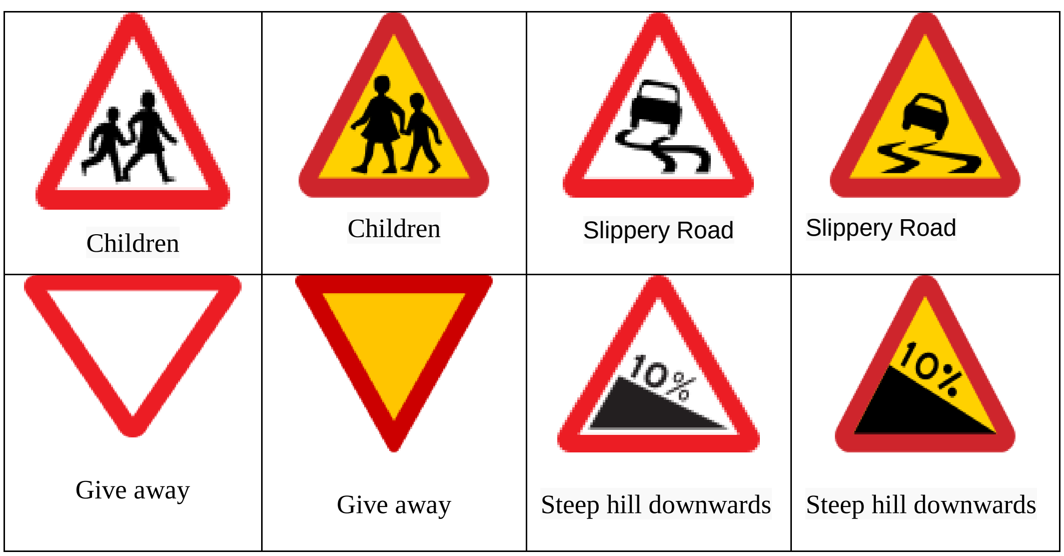


Figure 2.1 Warning signs

- Prohibitory signs: they are a circular shape with a red border and a yellow or white interior, Figure 2.2. They indicate a restriction to certain types of traffic, for example (speed limit signs, no entry, and no overtaking, etc.…), there are a few shape exceptions in this category: the octagonal is the STOP sign with a red background and white border, and other prohibitory signs are shown in Figure 2.3.

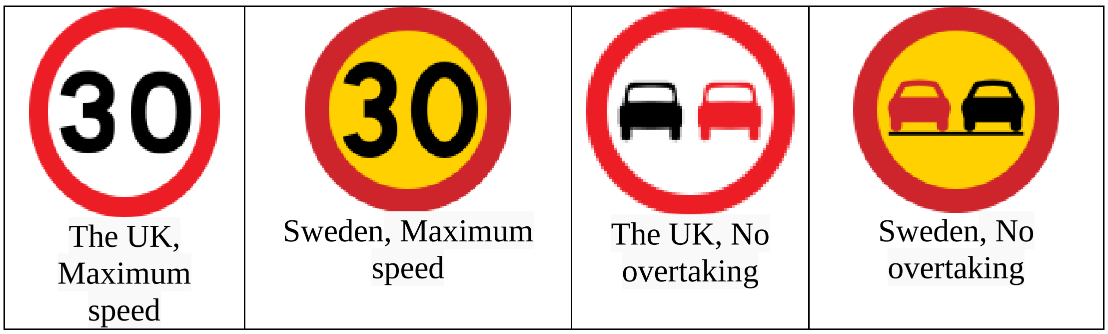


Figure 2.2 Prohibitory signs

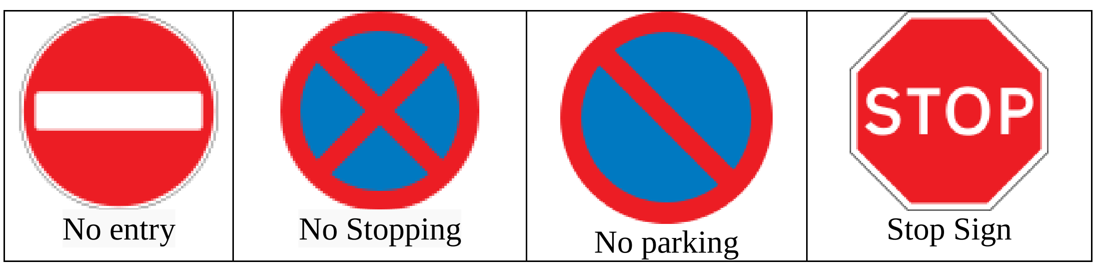


Figure 2.3 Stop and other prohibitory signs

- Mandatory and regulatory signs: are used to inform drivers and road users of certain laws and regulations to promote road safety. They are a blue circle with white arrows or pictograms, Figure 2.4.

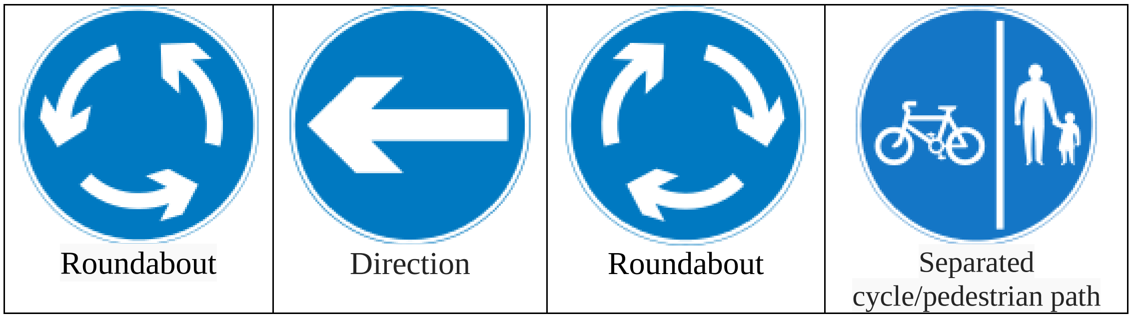


Figure 2.4 Mandatory signs

- Information signs: are generally square and rectangular-shaped signs with a blue, yellow, or green background colours as in Figure 2.5. They provide guidance with different pictograms either white or black, for example, parking areas, no-through roads and so on. This category includes shape exceptions such as the diamond shape with a yellow background to indicate priority roads, Figure 2.6.

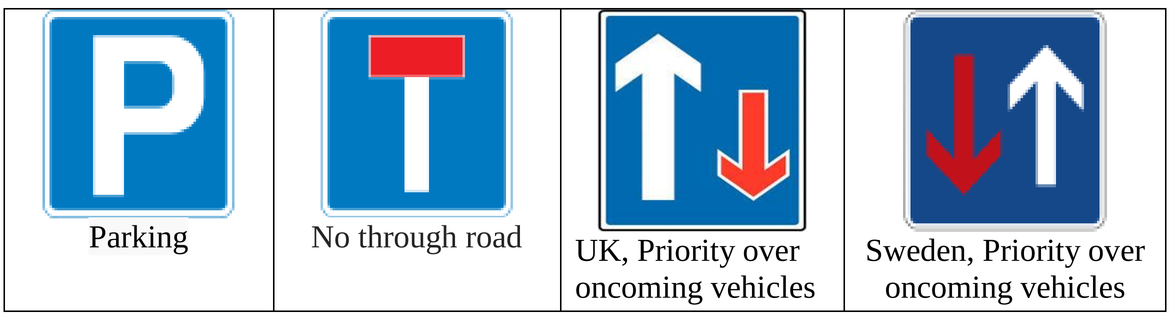


Figure 2.5 Information signs

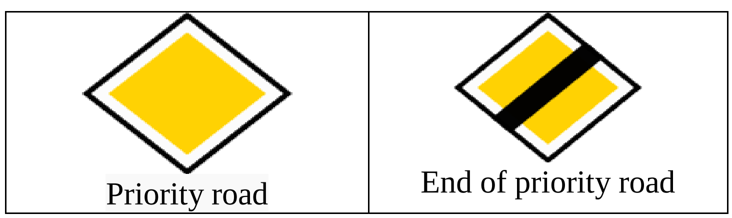
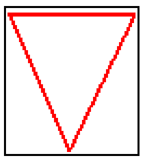
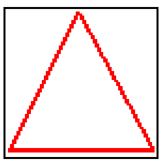
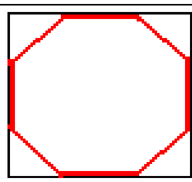
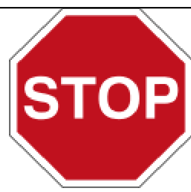
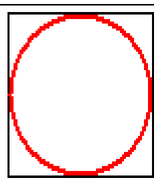
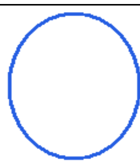
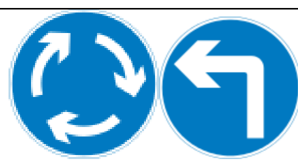
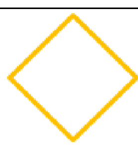
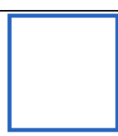


Figure 2.6 Diamond shape information signs

In general, road signs have a different appearance depending on the country, for example, "UK No overtaking" road sign vs. "Sweden, No overtaking" road signs shown in Figure 2.2.

As mentioned in previous sections, the colour and the shape of the road signs are used to determine their category. The colours and the shapes used on road signs must be visible and distinguishable from the surrounding. Table 2.2 described the colours and shapes for general road sign categories.

Table 2.2 described the colours and shapes for general road sign categories

Outer Shape	Shape Example	Road sign meaning
		Point Down Equilateral Triangle YIELD Sign
		Point Up Equilateral Triangle WARNING Signs.
		Octagon only for STOP Signs
		Red Circle Prohibitory Signs
		Blue Circle Mandatory and Regulatory Signs
		Yellow Diamond Road Priority
		Square and rectangle, for symbolic information sign

2.3 Road Sign Recognition

The standard road sign recognition process consists of three major phases as shown in Figure 2.7. The first phase is the image segmentation where the road sign areas of interest are cropped out from the whole image based on colour properties. Recent studies add another step before segmentation to enhance noisy-input images called a pre-processing step.

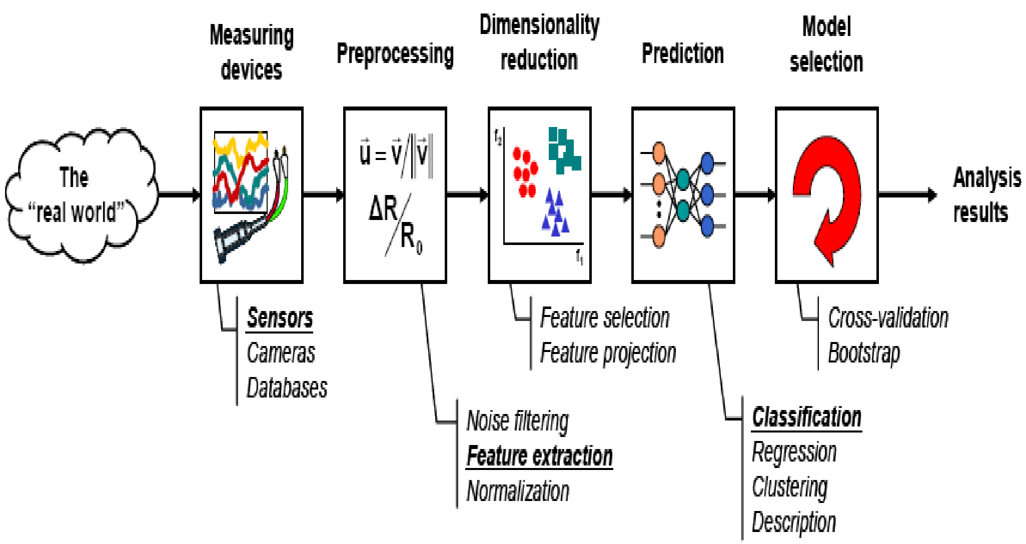


Figure 2.7 Major steps in pattern recognition

The second phase is to extract the cropped area features, where the discriminating features of the road sign are extracted from the normalized blob and stored in a feature vector. This vector is used in the classification phase to classify the data points into different classes relative to the problem; this phase is called recognition. Figure 2.8 shows the basic components of a pattern recognition system [40].

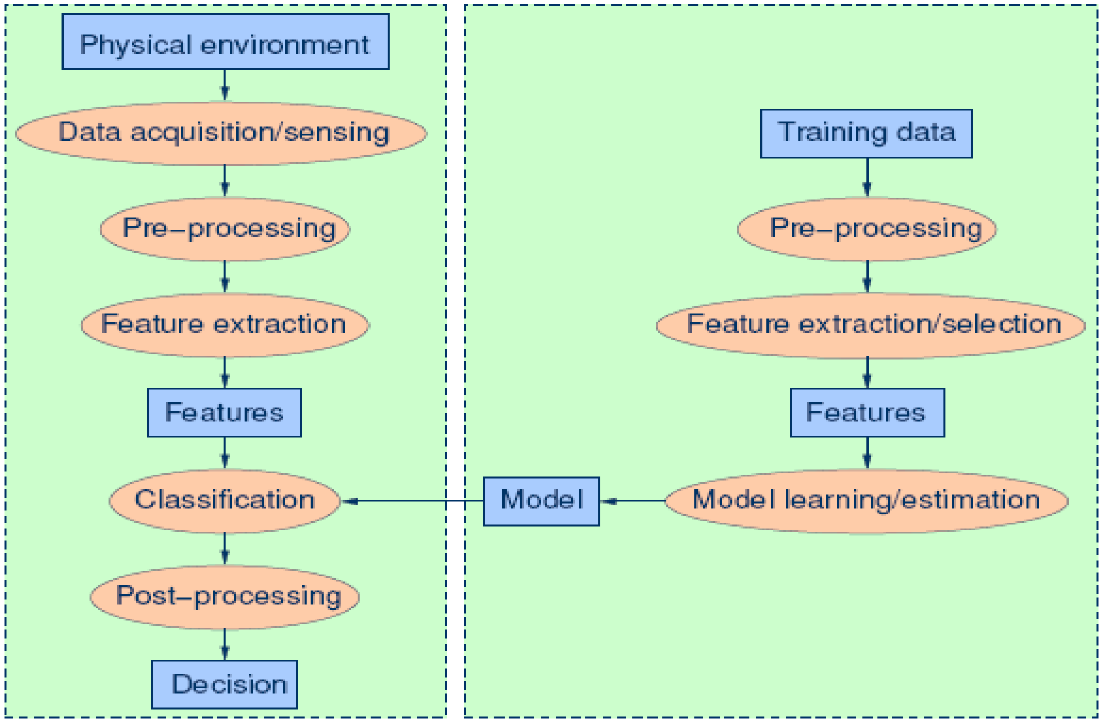


Figure 2.8 Basic components of a pattern recognition system [40]

The research on road sign segmentation, detection and recognition has recently gained attention in the literature [83, 99, 101, 102, 103, and 104]. To deal with these problems many studies have been proposed for automatic recognition systems [90–98].

2.4 Pre-processing and Segmentation

The pre-processing step is essential to segment a pattern of interest from the image background. Generally, many operations should be done in this step such as filtering, smoothing and normalization. Pre-processing is an enhancement technique that can highlight the image artefacts, or leads to a problem if the information does not correctly use. This step is essential in the road sign images because most of the images have different noise in the real environment. The pre-processing involves filtering, normalization, colour space selection, and poor lighting identification. The pre-processing step will be adding significant improvements on the segmentation results, because of the problems of poor lighting, faded, and image problems will be managed in this process. In segmentation, the image divided into different homogeneous regions [41][71]. Segmentation consists of extracting the candidate objects similar to the road sign from an outdoor scene. The segmentation can be done based on colour or shape or both. Figure 2.9 shows the road sign segmentation [26].

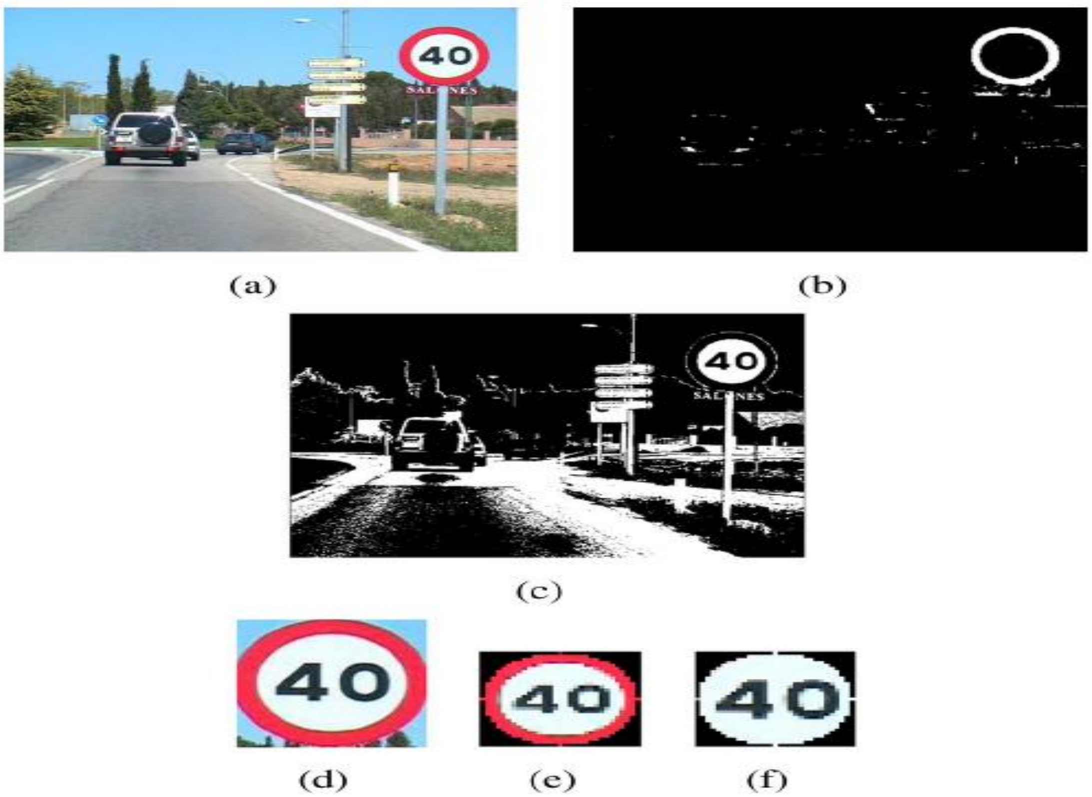


Figure 2.9 Road sign segmentation. (a) Original image.
(b) and (c) Red segmented regions (d) Extracted sign. (e) Outer and (f) Inner region [26]

In addition, pre-processing and segmentation will affect the feature extraction and classification accuracy results in the next step. Many colour spaces were used in the pre-processing step as colour-based segmentation methods. These colour spaces are used to solve illumination problems in the scene. Some of these colour spaces are illustrated in the next section.

2.5 Colour Spaces

Colour space properties are very important in computer vision systems. Many colour spaces were used in literature such as RGB, HSI, CIECAM97, CYMK, CIElab, YIQ, HSV, and YCbCr, etc. In the next subsections the three colour spaces that were used in the segmentation algorithm is illustrated; in addition to this, table 2.3 summarized the main characteristics of most colour spaces used in a related study to the road signs segmentation [121].

Table 2.3 Characteristics of colour spaces

Colour Space	**Advantages**	**Disadvantages**
RGB	Convenient for display	Not suitable for image processing because of the high correlation.
YIQ	Used to encode colour information in the TV signals, partly eliminates correlation of the RGB, less computation time, and Y channel is good for edge detection.	Correlation but less than the RGB colour space.

YUV	Encode colour information in the TV signals, partly eliminates of RGB correlation with less computation time	Correlation but less than the RGB colour space.
I1I2I3	Less correlation of RGB, less computation time, and can be used in colour image processing.	Correlation but less than the RGB.
HSI Hue, Saturation, and Intensity	Human colour perception; good for illumination problems (shading, and shadows, and separating objects of different colours).	It is numerically unstable at low saturation because of the nonlinear transformation
Nrgb (Normalized RGB)	Colour components are independent of the brightness of the image. Good to represent the colours even in the changing of illumination.	Very noisy at low intensities due to nonlinear transformation
International Commission on Illumination (CIE) CIE spaces (Luv or Lab)	Can use both colour and intensity information independently. Direct colour comparison can be performed on geometric separation within CIE space, and efficient in measuring small colour difference	Have the same singularity problem as other nonlinear transformations do.

2.5.1 RGB

RGB (Red channel, Green channel, and Blue channel) is the most common colour space used in computing, and several different binary representations, i.e. pixels. The RGB colour components are represented in the Cartesian coordinate system as a cube in which the x-axes for R, y for G and z for B [78]. For a given image I, RGB vectors are used to representing each pixel (x, y) as in the equation 2.1.

$$\mathrm{I}\ x, y = (R, G, B)! = (R\ x, y\ , G\ x, y\ , B\ x, y\ )! \qquad (2.1)$$

(Red Green and Blue) are three vector values that represent one certain colour in the RGB colour space. Figure 2.10 shows the RGB colour representation as in [78].

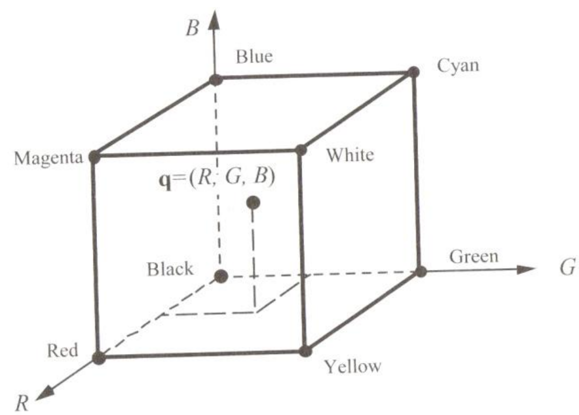
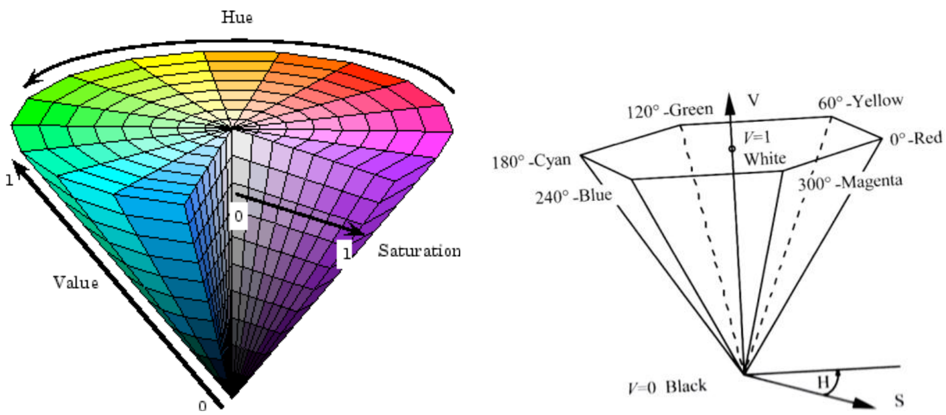


Figure 2.10 RGB vector for colour representation, $q=(R, G, B)$ [78].

2.5.2 H S V Colour Space

HSV (Hue, Saturation and Value) is a human perception of colour space. HSV is used in different image processing and computer vision applications. Figure 2.11 shows the HSV colour gamut where H defines the central colour of the pixel and its shades that represented when moving counter-clockwise start from 0 to 360 degrees. Saturation (S) is the number of pixels to a single colour where the highest and lowest saturation of a colour is 1 and 0, respectively. Value (V) indicates pixel information of the brightness or darkness and the highest (1) and lowest (0) values.



(a) (b)

Figure 2.11 HSV colour space representation, (a) HSV gamut [53]
(b) HSV representing different colour values [78]

The HSV colour space is preferred for manipulation of hue and saturation because of the greater dynamic range of saturation (shift colours or adjust the amount of colour). HSV was developed to be more intuitive in manipulating colours to approximate the way humans perceived colours. Table 2.4 lists the 75% amplitude, 100% saturated HSV colour bars.

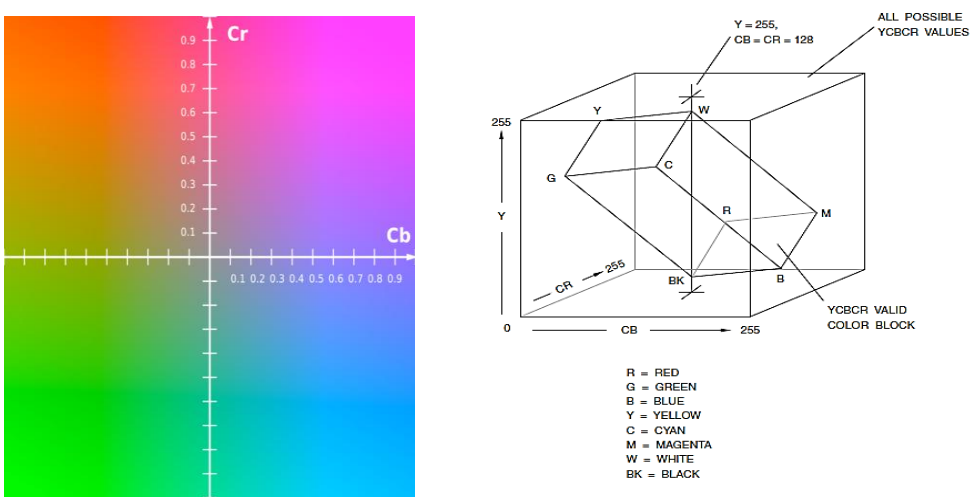
Table 2.4 HSV colour amplitude bars [78].

	Nominal Range	**White**	**Yellow**	**Cyan**	**Green**	**Magenta**	**Red**	**Blue**	**Black**
H	0^0 to 360^0	-	60^0	180^0	120^0	300^0	0^0	240^0	-
S	0 to 1	0	1	1	1	1	1	1	0
V	0 to 1	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0

2.5.3 YCbCr Colour Space

YCbCr colour space is widely used in digital video transmission and processing. It is like YIQ and YUV colour spaces that used in digital television. The Y channel represents luminance, Cb and Cr channels represent the chrominance. Figure 2.12 shows the YCbCr colour space, where Cb and Cr are represented along the X and Y axises with a values from -1 to 1 [52] and [78]. The translation of a pixel from RGB to YCbCr colour space is given by the following equation:

$$\begin{pmatrix} Y \\ Cb \\ Cr \end{pmatrix} = \begin{pmatrix} 16 \\ 128 \\ 128 \end{pmatrix} + 1/256 \begin{pmatrix} 65.738 & 129.057 & 25.064 \\ -37.945 & -74.494 & 112.439 \\ 112.439 & -94.154 & -18.285 \end{pmatrix} . \begin{pmatrix} RN \\ GN \\ BN \end{pmatrix} \tag{2.2}$$



(a) (b)

Figure 2.12 (a) YCbCr representation,

(b) RGB normalized limits transformed into YCbCr colour space.

2.6 Feature Extraction

Feature extraction is the process of finding high-level information of meaningful relative to the problem of research [43]. The feature can be represented as one or more measurements to specify an object property based on a defined function of some characteristics of the object [44], [45]. Features contain a great deal of information, including shape, colour, and texture. These features should be invariant and robust for different image situations such as scaling, rotation, and transformation [46]. In addition, the number of features generates the feature vector that is treated as a random vector that describes the content of the image.

Features may be divided into general features and domain-specific features. General common features are colour, texture, and shape. Features can be pixel-level features, local features, and global features. In pixel-level features calculation is done at each pixel, e.g. colour, and location. While local features calculation is done using the sub-regions of the image such as segmentation or edge detection. Global features the calculation is done for the specific sub-region of the image or the whole image. While the domain-specific feature is calculated based on the application domain, such as iris, faces, or fingerprints [47].

Several approaches of linear feature extraction are used such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), projection pursuit, Fisher Linear Discriminant (FLD), and Independent Component Analysis (ICA). In addition to non-linear methods such as kernel methods for PCA, and PCA network, and Curvilinear Component Analysis (CCA), etc. [46]. In our thesis, we use the following feature extraction methods as a hybrid feature vector as proposed in section 6.5.

2.6.1 Histogram of Oriented Gradients (HOG)

Edges and their orientations describe important features for the object detection and recognition of objects. Dalal and Triggs [156] introduced the HOG descriptors of the object edges to create a group of features to detect and recognize the objects. The technique calculates the existences of gradient orientation for a specific local portion of an image.

The HOG features are implemented by dividing the road sign blob into a number of cells; accumulated locally for one dimension histogram by calculation the edge orientations or gradient directions for each cell. Each pixel given a weighted vote based on orientation histogram bins in the gradient computation. These bins over the local spatial regions can be equally spaced over the interval 0°- 180° and 0°- 360° for unsigned and signed respectively. Edges in the blob contents of the road sign should fit into one of these bins. All cell histograms are normalized into overlapping blocks to form the HOG feature vectors. These overlapping blocks will improve the final image descriptors and solve the problem of the illuminations variance such as shadowing, and contrast-normalization [156]. This feature vector will be fed into the classifier to recognize the road sign image to a specific class. As illustrated, the number of features is used based on the orientation of bins and the number of cells. Figure 2.13, shows the structure of HOG feature extraction of the road sign blob image, this blob is divided into cells and accumulated into overlapped blocks. This intensive normalization process can generate a 324-feature vector based on 6 X 6 cells and 9 bins.

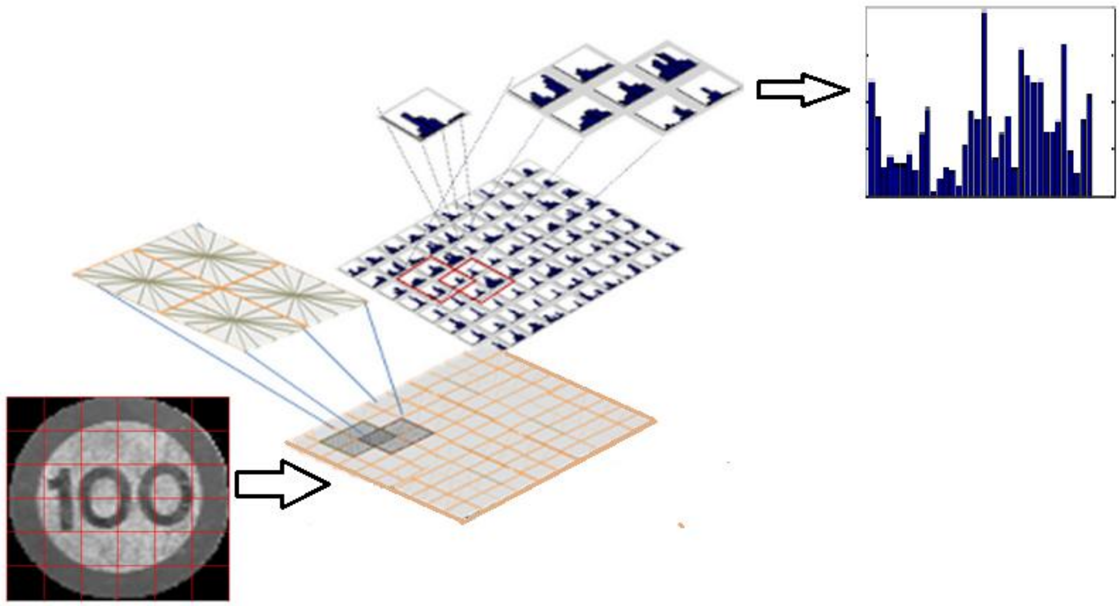


Figure 2.13 The structure of HOG feature extraction of the road sign image

2.6.2 Local Binary Pattern (LBP)

LBP is a texture feature extraction method presented by Ojala et al. [147] and [157]. In LBP they used of local 3×3 neighbouring pixels where the centre pixel intensity is compared with its connected neighbour pixels: the neighbour pixel is labelled as 1 if the neighbour pixel intensity is greater than or equal to the centre pixel intensity, otherwise, label as 0. Finally, the LBP code is created for the centre pixel. As shown in figure 2.14, we divide the input road sign blob image into blocks without overlapping. The histograms of each block are calculated by counting the number of occurrences of each local binary pattern in clockwise or counter-clockwise, describing the proportion of textural patterns in the image. All local histograms are combined as a final LBP feature vector. In order to reduce the dimension of LBP descriptor (number of bins of the histogram for each block), we use uniform patterns by dividing the road sign image into 12 X12 blocks with 3 X 3 pixels per block.

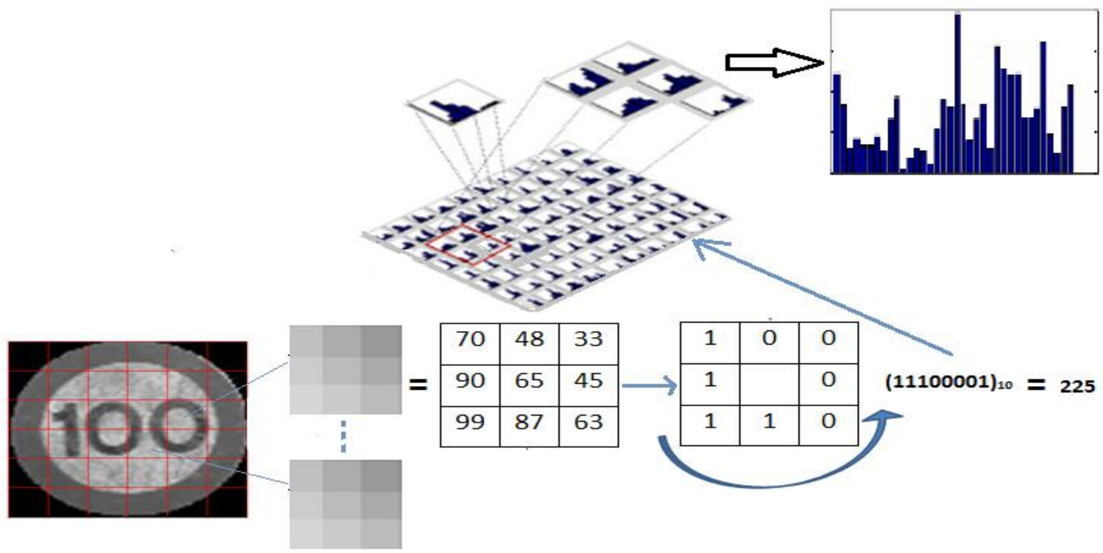


Figure 2.14 The structure of LBP feature extraction of the road sign image

In LBP, the features of each image are extracted, in a way that the road sign blob image is divided into smaller regions and then the binary pattern histograms are extracted (a binary code is extracted for each neighbouring pixel). The LBP feature is considered as a good feature for describing the image texture [150] [146]. The road sign image is divided into blocks B_0, B1,…, $B_{m-1,}$ and the extended histogram is found for each block to produce the concatenated histogram based on the equation.

$$H_{image} = \sum H_{Bi}, \quad i=0,..., m-1.$$

where H_{image} is the concatenated histogram, and H_{Bi} is the block histogram.

2.6.3 Scale Invariant Feature Transform (SIFT)

SIFT is a feature extraction method invariant to image scale and rotation that was proposed by Lowe [158][159][162]. It is a local feature descriptor that extracts features at the road sign image grid; SIFT is very similar to HOG. In our thesis, the blob image is divided into 9×9 cells with 4×4 pixels per cell to create the histograms based on 8 orientation bins, and the gradients are weighted by gradient magnitude; these histograms must be concatenated and normalized to compensate for illumination differences. Figure 2.15, shows the structure of SIFT feature extraction.

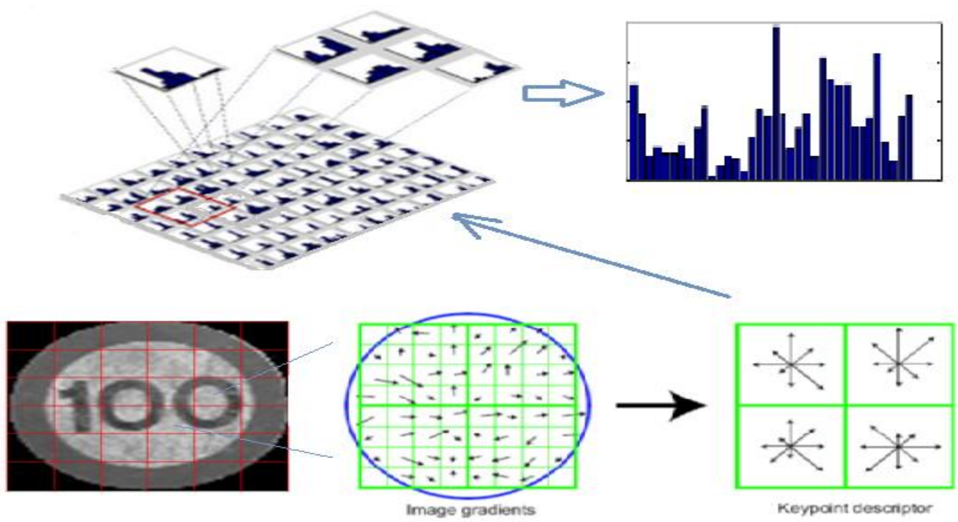


Figure 2.15 The structure of SIFT feature extraction.

2.6 Classification

Classification is the process that categorizes the input data into one of the several predefined classes those results from the feature extraction in the training phase. In addition, classification is a procedure to learn and classify the input objects using the predefined training set of objects that are labelled into correct classes. In general, the set of training classes are mapped as a class label to the extracted features from the input image with the highest probability label.

For example, a feature x is belongs to one of the C classes $(w1, w2, \ldots, wc)$ using the feature vector d, where, $x = (x_i, \ldots, x_d)$. So, the optimal rule for minimizing the risk given as below:

$$P(wi\ /\ x) = \sum_{j=1}^{c} L(wi\ ,wj\ ).\ \ P(wj\ /x)$$

Where $L(wi\ ,wj\ )$ is loss function when wj is the true class, and the $P(wj\ /x)$ is the probability if $P(wi\ /x)\ >\ P(wj\ /x)$ for all $j\ \#\ i$.

On the other hand, the function calculated based on a specific algorithm and maps the input feature to a specific class is called a classifier. There are mainly three classes of classifiers [19]. These classes classified based on different methods such as similarity maximization, probabilistic and geometric, methods, and methods. In the first method, classifiers search for maximizing similarity based on similarity metrics in order to assign the class labels such as template matching and a Nearest Neighbour (NNB) algorithm [21, 22]. The second is probabilistic methods search for the probabilities of classes based on conditional densities of the class instance like Bayesian classifiers, logistic classifiers using maximum-likelihood parameters [24]. The third method is based on minimizing the error criterion by using the decision boundaries; for example, using a Fisher linear discriminant, decision tree, neural network, multilayer perceptron network, and SVM.

Support Vector Machines are from the most robust and common algorithms in classification methods[20, 25, and 57].

SVM supports binary classification and multiclass classification by adding different parameters and constraints to deal with the different classes problems. Furthermore, SVM registered an efficient formulation with better implementation results [23]. In addition to our research, SVM proposed good results in road sign recognition systems.

2.6.1 Support Vector Machine (SVM) Classifier

SVM is one of the common classifiers used in classification, regression, machine learning or other fields. Its dimensional space can be one or more hyperplanes. Figure 2.16, shows the optimal hyperplane and the optimal margin to separate two-dimensional spaces between two classes [131, 133]. These Support Vectors (SV) are the training points that used to define the positions of the hyperplanes [119].

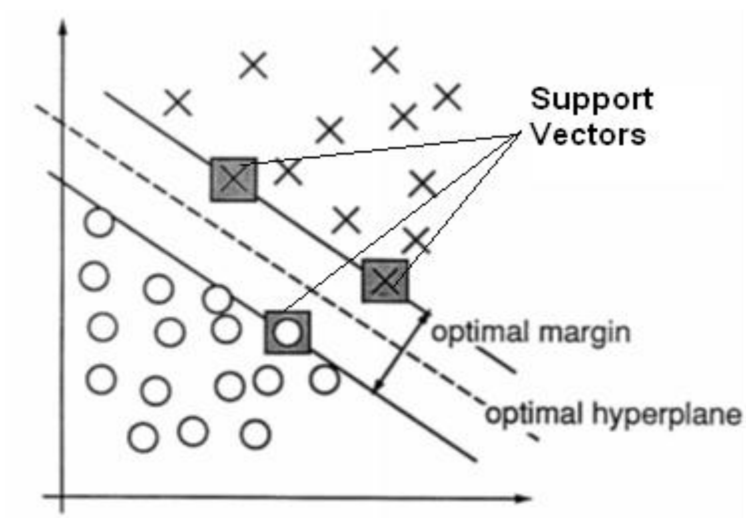


Figure 2.16 Optimal hyperplane separating two-dimensional spaces; the support vectors define two classes [131].

In linear SVM for a training dataset D and n points can be represented as the following:

$D = \{(x_i, y_i) \mid x_i \in \mathbb{R}^p, y_i \in \{-1|1\}_{i=1}^{n}$

where the y_i class is 1 or −1, in which the point x_i belongs.

We need to find the maximum-margin hyperplane between $y_i = 1$ from $y_i = -1$

The parameter $\frac{b}{||w||}$ is the distance from the origin of the normal vector **w** to the hyper plane, and $\frac{2}{||w||}$ is the distance between two hyper planes where $||w|$minimize by using geometry operation. To keep the point out of the margin a constraint for each i added.

$Min\ \Phi\ (w) = \ ½\ \|\ w\ \|^2 = \ ½\ (w,w), yi\ (w.xi\ +\ b) \geq\ 1$

Otherwise in non-linear SVM where the classes are not linearly separable, as shown in Figure 2.17.

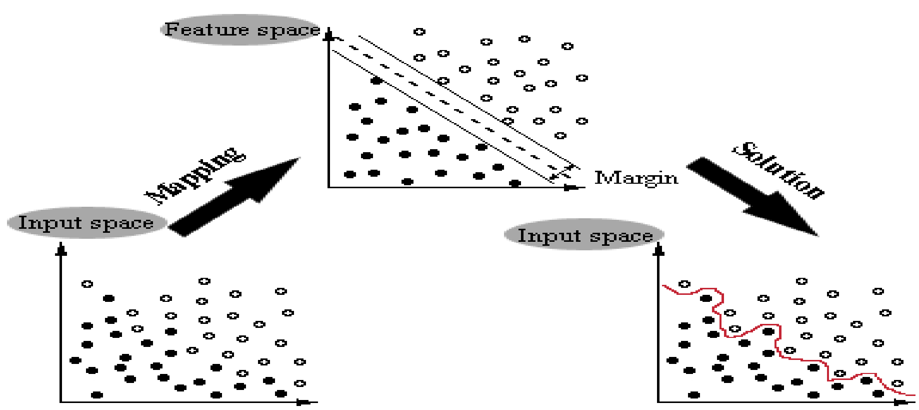


Figure 2.17 non-linear SVM where the classes are not linearly separable

2.6.2 Random Forest Classifier

Random Forest (RF) is a method used for classification in machine learning systems. It works by building a multitude of many decision trees during the training operation and find the class with the most likely to be sampled to the class of individual trees. In the testing process, a decision tree is produced for each classification, and the resulting class is used for the final results of the largest tree in the classification results.

Random forests algorithm use bootstrap aggregating, or bagging method for the training process to learn the tree. For a training set $x \ starts \ from \ x_i \ to \ \ x_n$ with responses $y \ starts \ from \ y_i \ to \ \ y_n$, so a random sample is selected to be replaced with the training set to feed the tree.

After training, the majority voting is used for the unseen samples x' by using the averaging of all the individual regression predictions [163].

$$f' = 1/B \sum_{b=1}^{B} f'_b(x')$$

2.6.3 *k*-Nearest Neighbours (kNN) Classifier

KNN algorithm calculated a weighted average based on the number of nearest neighbours (k), this weighted calculation is done by inverse their distance [163]. Each training vector is given a class label in the multi-dimensional feature space. In the training step, feature vectors are stored if they have a labeled class.

In the classification step, for each input feature vector the Euclidean or Mahalanobis distance from the labeled class calculated, then based a pre-defined constant number k the label has been assigned to the most frequent among the k training samples nearest to that query point.

Both SVM and KNN classification approaches are widely used due to good performance and high classification accuracy. KNN is a simple training and classification method implemented as an instant-based learning algorithm. In addition, it can manage a multi-class dataset sufficiently by requiring a few training samples. Also, the accuracy of KNN is based on distance metrics with less sensitivity to the dimensionality of the noisy data while the performance is reduced. Besides this, SVM is one of the most common high accuracy classifiers, but accuracy is not very high when the samples are close to the hyper-planes. SVM classifiers suffer from intensive computational demand due to the convoluted training and classifying process, especially when the training data set and a number of features are huge.

2.7 Road Sign Recognition Problems and Challenges

- The colour perception of a road sign can vary in relation to the lighting problems and environmental conditions. These problems, make the extraction of the road sign colour information is difficult. This includes environmental conditions such as fog, rain, snow, etc., as shown in Figure 2.18, and time of the day, for example, morning, dusk, night, etc., that affect the variations of illumination, as in Figure 2.19.

- Signs may appear in poor visibility, because of bad weather and lighting conditions Figure 2.20. Many obstacles, like buildings, poles, trees, and other vehicles may be partially occluded the road signs Figure 2.21 and Figure 2.22.
- Road signs images captured while a car is moving may have a motion blurring images with a different road sign sizes Figure 2.23.
- Colour fading is another problem, because of sunlight exposure and environmental conditions that affect the paint with time colour is changed and faded Figure 2.24.
- Many objects are shown in the background with the same colours and shapes on the road signs, Figure 2.25 and Figure 2.26.
- Other signs may be damaged, disoriented or partially occluded as shown in Figure 2.27 and Figure 2.28, these problems make it hard for the system to detect and recognize the road sign correctly.

Figure 2.18 Fog and Bad Lighting

Figure 2.19 Illuminated signs

Figure 2.20 Bad Lighting Condition

Figure 2.21 Bad Sign Positions (partially occluded signs)

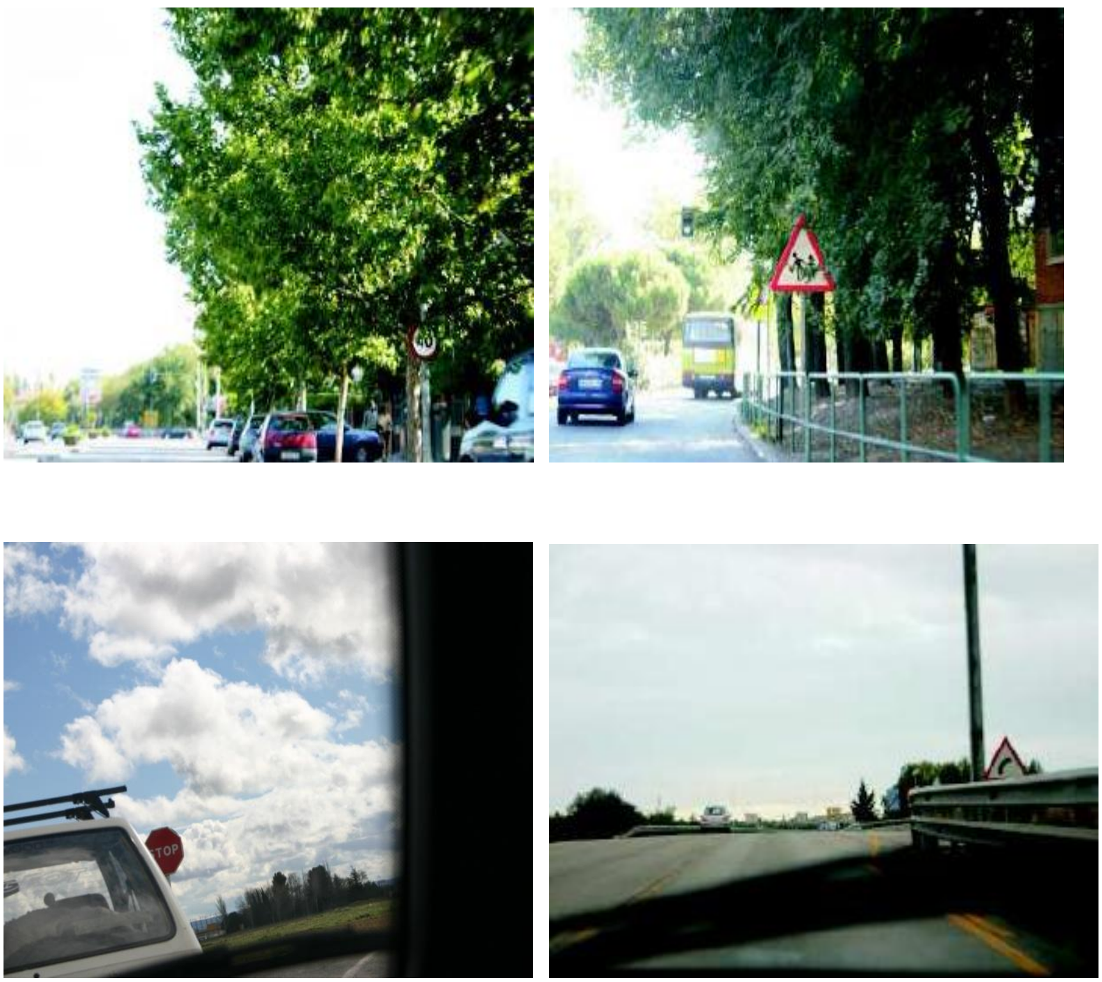


Figure 2.22 Road sign images (Partial Occlusion)

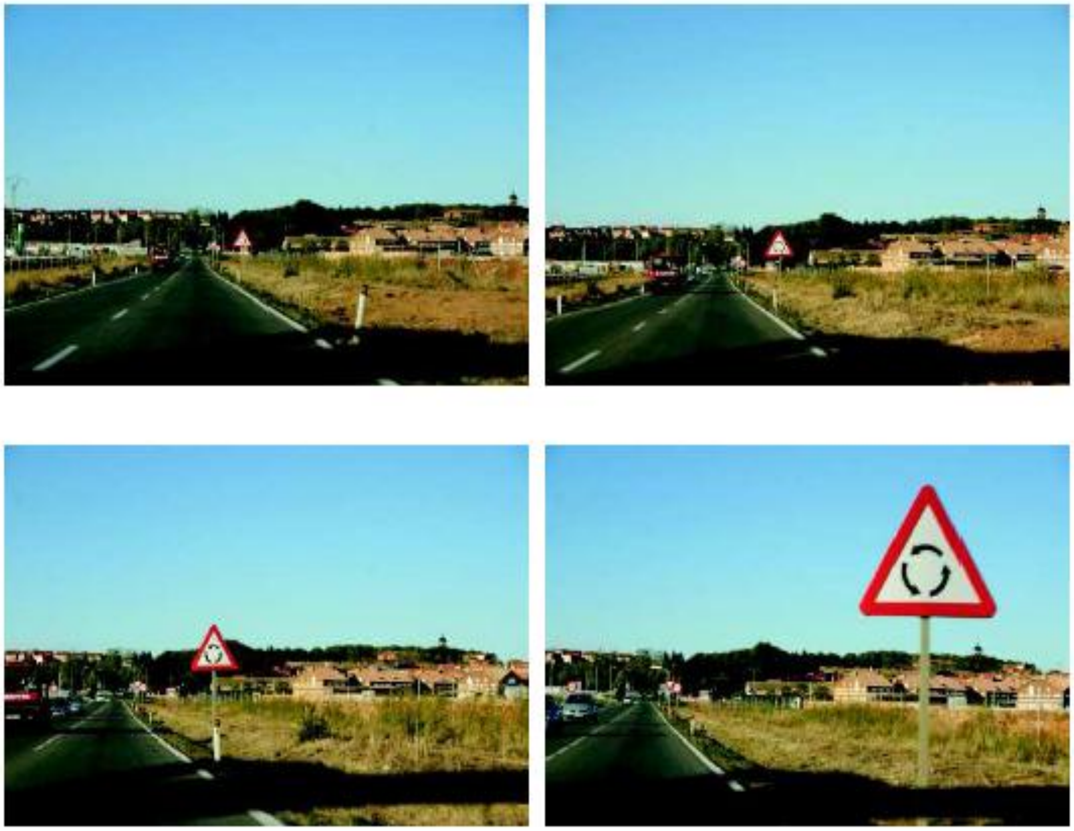


Figure 2.23 Different sized Road Signs

Figure 2.24 Faded Traffic Signs

Figure 2.25 Signs with background having same colour

Figure 2.26 Different signs and many similar colours and shape

Figure 2.27 Damaged and vandalized Signs

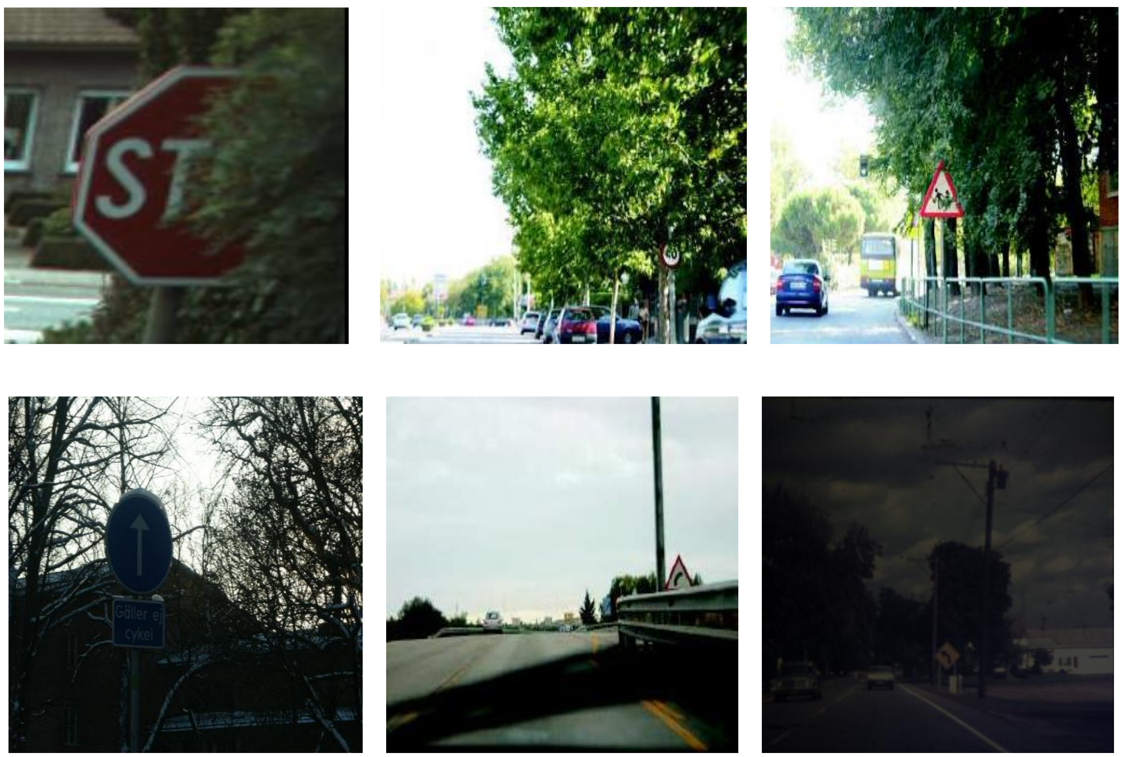


Figure 2.28 Different problems in road sign images (partial occlusion, poor lighting)

Furthermore, the complexity of inner road sign contents and pictograms make the extraction of road sign features challenging. For example, multi-classes of feature vectors will be extracted for UK warning signs of triangle shape [29] are about 74 different signs that contain different messages and pictograms see Figure 2.29. In addition, each road sign category (main class) has different subclasses. Each subclass has many road signs with different properties. Other problems in the feature extraction process are the rotation and translation of the road sign and its contents. Consequently, an automatic recognition system must be able to extract road sign features in different conditions even in road sign rotation, scaling and translation.

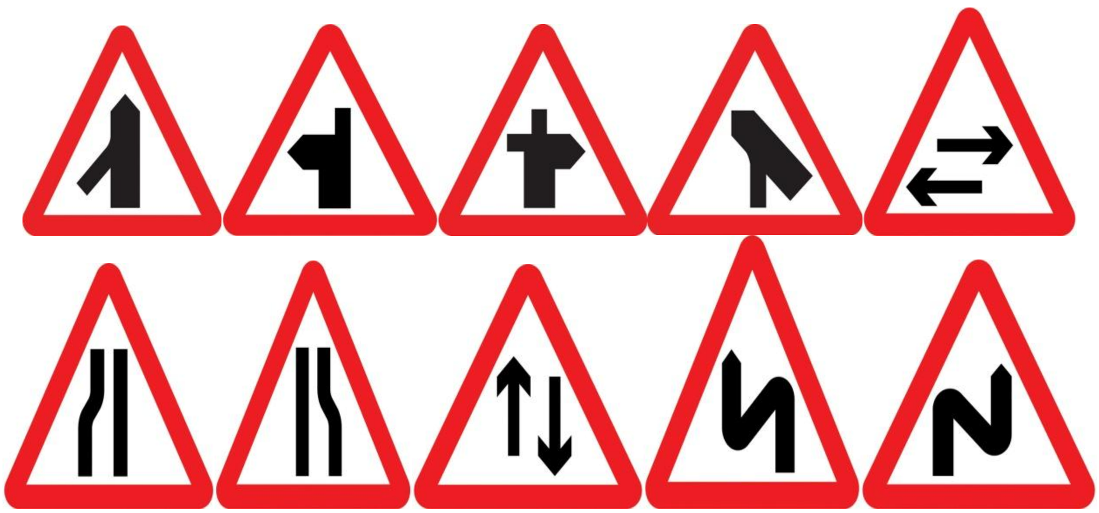


Figure 2.29 Warning signs that contain different messages and pictograms

Road sign recognition is aimed to detect and recognize the road sign images that captured with relaxed conditions. Complex backgrounds, weather conditions, lighting, shadows, and other image challenges make the task more complicated and difficult. Several approaches and methods have been proposed and developed for road sign recognition [11, 17, 26, and 35]. The poor lighting, partially occluded, and the size of the road sign are still problems for the computer vision research.

Chapter 3 Literature Review

3.1 Introduction

Several methods and approaches have been implemented for image-based road sign recognition systems. Relative to our research on road sign recognition, many approaches are proposed, with most of them focusing on the ideal environmental conditions. Some of them partially mention the cases of less lighting, partially occluded signs and the challenges listed in section 2.4.

The research on road sign segmentation, detection and recognition has recently one of active research topics [11], [14], [15], [17], [18], [19], [48], [120] and [132]. The Current image-based road sign recognition systems, work well under ideal conditions, but many problems were reported if environmental conditions are not relaxed. To deal with these problems, many researchers have been proposed an automatic road sign recognition system [4–12].

Road signs have unique properties make them distinctive from many other surrounding objects. These characteristics were exploited in many approaches for road sign segmentation, detection and recognition. In a majority of published work most approaches were searching for a region of interest, features of the road signs (detection) and classifying the type of the road sign in a specific category (recognition) [12,11,59, and 61]. Road sign colours and shape features were used in many studies for both segmentation and detection as in [11, 12, 13, 58, 61 and 62]. In addition, other approaches were based on the idealized templates of road signs [87]. In recognition, the classification step is preceded by a normalization of the candidate regions; usually by scaling the regions to a fixed size. The extracted features are mapped into one of the recognized classifier tools [26, 66, 69, and 67].

3.2 Colour-Based Segmentation

Previous research usually preceded by normalization the candidate regions of pixels; these regions are normalized by scaling to a fixed size taken in the ideal conditions of lighting. In literary works, the segmentation is the first step of the detection system can do by thresholding value using a given colour space to find the road sign colour regions from the scene.

Escalera et al. [11] use a colour threshold image to achieve the detection by a shape analysis using neural networks in classification. They proposed a nonlinear transformation using hue and saturation channels to enhance the (red and blue) colours in the image. Because HSI is invariant to light changes and HSI formulation is nonlinear and requires much processing power, RGB is preferred in this study. The same idea was used by Fang, in [108] where the similarity between the calculated hue component and the stored hue values of particular colours (red and blue) in road signs are calculated, and mapped into a perceptual analyser based on a neural network.

Kamada and Yoshida in [72] suggested the colour ratio between the intensity of the specified colour and the sum of the intensity of RGB. They used a threshold for red colour by using four different thresholds to apply to the resulting image followed by detection (circumference, corner) for circular and triangular signs respectively.

Another paper for Escalera et al. [88] presents an approach for detecting red colour using HSI colour space. Firstly, they converted RGB to HSI colour space where hue and saturation values are recalculated. The saturated red hues range is emphasized by using a lookup table. They have scaled the hue and saturation values to the range from 0 to 255 where the results are multiplied to be upper bounded by 255.

In [109], they proposed a radial symmetry transform for road sign detection; they used only circular road signs for speed limits of 60 and 40. They used the colour gradient map and convert the images into a grey scale. The red traffic sign is for circular is used in testing for different environmental conditions, the segmentation rates were more than 99% in sunny, 70.09% in rainy and 70.86% in the night. This method has many limitations such it detects only red circular shapes, size of the circle must be within a range of estimated radius and any changes in the estimated radius will be ignored. This method required additional processing using the template matching and a temporal filter to validate consistent candidates for the colour information.

Although other colour spaces are used, for example, in [16], a fixed threshold based on hue and saturation bands is used to segment the red and blue colours. In the work by Liu et al. [70], a threshold is used by looking for chromatic and achromatic colours using a simple vector filter (SVF) to detect the specific colour and remove all the outlines. In addition, Ruta et al. [34] first segment the image based on fixed thresholds and then enhance the obtained colours.

Other authors [90] used the red colour of a STOP sign during the daytime. They find the differences between the red, green and blue colour components, a static red colour having a value of 85 over the green and the blue components which are used to segment the red colour signs.

Maldonado-Bascon et al. [26] also used a static threshold. Their scheme can recognize road sign shapes such as triangular, circular, rectangular, and octagonal signs. In the detection phase, they used linear SVMs as geometric shape classifiers. They used colour segmentation for red, blue, yellow, white, or any combinations of them. In a segmentation process, they used HSI colour space with a static threshold; this threshold is used for all images in different environmental conditions. These static thresholds will not work efficiently in all environmental conditions, especially in poor lighting. This step will affect the results of the next steps of the feature extraction and recognition system. Blobs of interest (BoI) were detected after the colour segmentation. Distances to borders (DtBs) for (BoI) are executed by linear SVM to use as input vectors.

Gomez et al. [73], they used different colour spaces to evaluate the segmentation algorithm. They proposed a segmentation method based on SVM and using a lookup table (LUT) for speed enhancement. In addition to achromatic decomposition different colour spaces were presented, where achromatic information can be separated. In addition, SVM classifier is used for both detection and classification purposes as explained in detail in [26], to evaluate the segmentation algorithm presented.

Fleyeh [74] proposed a fuzzy approach for traffic sign colour detection and segmentation. The first step is to translate the RGB road sign image into HSV colour space. Then the segmentation process is done by a set of fuzzy rules, taking into consideration the channels of the hue and saturation. Three factors have used the colour of incident light depending on CIE (Commission Internationale de I'Eclairage) curve, reflectance properties of the object depending on the wavelength of the incident light, and the camera properties. Seven fuzzy rules were used depending on hue and saturation values (HSV).

Gao et al. [15] use the CIECAM97 colour model. Convert RGB to CIEXYZ values and to LCH (Lightness, Chroma, and Hue). The authors found that the lightness values of red and blue signs are similar, besides that, they used hue and Chroma components in the segmentation process. They use different lighting conditions (daylight, fog, and shadow, cloudy and rainy weather). A quad-tree approach was used in segmented the road signs, this done by recursively divided the image into square regions until all elements are homogeneous.

In [109, 27] the authors used RGB colour space to segment only road guidance signs. They used the eight-neighbour method to group the obtained regions, and shape properties were used to filter out nonrectangular regions. Because of the problem of lighting variation they used relations between the RGB colour components within this colour space.

Because, the standard colour spaces cannot always guarantee good colour segmentation results, several more complex colour classifications have been proposed. In [35] a hierarchical region-growing technique they use a database for the colour pixel classification. Moreover, these methods are computationally extensive, more complex and complicated than those using thresholding methods.

Recently, many studies have been proposed a combined colour spaces technique based on road sign colour segmentation. In [63], the authors used a logical AND operation to combine the Hue channel from HSV colour space and the chrominance (U, V) values from YUV colour space. In [64], they used colour variations of the image based on thresholding values using 256 RGB and HSL transforms. In another study [65] they jointly used RGB and HSI colour spaces to segment red and blue colours in the image. A joint colour space has been used in [66] they use RGB to extract the achromatic information and the HSI is used to extract the chromatic information. In [67] four colour space (HSV, RGB, CIElab and CYMK) were used to segment road signs based on colour classifier.

Malik et al. [54], converted the RGB image into the HSV colour to threshold the road sign images for only the red colour. The Fuzzy shape descriptor is used in the road sign detection. The result of segmentation is a binary image with white areas to reflect the road sign regions and the black regions for the background. They labeled the white 8-connected regions similar to a class of the selected sign. The required white regions were filtered based on area filtration. The passed region shape area and centre of the mass properties are calculated by using Fuzzy Shape Descriptor. Only red colours for triangular and circular shapes are used in experiments. They use 100 images to test the proposed system, the colour segmentation accuracy is 96% and the shape detection accuracy is 94%. The paper presents the approach in ideal conditions for only red colour road signs. By using the HSV colour space the Hue channel for the red colour is very relative to the lighting conditions. Because of this, the fixed threshold values based on HSV need to be adaptive relative to the lighting conditions to be segmented more effectively.

Farag and Abdel-Hakim [85] proposed another approach with five colours, where a Bayes classifier selects a colour based on the maximum probability of each colour, and an equal a priori probability for the five colours (red, yellow, green, blue, and white) is assumed.

Zhu and Jiang [80] presented a new solution to this problem by breaking the complex colour information to five standard colours and then using the same BP neural network for recognition.

Another paper [110] uses the HSI colour space to extract hue and saturation colour features to deal with brightness and shadow invariants. They used a static colour threshold as in [26] to get the segmented blobs. A DtB features are calculated for each blob to feed into a Gente Boost with sharing features detector to test each blob in the recognition process.

One recent study [169] proposed an illumination invariant colour segmentation method consisting of cluster centre tree-based segmentation and illumination estimation. They learned cluster centre tree with traffic sign images for four cases: day-sunny, day-cloudy, rainy and night to handle the illumination changes, where the leaf node is ready to classify. They use the k-means clustering algorithm to model the colour distribution to group up the colours for different illuminations to the same cluster. They trained the cluster centre tree for colour segmentation. This method achieves detection rates of 94.30% in sunny conditions, 86.03% in cloudy conditions, 87.85% in rainy conditions and 65.79% at night.

In most of the previous research, the occlusion problems did not take into consideration. A summary of colour-based road sign segmentation methods is given in Table 3.1.

Table 3.1 A taxonomy of road sign detection methods based on colour.

Authors	**Colour space**	**Type of**	**Colour of**
Ruta et al. [34]	RGB	static threshold & enhancement	Red, blue, yellow
Kuo and Lin [107]	HSI	static thresholding	Red
Fang et al. [108]	HSI	similarity measure	any
Escalera et al. [88]	HSI	thresholding	Red
Escalera et al. [11]	HSI	thresholding	Red, blue using two lookup tables
Escalera et al. [111]	HSV	thresholding	Red

Gao et al. [15]	CIECAM97 (Colour model. convert RGB to CIEXYZ)	thresholding	Red
Benallal and Meunier [90]	RGB	thresholding	Red
Maldonado-Bascon et al. [26] Gómez-Moreno et al. [73] Gudigar et al. [33] Jin-Yi et al. [110]	HSI	threshold	Red, blue, yellow, and white
Fleyeh [74]	HSV	fuzzy approach	Red, blue
Gil- Jimenez et al. [48] Fang et al. [27]	HSI	eight-neighbour method to group regions	Blue, yellow
Malik et at. [54]	HSV	fuzzy approach	Only red
Siogkas and Dermatas [139]	CIELab L*a*b	Thresholding	Red and blue

Generally, colour-based segmentation uses a thresholding value in some colour space to segment the input image. Many authors use the RGB colour space such as [93, 62, 34], but it is very crisp with regard to changes in lighting. Others [26, 36, 48, 50, 83, 107, 111 and 114] use HSI or HSV colour space which performs well than RGB and allows some variation in the intensity of light, but Hue and Saturation could not detect white colour because is it can be at any hue value. In addition, HSI works well in changing light intensity but it does not deal with the change in colour different weather temperature. Others [15] use the CIECAM97 model to deal with variations in colour temperature but with some variation in the intensity of light.

Because of this, we proposed a new dynamic colour space selection algorithm based on pre-processing to identify the noise factors affecting the input image. This algorithm is illumination invariant based on Hybrid Colour Model (HCM) to be used in colour image segmentation by selecting the colour space of (RGB, HSV, or YCbCr).

All the previous methods mentioned in Table 1 have limitations relative to the road sign segmentation. For example, static thresholds were used in [26, 108, 88, 34, 90, 15, and 107]. By using a static threshold any variation of the colour level will make the segmentation process to fail. Another limitation in the previous studies was the use of only one colour space [26, 42, 11, 108, 73, 74, 88, 34, 90, 15, 107, and 33] for all outdoor environment images. In addition, many studies used one colour in the segmentation such as [11, 88, 90, 15 and 107] while road signs have more than one colour that will be needed in segmentation. Another study [95] used a dynamic threshold based on Euclidian Distance. This method used the Hue, Saturation and Luminance colour space. The threshold value varied relative to the brightness of the image while the intensity levels of the road sign colours were not taken into consideration. This method works better than the static threshold, but many intensive computations were done.

In this thesis, the proposed dynamic segmentation algorithm is a novel algorithm using three colour spaces to generate a dynamic threshold relative to the intensity levels of the road sign colours during the daytime. Because of this, the proposed algorithm is suitable for different environmental conditions even in poor lighting.

3.3 Shape-Based Detection

Several approaches in road sign detection research used shape-based techniques. Escalera et al. [11] used detection by a shape analysis and neural networks for the classification. The detection was done for (circumference, corner) of circular and triangular signs, respectively; the training was done by two separate multilayer perceptron NNs. More research was done by Escalera et al. in [88] where they used a lookup table to emphasize the results.

Maldonado-Bascon et al. [26] proposed a road sign recognition system that deals with illumination conditions. They used HSI colour space and fixed threshold value to find the regions that contain the road sign blobs. The aspect ratio is used to select the right size of the objects; other objects are considered as false positives blob or noisy blob. The true objects are passed into a shape classifier of DtB features with linear SVM classifier. This step reduces the false detections of the segmentation process. The DtB vectors shown in Figure 3.1 used 20 values for each of the blob sides for a normalized image of 31 X 31 pixels.

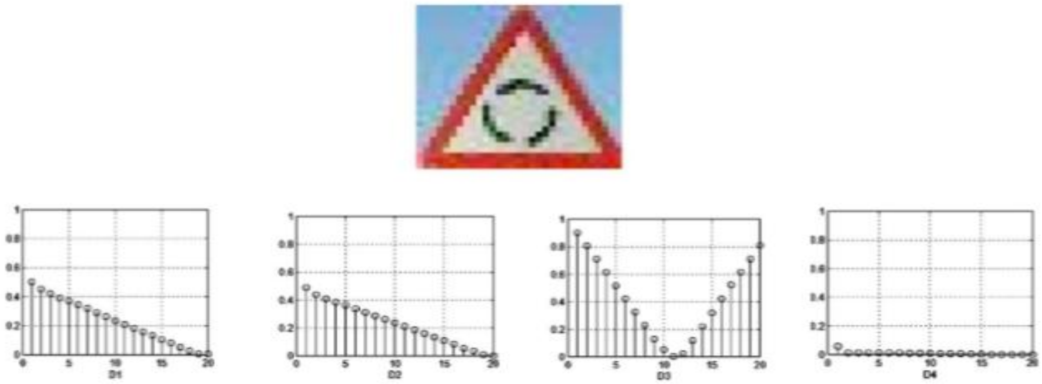


Figure 3.1 DtB vectors represented the triangular road sign [26]

They reported that Distance to Border vectors cannot detect the octagonal shapes such as STOP signs. The result of the previous step is normalized to input to the recognition phase that consists of an SVM with a Gaussian kernel. These static thresholds will not work efficiently in all environmental conditions especially in poor lighting. In addition, the 20 features of the DtB vector does not represent all the pixels of interest in the normalized blob, especially for partially occluded signs.

Andrey et al. [62] proposed a road sign recognition algorithm for mandatory and informative road signs. They used RGB colour space on segmentation. The candidate shapes were detected by using a background vertical shape histogram and horizontal shape histogram as shown in figure 3.2. The input was normalized relative to template sign shape. They used the difference calculation between them to find the correct road sign shape. While the binary mask is used in the inner area of the road sign and a template matching method was used in the road sign recognizing.

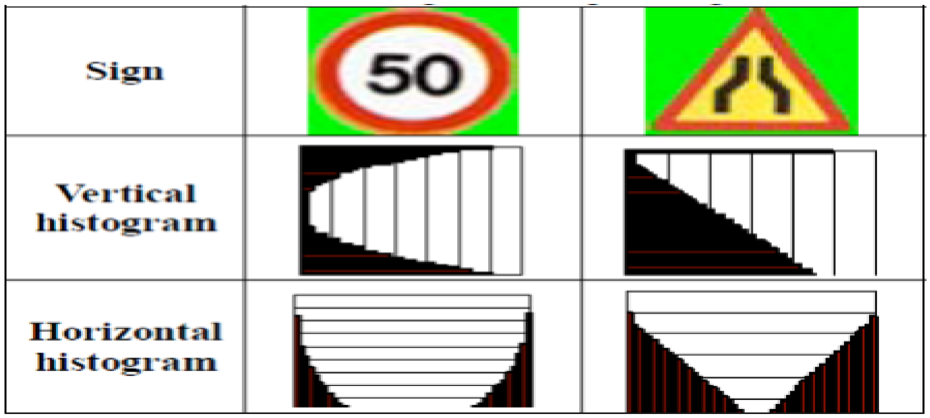


Figure 3.2 Background shape histogram [62]

Fleyeh [49] presents a fuzzy road sign detection and recognition approach. In the segmentation process, he used HSV colour space to deal with the lighting problems. Seven fuzzy rules were used based on HSV colour space using the Hue and Saturation components to detect and segment the road sign colours from the image as shown in Figure 3.3. The resulting blobs are normalized into square blobs to be used in the seven fuzzy rules.

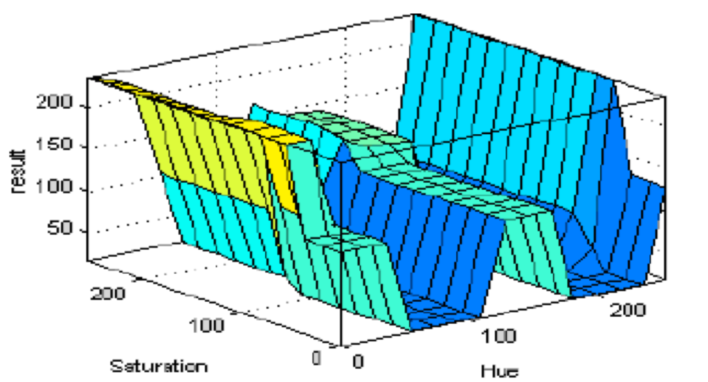


Figure 3.3 The Fuzzy system surface [49]

A fuzzy shape recognizer uses four shape measures (octagonal, triangular, circular, and rectangular) by using affine moment invariants. In addition, for classifying the road sign contents, a fuzzy shape recognizer is used based on five variables for input and one variable for the output. The best performance reported was 95% for sunny image conditions.

Fang et al. [27] propose colour features and shape features by using two NNs for sign detection. Shape and colour features were applied by a fuzzy approach to detect the signs. A Kalman filter is used in frame tracking for signs of a specific size of (8-pixel radius) to find the values of the gradient for specific colour regions based on edge detection method. This method was used to construct the edges of the image. Combinations of colour and shape features are used by applying a fuzzy approach.

Ruta et al. [34] proposed a road sign detection, tracking and recognition from video inputs. RGB colour space is used with colour-enhancement to be used for Haar-Wavelet feature extraction. In shape detection, they used a Hough Transform on polygon-shaped signs by using directional gradient information. A Kalman filter is used to minimize the search region for the sign. The maximum likelihood approach based on template matching is used in recognition, with an accuracy rate of 93% and processing speed was from 20 to 25 frames per second.

Aryuanto and Koichi [81] proposed a new technique for fast and robust detection of traffic signs using Geometric Fragmentation. They focused on detecting red circular road signs by detecting the outer ellipse of the sign combining the right and left parts and then using geometric fragmentation to find ellipse parts. A summary of road sign detection methods is given in Table 3.2.

Table 3.2 Summary of road signs detection methods.

Authors	Colour Segmentation	Shape Detection
[26] Maldonado-Bascon et al.	HSI Colour Space	DtB Vectors
[93] Broggi et al.	RGB colour space	Pattern Matching
[83] Escalera et al.	Use lookup table and HSI colour space	Canny edge detection based on gradient energy with probabilistic technique
[62] Andrey et al.	RGB colour space	Background Shape Histogram
[64] Matsuura et al.	HSL Colour Space	Horizontal and Vertical Histogram
[50] Wang et al.	Hue, Saturation and Value	Area of the shape and the ratio of width and height
[34] Ruta et al.	Red, Green and Blue (RGB) Colour space	By using the shape parameters based on the shape boundary points using Hough Transform and Gradient Information
[48] Gil- Jimenez et al.	HSI Colour Space	Fast Fourier Transform
[36] Arroyo et al.	HSI Colour Space	Use distance to border features based on Linear SVM classifier
[107] Kuo and Lin	HSI Colour Space	Hough Transform with Sobel Operator
[61] Eichner et at.	YCbCr Colour Space	Using a Random Sampling and Consensus method based on geometric circle shape detection
[60] Lafuente-Arroyo et at.	HSI	DtB vector

Most papers have used different colour spaces in the segmentation process. In the detection process, most studies used different methods to detect the road sign. None of the previous studies deal with the partially occluded signs. Because of this, if the region objects resulting from the segmentation process have some occlusion, then it is discarded. Consequently, we present a novel dynamic shape geometrical symmetry detection and reconstruction algorithm, which reset the outer road sign shape if it is partially occluded to the ideal one.

3.4 Feature Extraction and Classification

The appearance of road signs may vary in different weather conditions. To overcome these difficulties, several approaches have been proposed including Multi-Layer Perceptron (MLP), and Neural Networks [55] using the topology as described in [139]. Other authors [54] have proposed a template matching technique to recognize road signs. Different methods of NN were used in the classification and recognition of road signs such as 3-layered [141], backpropagation [94], in [88] NN used for classification using the Adaptive Resonance Theory paradigm for binary inputs (ART1), and SIFT is used in many road sign recognition systems [85] in which the similarity measures of the features are calculated through proposed functions in [63]. In [97], the authors propose a local intensity normalization method to handle lighting variations; to obtain local features; they used a Gabor transform method, a Linear Discriminant Analysis (LDA) used for feature selection.

Other approaches used an SVM in classification and recognition such as Arroyo et al. [56] who proposed an SVM Gaussian kernel for content recognition. Another study by Kouzani [58] proposed the ensemble learning approach used in road sign identification systems based on a polynomial kernel SVM and an AdaBoost-Naive Bayes classifier.

The ensemble learning method is used to combine the decisions of multiple classifiers for more effective identification results.

Siogkas and Dermatas [139] proposed a complete road sign detection system for tracking and classifying road signs. The shape detection is used by localizing the road sign shape symmetry based on a template matching is classification method. This research used only circular road sign shapes. Normalized Cross-Correlation rules-based on template matching was used in the classification module to detect the shapes of candidate road sign. The accuracy recorded for road sign detection was 95.3% and classification accuracy was recorded as 81.2%.

Broggi et al. [93] proposed two different methods for shape detection: a simple models pattern matching method and shape edge detection and geometrical cues. The recognition is completed by building and training a set of neural networks.

Fatmehsan et al. [137] present a road sign detection and classification method. The method was based on three steps relative to the red sign object. In the first step they transferred the RGB image into YCbCr image; then the red regions containing the road signs are detected. In the second step, a Gabor wavelets feature vector is extracted for classification. Finally, a hybrid classifier using one-vs.-rest (OVR SVMs) and Naive Bayes (NBs) classifier is used.

Maldonado-Bascon et al. [26] used an SVM with a Gaussian kernel by normalized input blob to 31X31 pixels as DtB features as shown in Figure 5.2. In this method reported that DtB vectors fail to detect octagonal-shaped STOP road signs. In this study, they normalized the segmented road sign in a bounding box to a grey-scale block of 31x31 pixels as a candidate blob. This process will reduce the feature vector in the recognition module. Figure 3.4 (e) shows the DtB of two road sign images (blobs of interest) BoI with a partially occluded sign since the occlusion will change the DtB feature vector of an ideal road sign image. Figure 3.5 shows other blobs of interest of a road sign with different DtB feature vectors. This problem may exclude the road sign blob to be passed to the next classification of the interior road sign content and to final recognition step. The occlusion or partial occlusion in this method will not be detected in the detection phase.

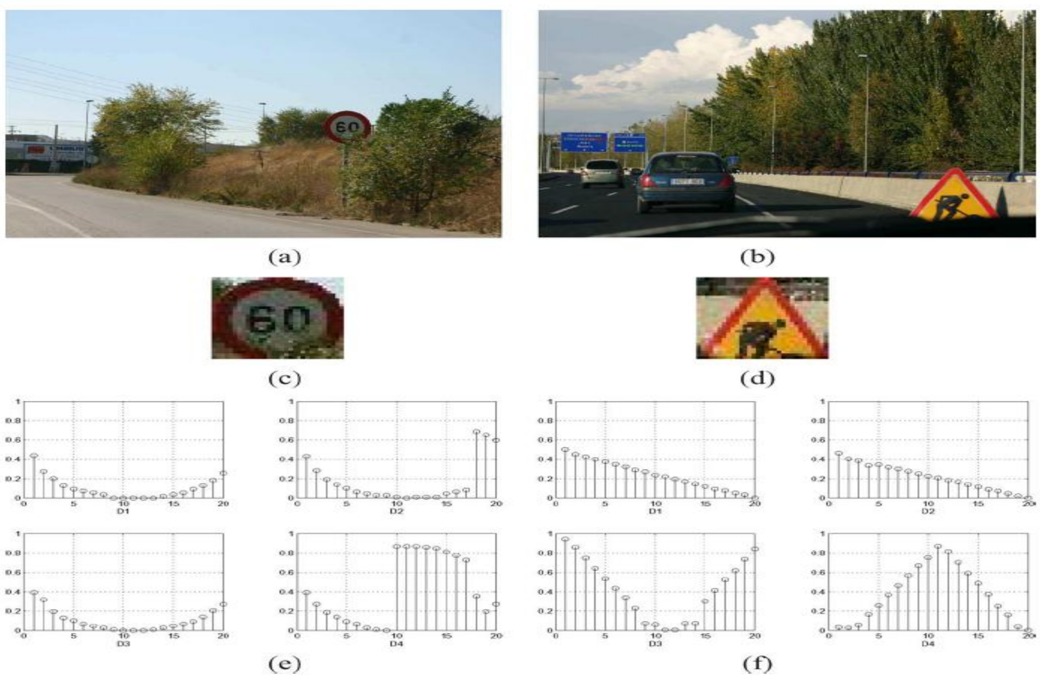


Figure 3.4 The original images (a) and (b), blobs of interest (c) and (d), distance to border vectors (e) and (f).

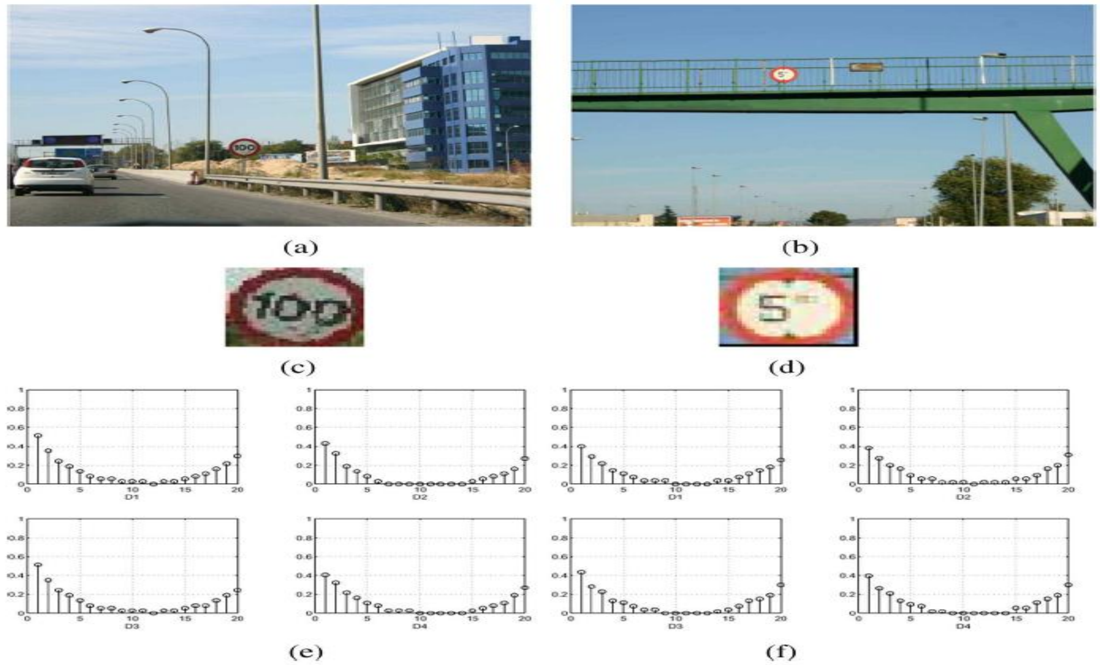


Figure 3.5 Blobs of interest of a road sign with different DtB feature vectors.

Another main problem with this method is that it fails to detect the octagonal-shaped STOP road signs because the DtB feature vector will be mostly like the circular DtB feature vector. Because of this, some road signs with octagonal shapes were recognized as circular ones in the detection phase, which aims to discard them in this step. In this study, an SVM classifier was used for both detection and recognition phases. In the detection phase, a linear SVM classifier was proposed based on DtB feature vectors. In the recognition phase, different one-versus-all SVM classifiers based on a Gaussian kernel were used. The implementation of the system in [26] shows the accuracy of 93.24% for ideal images.

Kellmeyer and Zwahlen [138] recognize only the warning signs using a back propagation neural network with a layer of 30 nodes. They used the yellow interior warning sign with a 10x10 pixel boundary square, which is mapped to an input of 100 neuron layers, and the output-layer was either “sign” or “non-sign”. The proposed method could detect 86% of the large ideal signs and 55% of warning signs in 55 images.

Kuo and Lin [107] proposed a two-stage classification technique for traffic sign detection and recognition. Colour and shape features are used in the road sign detection process. They reduce the image noise by adopting the HSI colour space and anisotropic diffusion method. The edge map using a Sobel operator is used for geometric analysis for both circular and triangular road sign shapes. Hough is used for both triangular and circular sign features. They used a circular Hough transform and triangular Hough lines intersected with edge map used to find the region of interest. For removing noise, they used the median filter with a dilation processes for the candidate region. This region is normalized to a size of 100×100 pixels using bicubic interpolation in the recognition stage. In the recognition stage they use: First, an (RBF) neural network (Radial Basis Function) is used to utilize the class of the road signs blobs to reduce the false objects in the next step. The second step is to achieve final recognition of the road sign using K-d trees. They recorded accuracy of 92.45% for triangular and 97.78% for circular road signs.

Kiran et al. [77] introduce an SVM Learning method for road sign classification. They used colour segmentation with Hue and saturation channels in the detection phase. In addition, a linear SVM method was used for shape classification and for feature extraction, they used DtC and DtB features. The segmented blob has four features vectors using on the DtB and another four vectors using DfC. By using the eight vectors the proposed method was invariant of rotation and scaling. DtB is used in classification, in addition to combining DtB and DfC feature vectors.

Bahlmann et al. [76] proposed Haar wavelet and AdaBoost features used for detection phase, and a Gaussian probability for classification. Colour and shape detection were applied separately one after the other. In the colour segmentation phase, false regions were rejected. Within the AdaBoost framework, they combined colour and shape modelling. The authors used AdaBoost with greyscale wavelet features based on width, height and position parameters in addition to using RGB colour images.

Ruta et al. [35] developed a two-stage symbolic road sign detection and classification system. The detection step is colour pre-filtering for a circle or regular polygon detector. In the classification step, they proposed a new feature selection algorithm that depends on the dissimilarity between the candidate regions using distance metrics based on colour distances. A Kalman filter tracker was used to reduce computation.

Paclík et al. [17] proposed an approach based on similarity methods, they represent the candidate sign as a set of similarity features compared to a stored prototype one. In each class, a different set of local regions in testing are compared with a refined in the training process. Soft independent modelling of class analogy (SIMCA) and Fisher linear discriminant (FLD) classifier were used in the classification phase.

A recent study [170] proposed a highly discriminative means of detecting road signs by using spatial regions. They normalized the blob size into smaller sub-regions and each sub-region is a cluster of signs characterized by unique region patterns consisting of homogeneous and discriminant 2-D regions. The mean intensities of these regions are used as features. They evaluate the discriminative attributes corresponding to detected regions by classification experiments using an SVM classifier. This method has been tested in a real traffic sign database and the results achieved a considerable reduction of features with respect to extraction from raw images. The accuracy rates were 96.01% for blue rectangular, 96.30% for red triangle, and 94.83% for red circular. This paper tested for ideal situations and it has many limitations when the road signs were rotated, translated, and for any other geometrical road sign shape and even if the road sign was partially occluded.

In [79], a robust, flexible Matching Pursuit MP filter is proposed, this method used to reduce the training into a two-dimensional wavelet expansion. Unlike the template matching, they use local information to encode the information globally. Features are extracted by using the Pursuit MP filter that differentiates the road sign classes. The training of the MP filter is done off-line, and the comparisons between the input signals with the actual template are done by using a conventional template matching method to find the optimal match. The accuracy rate of 94% was recorded for triangular signs, where it was 91% for circular signs. The same authors [87] used template matching for road sign recognition based on the regions of interest (ROI) features. ROI is determined by colour information of the image or expecting the possible location of the sign.

In [89], shape detection was done based on two algorithms for shape analysis: the first is Genetic Algorithms (GA) and the second is Simulated Annealing (SA). The classification was done using neural networks on normalized correlation. The reported the achieved detection accuracy for GA 90.4% compared with SA of 82.9%.

A traffic sign detection and classification system for circular (prohibition and obligation) and triangular signs was proposed by Garcia-Garrido et al. [18]. The system is composed of three phases. First, Hough transforms (HT) and canny edge detectors are used by a dynamic threshold used in the Canny algorithm. The second phase involves the classification where the road sign images are normalized into 32 X 32 pixel-sizes, and the third phase involves the tracking by making use of a Kalman filter. This classification was done using two neural networks. One for triangular signs and the other is for the circular signs.

Liang et al. [167] propose a complementary feature extraction method that combines HOG and LBP features. This combination is used to reduce the computation complexity of road sign detection while using the SVM classifier in the traffic sign classification. The complementary combined features used in [167] include HOG feature as in [144] and LBP features as in [157]. The method shows accuracy rates of more than 95%.

In addition, the combination of HOG and LBP improves the detection and classification performance [33], [150] and [151].

A summary of the literature on road sign classification and recognition methods is given in Table 3.3.

Table 3.3 Summary of road signs classification and recognition.

References	Features	Classification
[26] [48]	DtB Vectors and FFT A blob signature based on Fast Fourier Transform was applied.	SVM linear and SVM with a Gaussian kernel
[76]	Haar wavelet, AdaBoost and Gaussian probability Model feature used for detection.	Bayesian Generative Modeling
[93]	Edge features vector.	Template Matching
[83]	Normalized Correlations	Genetic Algorithm (GA) and simulated annealing (SA)
[139]	Normalized Cross Correlation-based rules	Template Matching
[60]	DtB vector	SVM with Gaussian kernel
[13]	Kernel Radial Basis Function (RBF).	One-versus-all SVM classifier
[107]	Hough Transform with Sobel Operator	RBF with K-d Trees
[137]	Gabor wavelets used to extract feature vectors	(OVR SVMs) and Naive Bayes (NBs)
[152]	Histogram of Oriented Gradients (HOG)	Random Forest (RF)
[166]	Combine HOG and colour features	kernel SVM

3.3 Limitations

The method presented by Maldonado-Bascon in [26] faces some limitations such as similarity between the road sign and the background environment, the sign is not detected since this step must appear clearly in the segmentation process that only oriented to the segmentation of colour. On the other hand, this approach needs improvements to be applied in real time. Feature space dimensions contain many of the features; this dimension may be reduced to the only necessary one in order to increase the performance. In addition, poor lighting conditions and partially occluded signs are not well identified where the recognition success probabilities are 67.85% for medium-sized and 44.90% for large masks.

In [77], the SVM solution was tested in ideal sign conditions, in addition to the use of three colours (red, blue and yellow) in pattern recognition and segmentation thresholding. In [26], many limitations were reported such as DtB features cannot detect the STOP signs, the static threshold cannot deal with different illumination conditions, and partially occluded shapes will be discarded in the detection phase, in addition to the poor lighting segmentation conditions. Rotation problems of segmented blobs still exist and depend only on the training dataset. In [87] and [79], the use of template matching schemes caused many difficulties, namely: the process was slow relatively. In [11], only ideal signs were used for training, and no environmental conditions were tested. In addition, only a red-colour threshold was used.

In [18], the Hough Transform (HT) cannot specify the lines start and endpoint. By applying this approach to the whole image, too many intersecting lines will be generated which made the feature space very large. To achieve this, HT is used for each contour successively, which results in identifying only triangular lines and rectangular signs are not detected. Paclík et al. [17] struggled with simple problems involving significantly dissimilar signs that may not be found in the training set. Fleyeh [74] approach had major problems in colour detectors such as poor lighting and shadows generated by other objects. Another problem is the stability of the hue caused by reflection in outdoor images.

In [35], the issue was the insufficient number of road sign categories that cannot cover all the classes. The road sign's colour and background colour similarity did not distinguish in segmentation. The approach could not capture the partially occluded road signs, in addition, to use threshold for each category of the features relative to the real-data features.

Many studies combined feature extraction methods such as [18], [77], [107], [166], and [167]. There are many limitations such as in [18] in which the feature combination did not deal with rotation or scaling and any image noise affected the results. In [77], the authors combined DtB and DfC feature vectors. The problem in [77] is that the illumination changes and the lack of the inner details of the road sign blob. In addition, the system was tested in ideal conditions. Sobel and Hough features used in [107] still have the problem of scaling and rotation. Other feature combinations used HOG and colour features in [166] reported illumination problems relative to the colour feature sensitivity, in addition to the texture features that depend on the HOG blocks and the number of histograms. In [167] the combination of HOG and LBP features cannot deal with the rotation, scale, and illumination problems.

We propose a novel hybrid feature extraction method that consists of HOG, LBP, and SIFT features. This method deals with all the previous limitations with respect to rotation, scaling, translation, and illumination. The SIFT feature vector deals with rotation, scaling, and translation problems. The LBP with uniform patterns shows a very robust texture feature to supplement other features [168] to combine with components such as HOG or SIFT by filtering out the noise. LBP is a feature extraction method that is highly discriminating, invariant to illumination for the monotonic grey level changes, and computational simple. LBP will be a complementary feature extraction for the candidate road sign blobs. Furthermore, HOG is adapted to be more oriented for each pixel of the road sign blob, since the image is normalized into 36x36 pixels. The proposed algorithm is an adaptive hybrid feature extraction method that shows significant improvements in road sign feature extraction methods compared to previous work.

Chapter 4 Road Sign Segmentation

4.1 Introduction

The most important step in all road sign recognition approaches is the segmentation process. Many segmentation approaches performed well under ideal situations, and in good environmental conditions. But, many problems still require more research on issues such as different outdoor environmental conditions, especially poor lighting as shown in Figure 4.1. This thesis addresses the colour segmentation problems in different outdoor environmental conditions by proposing, first, an illumination invariant dynamic colour space selection algorithm to deal with the variations of colour sensitivity in different environmental conditions, mainly in poor lighting conditions. Second, a novel segmentation algorithm is proposed based on a dynamic threshold based on the proposed dynamic colour space.

In this chapter, a new hybrid dynamic segmentation algorithm is introduced based on two steps: the first is a pre-processing step that uses the hybrid colour space based on histogram analysis. The second step is the new dynamic threshold algorithm based on colour image segmentation. The experimental results analysis and a comparison with state-of-the-art methods are presented. The end of this chapter shows the conclusions and points out what future studies can consider.

Figure 4.1 Different problems in road sign images (environmental and poor lighting)

4.2 Segmentation Proposed Approach

The overall proposed algorithm and methodology is shown in Figure 4.2. The algorithm is composed of three phases: the first phase is the histogram analysis, and the second phase is to convert RGB colour space into a suitable colour space based on a hybrid of (RGB, HSV, and YCbCr) colour spaces using the histogram analysis. The third phase is to find the dynamic threshold using the previous two phases. The three phases will be used to find the output-segmented road sign region based on a dynamic colour threshold.

The proposed methodology and algorithm will address the following problems:

- The colour variations in the outdoor lighting and environmental conditions such as rain, fog, snow etc.

- Poor visibility signs were many obstacles, like buildings, poles, trees, and other vehicles may be partially occluded the road signs.

- Blurring road sign images and different road sign sizes.

- Colour fading is another problem, because of sunlight exposure and environmental conditions that affect the paint with time colour is changed and faded.

- Many objects are shown in the background with the same colours and shapes of the road signs,

By using the histogram analysis, we can classify and calculate the image intensity and brightness, based on this calculation a suitable colour space is dynamically selected. In addition, three dynamic thresholds will be generated relative to the histogram analysis of the road sign images, where the variation of the colour in different images will cause a variant threshold based on using a hybrid dynamic threshold algorithm using red, blue and yellow colours.

As shown in the block diagram of Figure 4.2, the input image is firstly pre-processed as presented in section 4.3.1. In addition to this, the hybrid colour space and the transformation of RGB images into colour space conversion are explained in section 4.3.2. The proposed hybrid pre-processing algorithm based on histogram analysis is illustrated in section 4.3.3. Further detailed analysis on the proposed Hybrid Dynamic

Threshold Colour Segmentation based on Histogram Analysis (HDTCS) and the pixels of interest is presented in section 4.5.

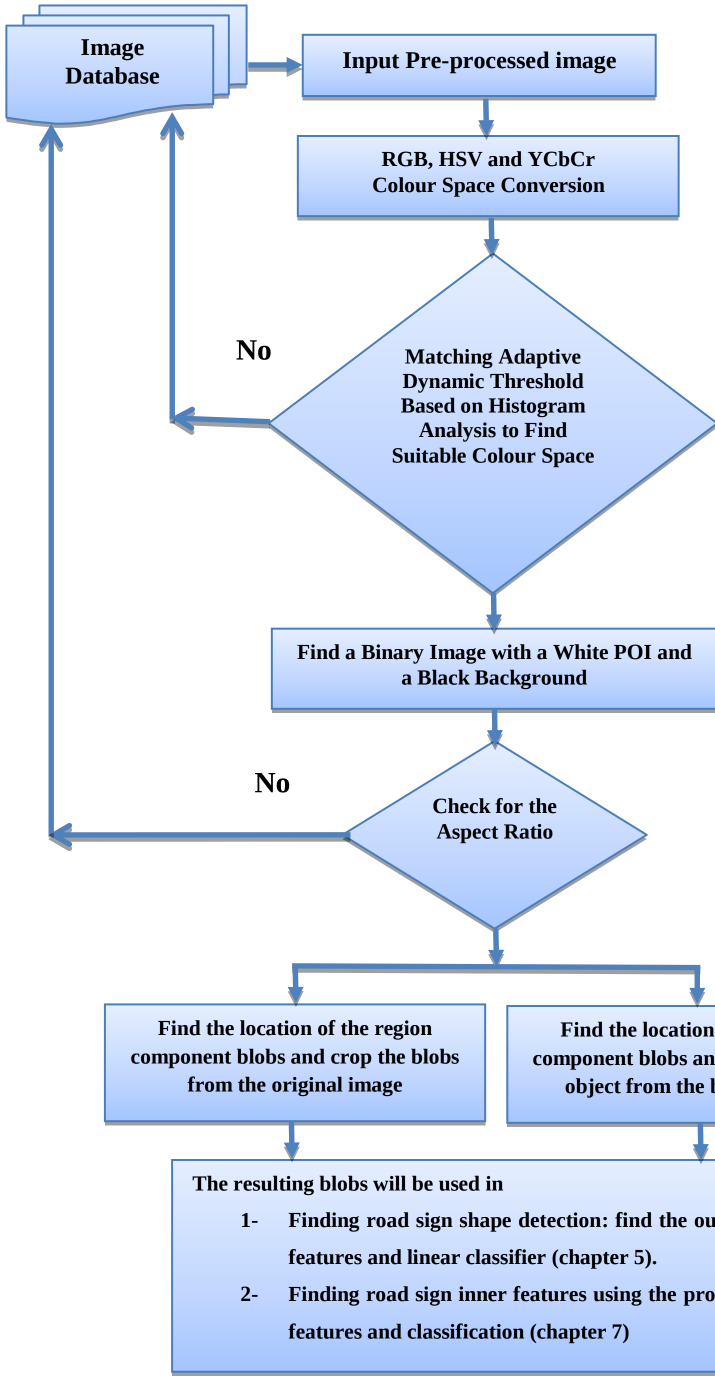


Figure 4.2 Methodology of Proposed Road Sign Segmentation Algorithm

4.3 Pre-Processing phase

This chapter proposes a new robust dynamic segmentation method of road signs in poor lighting conditions. The method is based on adaptive histogram equalization (AHE), colour adjustment, RGB colour space, HSV colour space that uses hue, saturation, and value images to create a binary image of the road sign for a certain colour. A pre-processing step is used to enhance the image quality before the segmentation in different environmental conditions and even in poor lighting. The aim of pre-processing is to manipulate the image to be more suitable than the original one. The input can be affected by motion blurring, noise, brightness or distortion caused by the resolution problems, and poor lighting. The RGB image is converted to its channels (R, G and B) to find the histograms for each channel. Each histogram is enhanced separately for red, green and blue in a pre-processing step.

4.3.1 Pre-processing and Colour Space Selecting Based on Histogram Analysis

Our method is shown in Figure 4.3 and summarized below.

Input: RGB image (I_{RGB})

Output:

1- Convert the given image (I_{RGB}) into a grayscale image using the luminosity technique using a weighted sum of the Red, Green, and Blue channels to find the grayscale image as $I_{grayscale} = 0.2989 * R + 0.5870 * G + 0.1140 * B$, then compute the histogram of $I_{grayscale}$.

- Find the minimum and the maximum peak of the histogram for all levels > 256/2
- Find *maxlevel = (minimum peak + maximum peak)/2*
- Find the minimum and the maximum peak of the histogram for all levels < 256/2
- Find *lowlevel = (minimum peak + maximum peak)/2*

Where the minimum peak is the minimum frequency of the intensity values in the image and the maximum peak is the maximum frequency of the intensity values in the image in each grey level form [0,128) and [128,255] (the frequency of the intensity values must be greater than zero)

2- Compute the histograms for the Red, Green and Blue *components of the input image.*
3- Find the minimum peaks and maximum peaks in the histograms and denote them by *Hr_min.p, Hr_max.p, Hg_min.p, Hg_max.p, Hb_min.p, and Hb_max.p*.
4- Find the average of the minimums and maximums as follows
   - *HAv.min = Average (Hr_min.p, Hg_min.p and Hb_min.p)*
   - *HAv.max = Average (Hr_max.p, Hg_max.p and Hb_max.p)*
   - *Hav= (HAv.min+ HAv.max)/2*.
5- Select the suitable colour space
   - Case1: *Hav < lowlevel : use Gaussian and Adaptive Histogram Equalization (AHE)* as *a pre-processing step (poor lighting) and convert into HSV colour space and compute the histogram of Hue (Hh), Saturation (Hs), Value (Hv).*
   - Case2: *Hav > maxlevel : convert* I_{RGB} *image components into YCbCr colour space and compute the histogram of Y, Cb and Cr components. (bright and faded image)*
   - Case3: *Hav in the interval (lowlevel, maxlevel): convert* I_{RGB} *image components into HSV colour space and compute the histogram of Hue (Hh), Saturation (Hs), Value (Hv)*

The values used in the algorithm were found by iteration of experiments using different road sign image histograms. From our experiments, we found that: if Hav is smaller than lowlevel, then the lighting is poor. If Hav in the interval [lowlevel, maxlevel], then lighting is ideal. Finally, if Hav is greater than maxlevel, then the image is too bright or faded.

The histogram equalization improves the image contrast by mapping the grey values to approximate a uniform distribution. However, this method still leaves gaps in the final histogram unless pixels have the same grey levels in the input image (spread across several grey levels in the output image). This method required using a colour constancy algorithm to recognize the object’s true colour relative to a variations factor such as lighting problems [112]. In addition, colour constancy is difficult to regularize the estimation of illumination chromaticity and it is computationally expensive in terms of time [91].

To deal with this problem, we use Adaptive Histogram Equalization (AHE); it works by dividing the image into small regions that enhanced by histogram these regions to approximately match a specified normal histogram. This method is used to avoid any noise or lighting conditions that might be present in the image. After applying the histogram equalization, AHE joins the neighbouring subregions using bilinear interpolation to discard the artificially induced boundaries. To achieve good results in the AHE process, Gaussian filters are used as a linear smoothing filter to remove Gaussian noise [98]. The hybrid pre-processing diagram and methodology is shown in Figure 4.3.

The hybrid pre-processing method in this chapter is a new dynamic robust method based on histogram analysis. It is a new method to select a suitable colour space based on a histogram analysis; the method shows very good results in choosing the most suitable colour space for road sign colour segmentation.

The HSV colour space is used because of its invariant to different lighting problems besides of its invariant to translation, rotation, scaling and under saturation changes. In addition to HSV, we used YCbCr colour space because it is more robust for colour and grey level operations by using YCbCr chromaticity information. [92]. Our colour segmentation method is implemented to be robust to work in different environmental conditions as shown in the segmentation experimental results.

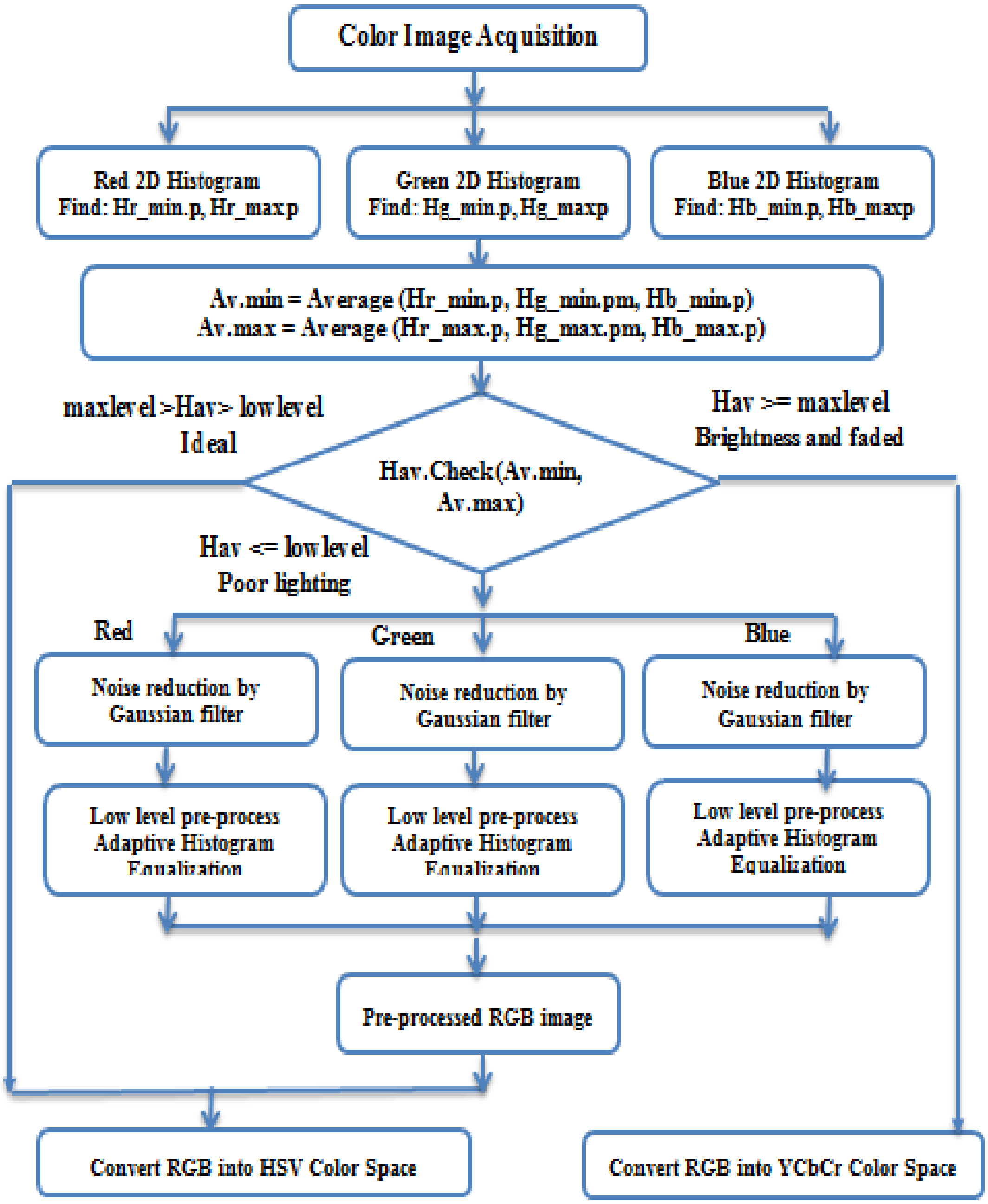


Figure 4.3 Hybrid pre-processing algorithm

4.4 Hybrid Colour Space Transformation

Choosing a suitable colour space makes the algorithm robust for colour segmentation. The RGB colour space contains primary colours within the range of the visible electromagnetic spectrum, including RGB colour space. The disadvantage of the RGB colour space is the luminance information embedded into each layer of the image. To deal with this problem, RGB colour space is transformed into suitable colour spaces that are invariant to illumination. Because of this, HSV, and YCbCr colour spaces are suitable to be used in our research. In this section a hybrid colour space will reduce the computational complexity; furthermore, in the pre-processing step, a suitable colour space for the image will be selected, as shown in Figure 4.3.

The colour space used is also very important. In this chapter, we use RGB, HSV and YCbCr colour spaces [113]; Figure 4.4 shows the hybrid colour space transformation.

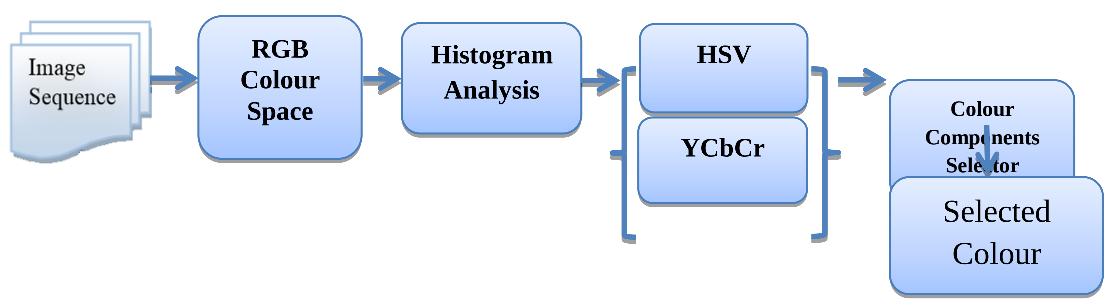


Figure 4.4 Hybrid Colour Space Transformations

4.5 Hybrid Dynamic Threshold and Colour Segmentation

The selection of a threshold value is critical. A value that is too low will swamp the difference image with spurious changes, while a value that is too high will suppress significant changes. The proper value of the threshold depends on the scene. This indicates that the value of the threshold should be generated dynamically relative to the image information.

In this chapter, a novel robust dynamic thresholding method is introduced. The first step is the colour-based segmentation using hybrid colour spaces of the RGB, HSV and YCbCr colour spaces. Histogram-based thresholding is used to find an optimal threshold. Because of computational simplicity, a threshold value is calculated using the histogram analysis and the segmentation of the image is done using this threshold into a binary image. A dynamic robust algorithm is used to select the suitable thresholding method based on histogram analysis shown in Figure 6. The proposed algorithm is given below:

4.5.1 Dynamic segmentation algorithm based on histogram analysis of HSV Colour Space

If (Hav < lowlevel)

- Use the pre-processed HSV colour space channels and histograms *(hImage for Hue, sImage for saturation and vImage for value channels)*
- Use Adaptive Dynamic Otsu method [86] as a dynamic segmentation method.
- *Let* $\{Pi\}_{i=0}^{L-1}$ be the probabilities of the (hue, saturation and value) image histogram, where L is the range of intensity levels.
- Use the histogram and compute the probabilities of each intensity level in each image components as the following

Since the histogram is the probability distribution of image pixels, we use the *Hav* value to divide the image pixels into two classes: background (P_B) with gray levels [0,1,…t] and a foreground (road signs) (P_O) in grey levels between [t+1, …L-1] by the threshold t. The probability of the grey levels distribution for the two classes is used to get the optimal minimum and maximum threshold values.

$$P_B(t) = \sum_{i=0}^{t} P_i$$

$$P_O(t) = 1 - P_B(t) = \sum_{i=t+1}^{L-1} P_i$$

The mean associated with the background and the object is then calculated using the following equations:

$$\mu B(t) = \sum_{i=0}^{t} \frac{i \,.\, Pi}{P_B\,(t)}$$

$$\mu O(t) = \sum_{i=t+1}^{L-1} \frac{i \,.\, Pi}{P_O\,(t)}$$

Next, we compute the variances in the background and object:

$$\sigma B(t) = \sum_{i=0}^{t} (i - \mu B(t))^2 \frac{i \,.\, Pi}{P_B\,(t)}$$

$$\sigma O(t) = \sum_{i=t+1}^{L-1} (i - \mu O(t))^2 \frac{i \,.\, Pi}{P_O\,(t)}$$

The between-class variance ($\sigma_{\text{between-class}}(t)$) which is the weighted variance of the cluster means around the overall mean is defined as follows:

$$\sigma_{\text{between-class}}(t) = P_B(t)\,(\mu B(t) - \mu)^2 + P_O(t)\,(\mu O(t) - \mu)^2$$

where μ is the global mean of the image, i.e.,

$$\mu = \sum_{i=0}^{L-1} i \,.\, Pi$$

Furthermore, the within-class variance ($\sigma_{\text{within-class}}(t)$) expressed as follows:

$$\sigma_{\text{within-class}}(t) = P_B(t).\ \sigma B(t) + P_O(t)\ .\sigma o(t)$$

Since maximizing the between-class variance and minimizing the within-class variance are equivalents, we find the mean of the values less than the maximizing between-class variance and the mean of values greater than the minimizing within-class variance as follows:

$$max = \underset{0 \le t \le L-1}{\arg\max}(\sigma_{(\text{between-class})}(\text{t}))$$

$$\text{t}_{\text{-opt}}(max) = \text{mean}\left((\sigma_{(\text{between-class})} < max) \right)$$

$$min = \underset{0 \le t \le L-1}{\text{argmin}}(\sigma_{(\text{within-class})}(\text{t}))$$

$$\text{t}_{\text{-opt}}(min) = \text{mean}\left((\sigma_{(\text{within-class})} \ge min) \right)$$

- *Let THigh* = $\text{t}_{\text{-opt}}$*(max)* *and* TLow = $\text{t}_{\text{-opt}}$(min).
- Find (*THigh*, *TLow*) for each channel of *(hImage, sImage and vImage)*
- Find the region of interests that lie between the low and high threshold using a particular threshold for each colour channel as:

The segmented image (*I*1) for hue is

- $I1 = \begin{cases} 0, & if\ (H < TLow_{hue}\ \ or\ \ H > THigh_{hue}) \\ 1, & if\ (H \ge TLow_{hue}\ and\ H \le THigh_{hue}) \end{cases}$

The segmented image (*I*2) for saturation is

- $I2 = \begin{cases} 0, & if\ (S < TLow_{\text{saturation}}\ \ or\ \ S > THigh_{\text{saturation}}) \\ 1, & if\ (S \ge TLow_{\text{saturation}}\ and\ S \le THigh_{\text{saturation}}) \end{cases}$

The segmented image (*I3*) for value is

- $I3 = \begin{cases} 0, & if\ (V < TLow_{\text{value}}\ \ or\ \ V > THigh_{\text{value}}) \\ 1, & if\ (V \ge TLow_{\text{value}} and\ V \le THigh_{\text{value}}) \end{cases}$

- Find the final segmented image as

segmentedImage = *I1* + *I2* + *I3*

4.5.2 Dynamic segmentation algorithm based on histogram analysis of YCbCr colour space

Input the image result from the pre-processing step

If (Hav > maxlevel)

A dynamic threshold using YCbCr colour space is proposed based on histogram analysis of Y, Cb and Cr components. Based on observation of blue channel data distribution in YCbCr colour space, where Y channel is the luminance component and Cb is the blue-difference and Cr is red-difference Chroma components.

Y is defined to have a normal range of 15 – 235 (1)

Cb and Cr are a normal range distribution of 16–240 (2)

From (2), the normal distribution of Cb and Cr histograms are around 128 as shown in Figure 4.5 Based on this value, a threshold for red and blue is found by the following algorithm:

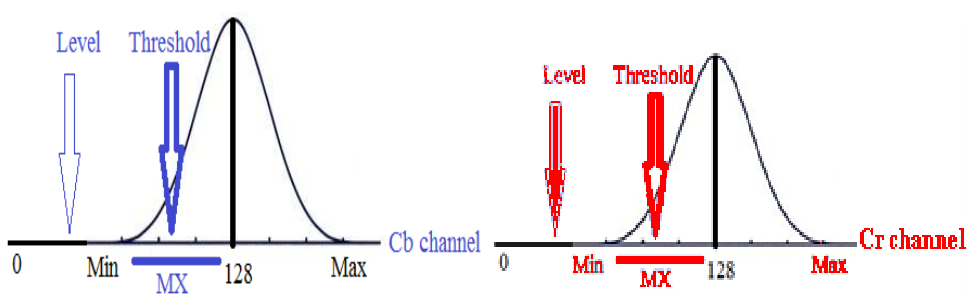


Figure 4.5 Distributions of Cb and Cr

1- Use the Pre-Processed YCbCR colour space and the histogram of the channels *(*Cr *for red colour image, Cb for blue colour image).*

2- Based on the Cr and Cb histograms, find the minimum values for both blue (Min_Cb) and red (Min_Cr) channels, where Min_Cb and Min_Cr are row vectors containing the minimum element from each column in Cb image, and Cr image respectively.

3- Find the mean values for the Min_Cr, Min_Cb, Max_Cr, and Max_Cb vectors as:

meanMin_Cr = mean(Min_Cr)

meanMin_Cb = mean(Min_Cb)

4- Find the standard deviation for both blue (std_Cb) and red (std_Cr) channels.

5- Find the dynamic threshold as:

Red_threshold = (meanMin_Cr+std_Cr)/((meanMin_Cr - std_Cr)*2)

Blue_threshold = (meanMin_Cb+std_Cb)/((meanMin_Cb - std_Cb)*2)

This threshold will be applied on black and white image for Cb channel and Cr channel

Cb segmented image (I_{Cb}) for $blue\ road\ signs$

$$= \begin{cases} 0, if\ Cb < Blue\_threshold \\ 1, if\ \ Cb \geq Blue\_threshold \end{cases}$$

Cr segmented image (I_{Cr}) for $red\ road\ signs$

$$= \begin{cases} 0, & Cr < Red\_threshold \\ 1, & Cr \geq Red\_threshold \end{cases}$$

$$\text{SegmentedImage} = I_{Cb}\ \&\ I_{Cr}$$

4.5.3 Dynamic segmentation algorithm based on histogram analysis of RGB and HSV colour spaces

If (lowlevel < Hav < maxlevel)
Input the image result from the pre-processing step

- Compute the summation of RGB channels (r,g,b) absolute values as:

$$SR_{(r,g,b)} = |r-g| + |g-b| + |(b-r)| \qquad (1)$$

- Compute the summation of HSV channels (hImage, sImage, vImage) absolute values as:

$$SH_{(h,s,v)} = |hImage - sImage| + |sImage - hImage| + |(hImage - vImage)| \qquad (2)$$

- Compute the *standard deviation* $STD_{(sr\_sh\_mean)}$ of the variance of mean values of $SR_{(r,\ g,\ b)}$ and $SH_{(h,\ s,\ v)}$ as:

$$STD_{(sr\_sh\_mean)} = std\ (mean(SR_{(r,\ g,\ b)} - mean(SH_{(h\ ,s\ ,\ v)}\ )\ (3)$$

- Find the absolute ratio between the HSV channels to the RGB channels as:

$$T_{max} = abs\left(\frac{\mathrm{std}\left(\mathrm{mean}(SR_{(r,g,b)})\right) - \mathrm{std}\left(\mathrm{mean}(SH_{(h,s,v)})\right)}{\mathrm{std}(\mathrm{mean}(SH_{(h,s,v)}))}\right) \qquad (4)$$

$$T_{min} = abs\left(\frac{\mathrm{std}(\mathrm{mean}(SH_{(h,s,v)}))}{\mathrm{std}\left(\mathrm{mean}(SH_{(h,s,v)})\right) - \mathrm{std}\left(\mathrm{mean}(SR_{(r,g,b)})\right)}\right) \qquad (5)$$

where abs is the absolute value and std is the standard deviation.

- Find the region of interests that lie between the minimum and maximum threshold values using the computed Tmin and Tmax thresholds for red channels and blue channels as:
-

$$I1 = R_{channel} \le (T_{max} - STD_{(sr_{sh_{mean}})}) + R_{(chennel)}$$
$$\ge (\ STD_{(sr_{sh_{mean}})}\ + (T_{min} + T_{max})/2\ )$$

$$I2 = B_{channel} \le (T_{max} - STD_{(sr_{sh_{mean}})}) + B_{(chennel)}$$
$$\ge (\ STD_{(sr\_sh\_mean\ )}\ + (T_{min} + T_{max})/2\ )$$

Segmented image = I1 + I2

After applying the dynamic threshold, the segmented regions are manipulated by morphological operations as follows:

- Discard the small area objects less than 100 pixels.
- Binary object regions (blobs) in the image are manipulated by image close and image fill operations.
- Find the blob bounding box and area.

- For each blob, calculate the aspect ratio based on the bounding box, and discard the blobs that have an aspect ratio less than 1/1.9 and greater than 1.9.
- For each blob, calculate the ratio between white pixels and the area of bounding box and discard the small blobs with a ratio less than 50%.
- Crop the segmented blobs (mask) from the input image based on bounding box for the red, green and blue channels and concatenate them.

These steps will improve the segmentation results by reducing a large number of small and noisy blobs. The block diagram in Figure 4.6 illustrates the hybrid dynamic thresholding algorithm.

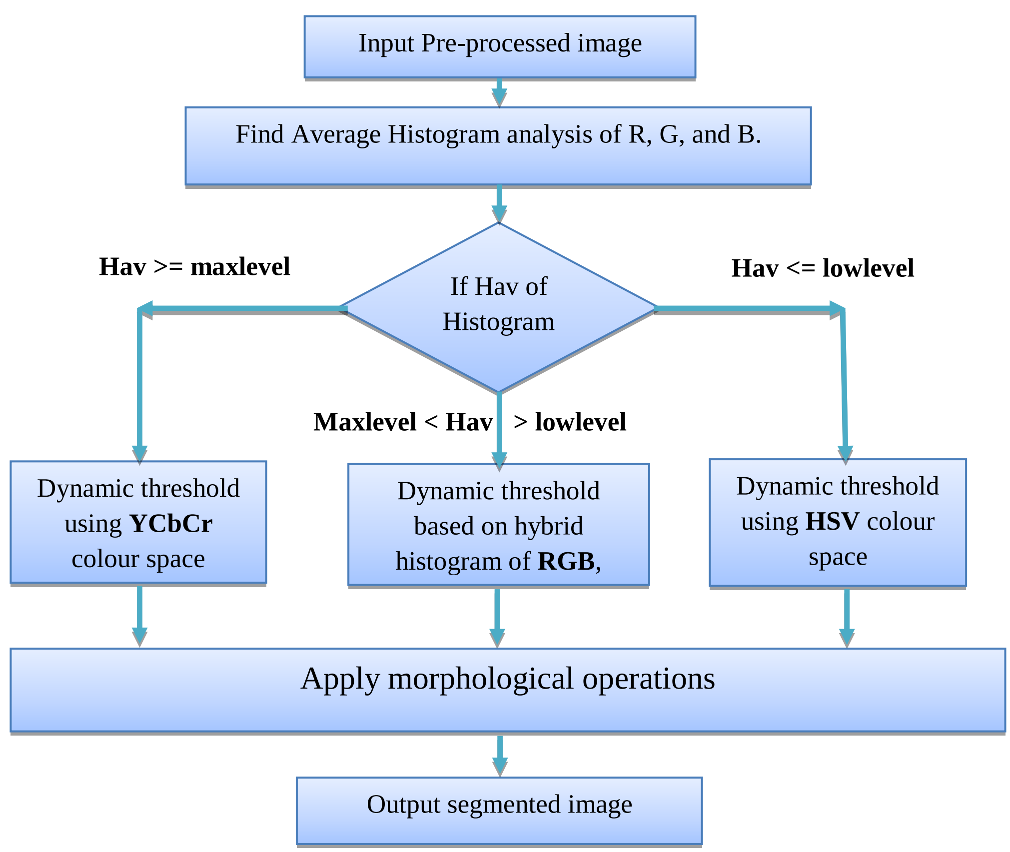


Figure 4.6 Hybrid Dynamic Threshold Segmentation Frameworks

4.6 Experimental Segmentation Results

To evaluate the performance and the accuracy of the proposed road sign segmentation method, we used a database of 615 images [118] containing different road sign colours, shapes, and environmental conditions. In the training process, we used a variety of 300 images containing different categories. Besides that, in testing, we used 315 images containing 456 road signs (an image may contain more than one sign) of various shapes and types. Table 4.1 shows the different categories and types of road sign database images used in both training and testing phases.

Table 4.1 Different categories and types of road sign database images [118]

Image categories and types	**Number of images**	**Number of testing images**	**Number of training images**
Illumination	40	20	20
Different Colors	175	88	87
Different Shapes	110	56	54
Different Signs	40	20	20
Segmentation Problems			
Clustering signs	39	20	19
Deformed	23	13	10
Different Sizes	40	20	20
Occlusion	37	20	17
Rotation	30	15	15
Other problems	11	6	5
Shadow	30	15	15
Translation	40	22	18
Total number of images	**615**	**315**	**300**

We compared our results with those obtained using the method by Maldonado-Bascon et al. [26]. We used this method as our benchmark because many road sign segmentation and recognition papers used it for comparisons, including recent ones such as [33, 117, and 170]. In addition, the database used in our research is good to analyse the accuracy of the road sign segmentation, where it contains a different real-world road sign images. Where, other databases contain the road signs without the background and focus on classification, rather than segmentation and detection. Because of this, we re-implement the Maldonado-Bascon et al. [26] method. , so the results from the implementation will be used in comparisons with our proposed method. In addition, we compared our results with other papers that used the different database.

We used the Maldonado-Bascon et al. [26] as our benchmark paper, for the following reasons:

- We found that most road sign recognition research papers used this paper as one of the literature studies such as the most recent ones by Anjan Gudigar, et al. [33] and Tae-Jung Eom, et al. [117].
- In addition, recent research papers used the same fixed threshold values in their segmentation and detection process as in Maldonado et al. paper [26].
- Based on the availability of a road sign database used by many recent researchers in the road sign recognition field.

Figure 4.7 shows segmentation results of a poorly lit image. The segmentation of a yellow sign is clear in Figure 4.7(c). While Figure 4.7(d) shows the segmentation by Maldonado-Bascon et al. [26] that performs poorly in different environmental conditions and some poorly lit images fail in segmentation. On the contrary, the use of the hybrid dynamic threshold algorithm provides very good results. Moreover, our proposed method does not need any colour constancy algorithms; so it is a very simple method. Another experiment is done in an ideal image environment (normal image colours); the results are shown in Figure 4.8; also excellent results are achieved compared to the results of Maldonado-Bascon et al. method in [26].

Segmentation results using the entire data set are summarized in Table 4.2. From the 456 road signs, 435 are correctly segmented by the proposed method, which results in a correct segmentation rate (dividing number of correct signs by the total number of road signs) of more than 95% for various road sign shapes and types in different conditions. Furthermore, under normal conditions, the proposed method gives a correct segmentation rate of more than 99%, considering that from 177 road signs, 176 are correctly segmented. The method in [26] did not perform as well, as it correctly segments less than 74% of the road signs. In addition, the proposed method shows fewer blobs, which improves the segmentation and will be very helpful for the next step of the recognition system.

One of the benefits of our proposed method is that it deals with any kind of image, any size, any shape of road signs, and in different environmental conditions. Another advantage of using the dynamic threshold is the successful results for different colour levels of road signs. So, this method can be applied in any country with any recognition system.

Table 4.2 (HDTCS) analysis results.

No. of Road Signs	Different Image types and shapes	Total no of correct blobs		Segmentation accuracy Rate	
		[1]	Proposed method	[1]	Proposed method
177	Ideal	153	176	86.44%	99.43%
137	Noisy and faded	101	128	73.72%	93.34%
75	Poor lighting	49	70	65.33%	93.33%
67	Partially Occluded and other problems	32	61	47.76%	91.05%
				73.46%	95.39%

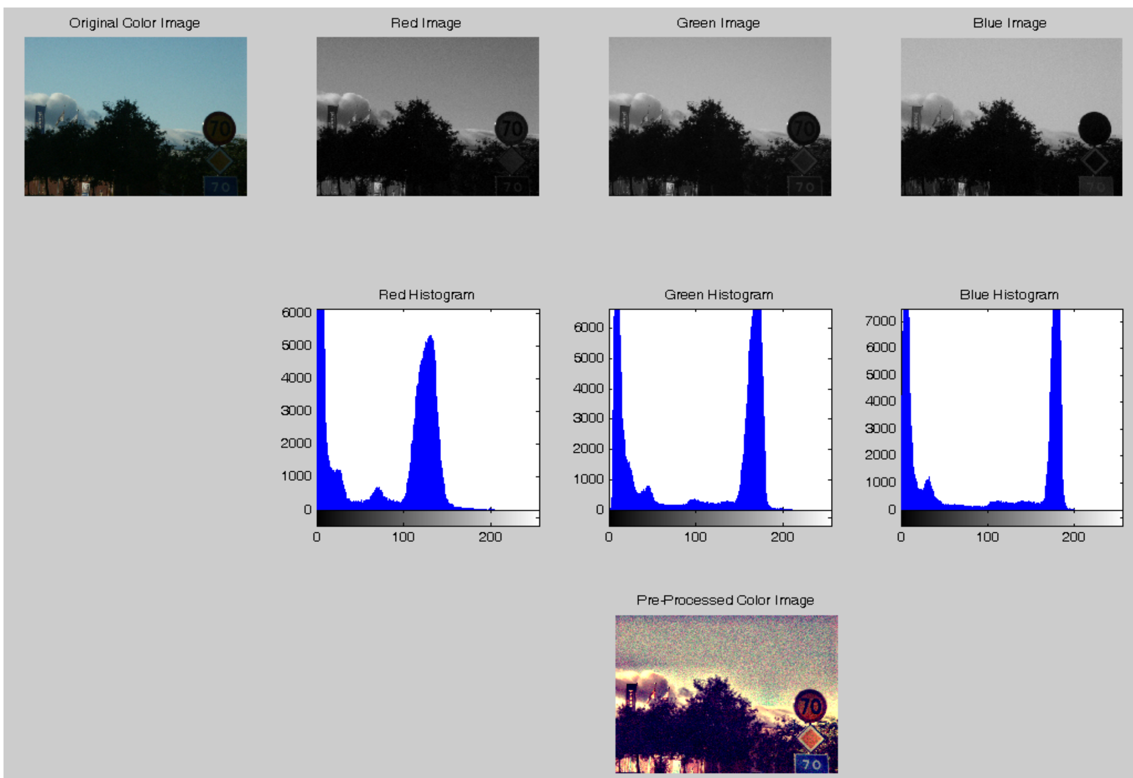


Figure 4.7 a) Original and pre-processed image in RGB space.

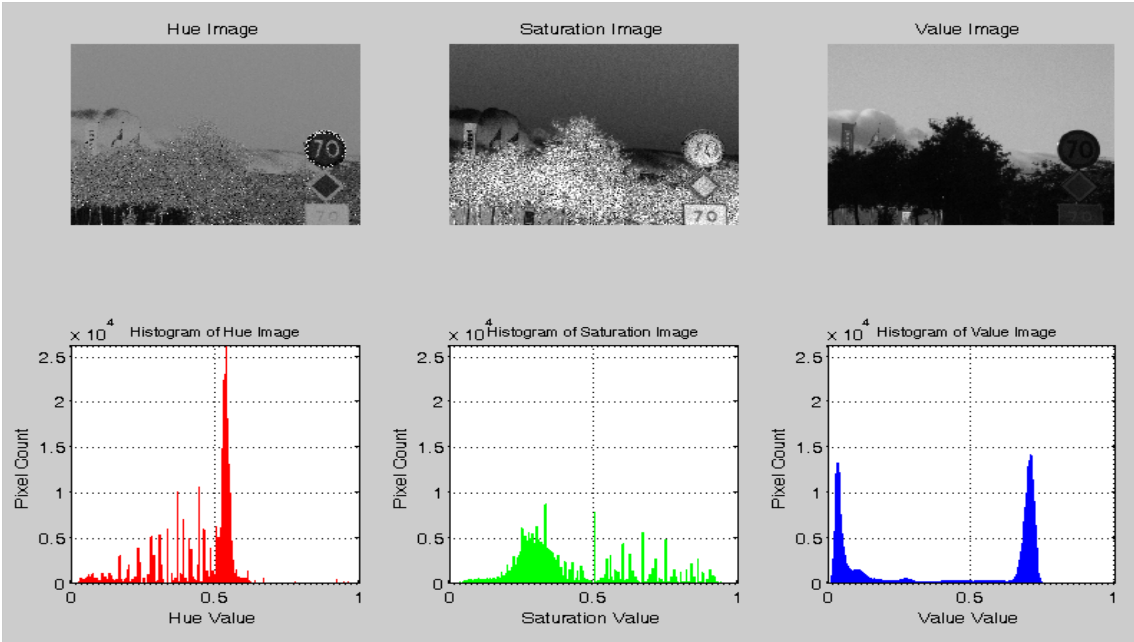


Figure 4.7 b) HSV colour space and histogram.

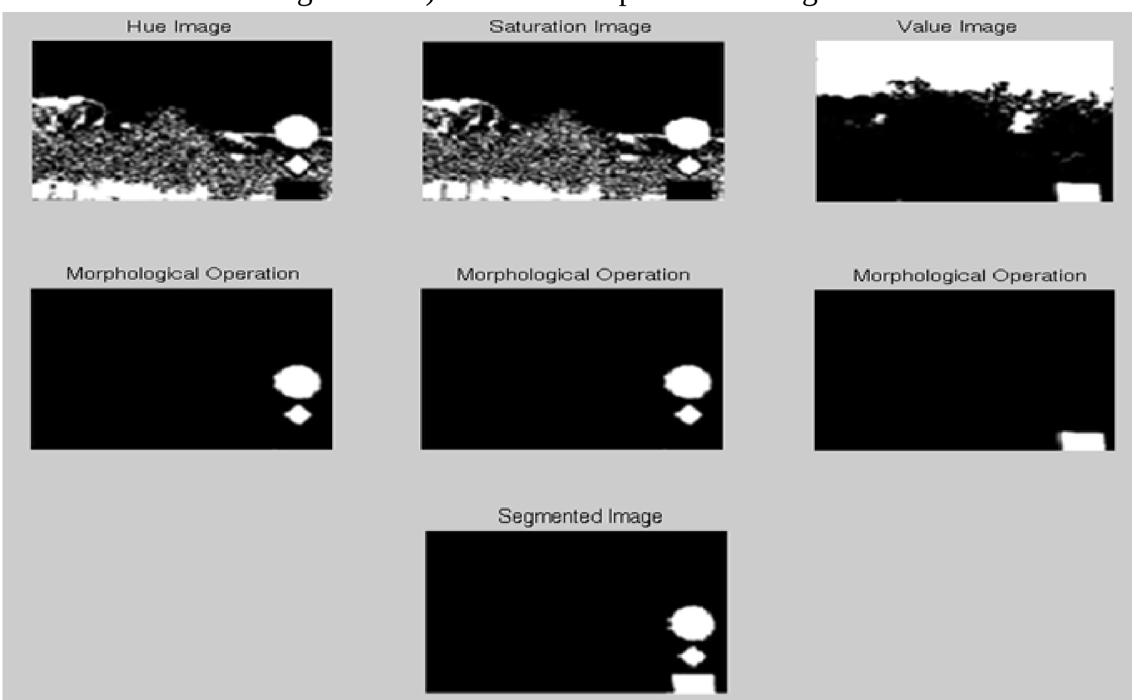


Figure 4.7 c) Segmentation using the proposed method, the final segmented image results are three blobs for Red, yellow and Blue.

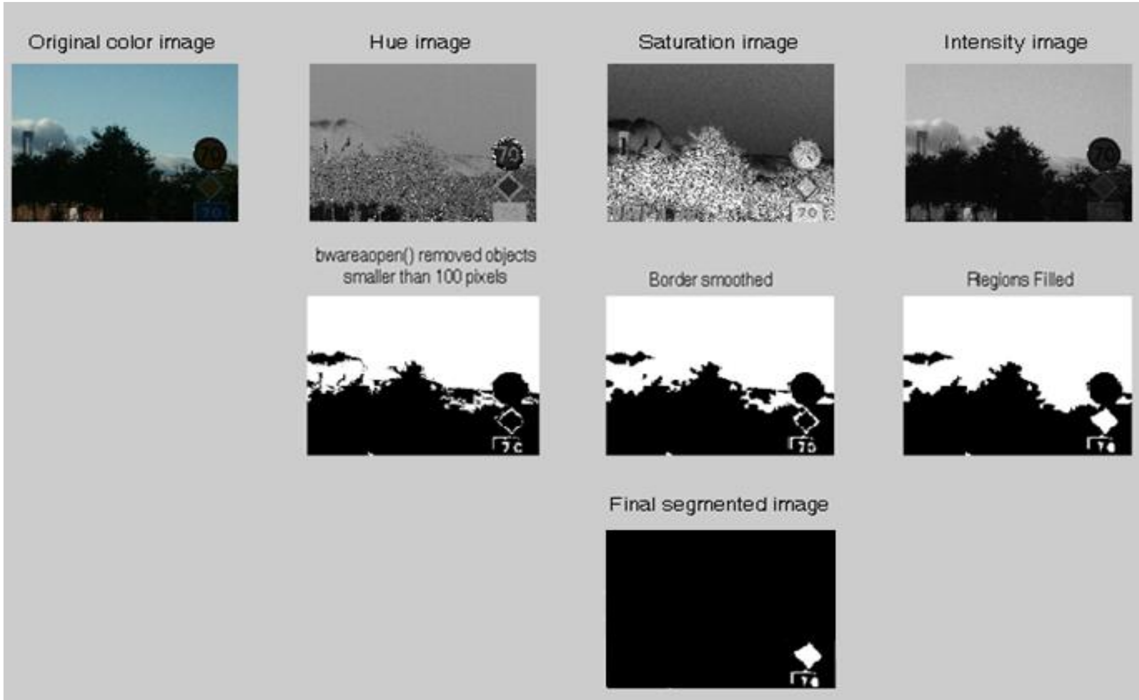


Figure 4.7 d) Segmentation using the method of Maldonado-Bascon et al. [26], and the final segmented image result is one blob.

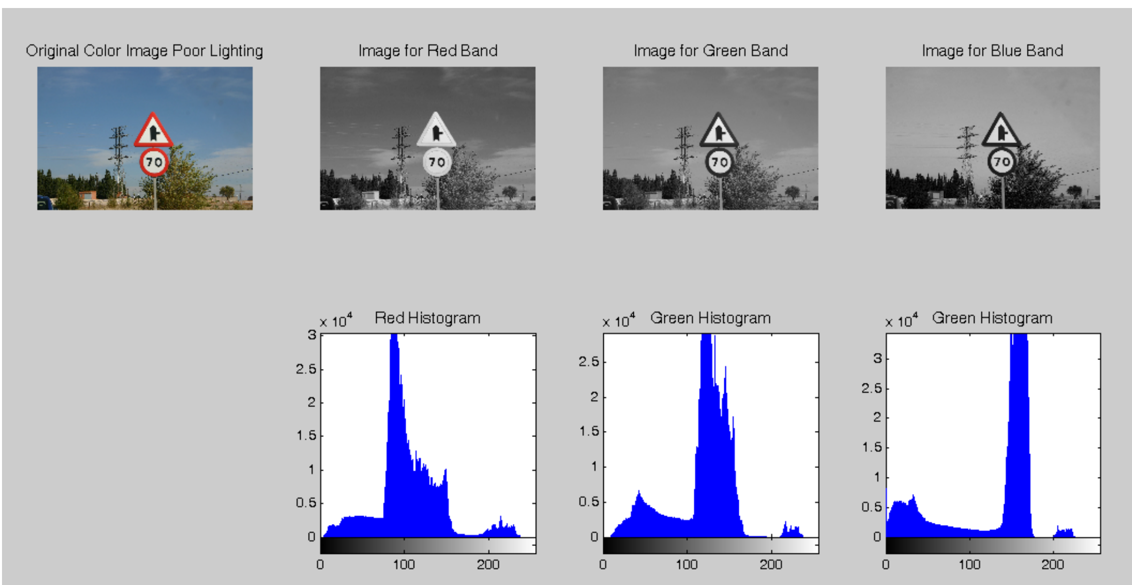


Figure 4.8 a) Original image and histogram(R, G, B)

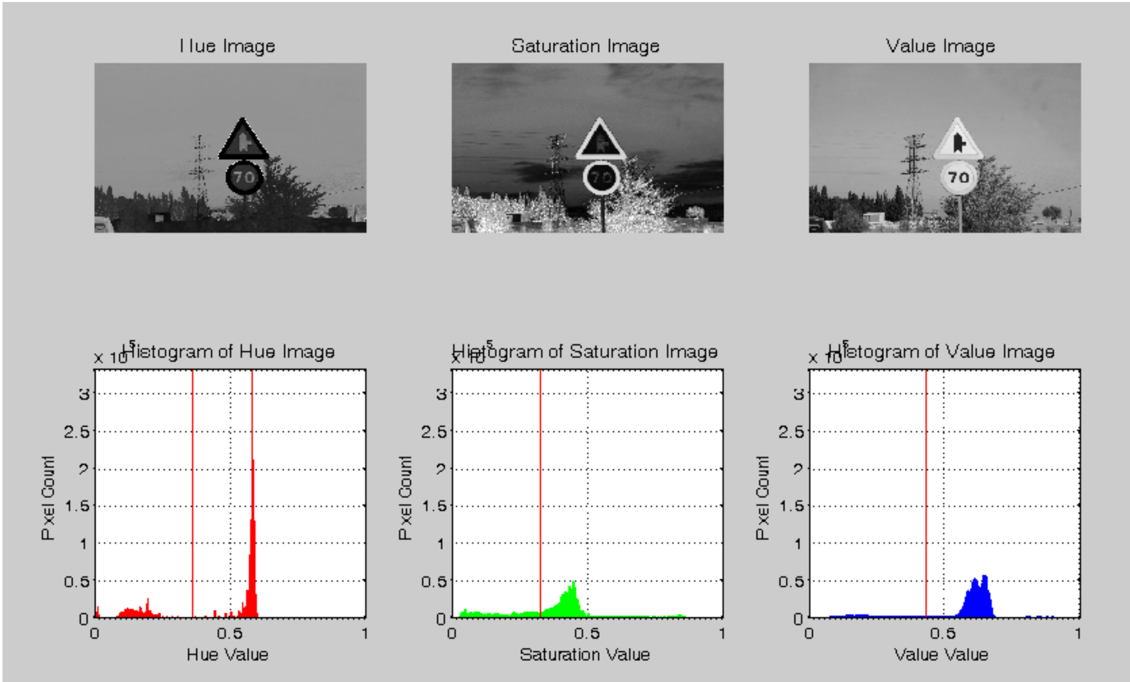


Figure 4.8 b) HSV colour space and histogram (H, S, V)

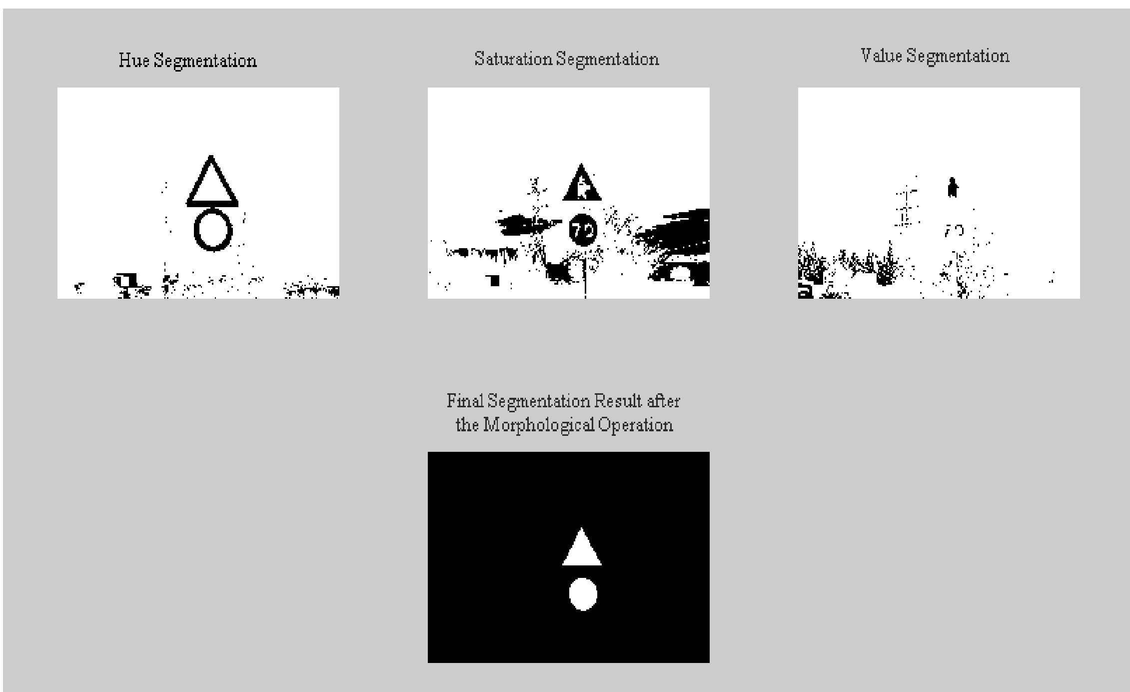


Figure 4.8 c) Segmentation using the proposed method, and the final segmented results are two blobs for Yellow and Red signs.

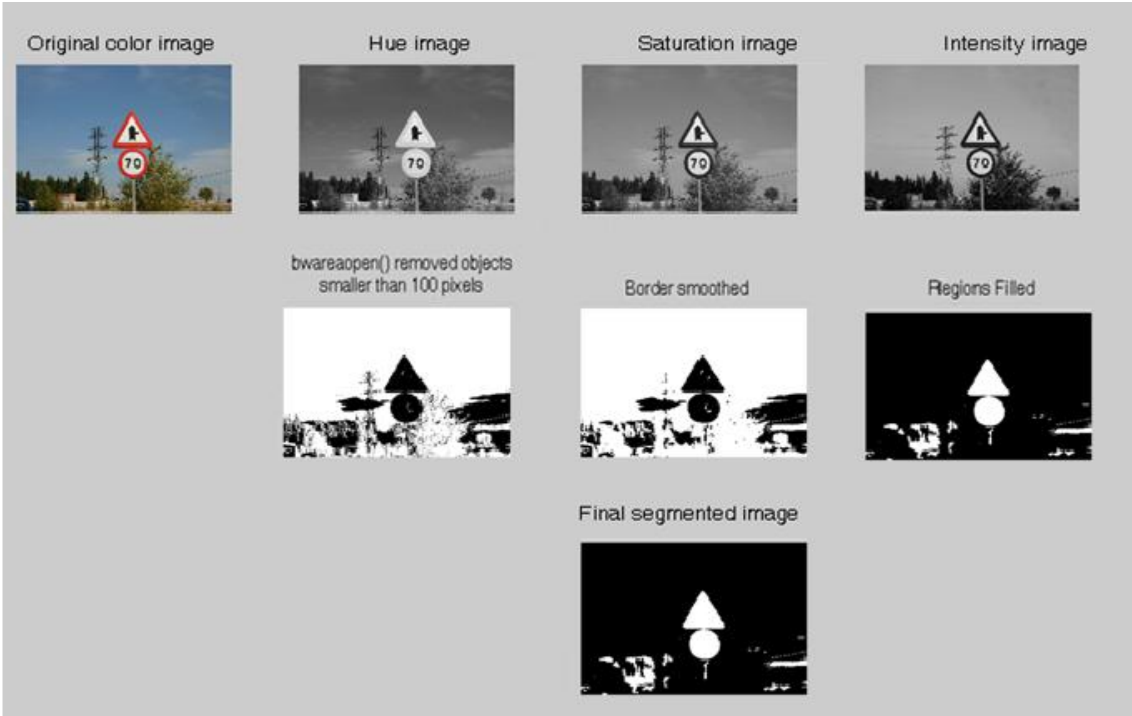


Figure 4.8 d) Segmentation by Maldonado-Bascon et al. [26], and the final segmented results are two blobs.

Many state-of-the-art studies used the database in [118]. We compare our results to those of these studies. Besides that, to compare our results with a method that was used the same database [118] we re-implement the Maldonado-Bascon et al. [26] method for comparison purposes. Our proposed method shows significant improvements with high accuracy results compared to Maldonado [26]. Besides that, we compare the accuracy of our results with different studies that used different databases such as in [109] and [169] where our results show a high accuracy rate.

The proposed method shows significant improvements compared with other studies as shown in Table 4.3. In addition, many studies have a problem with the partially occluded road signs and record their results in ideal, noisy, faded, and night environments such as [169], [109], and [110]. Other studies such as [26] deal with some of the partially occluded cases in addition to different environmental conditions. The overall comparisons between our proposed method and the previous methods are illustrated in Table 4.3 and Figure 4.8.

Table 4.3 Segmentation accuracy rates for different studies

Reference	**Reference**	**Segmentation accuracy**
[169]	Ideal	99.25%
	Noisy and faded	93.09%
	Poor lighting	88.70%
[109]	Ideal	99.25%
	Noisy and faded	70.09%
	Poor lighting	70.86%

[26]	Ideal	86.44%
	Noisy and faded	73.72%
	Poor lighting	65.33%
	Partially occluded and other problems	47.76%
Proposed method	**Ideal**	**99.43%**
	Noisy and faded	**93.34%**
	Poor lighting	**93.33%**
	Partially occluded and other problems	**91.05%**

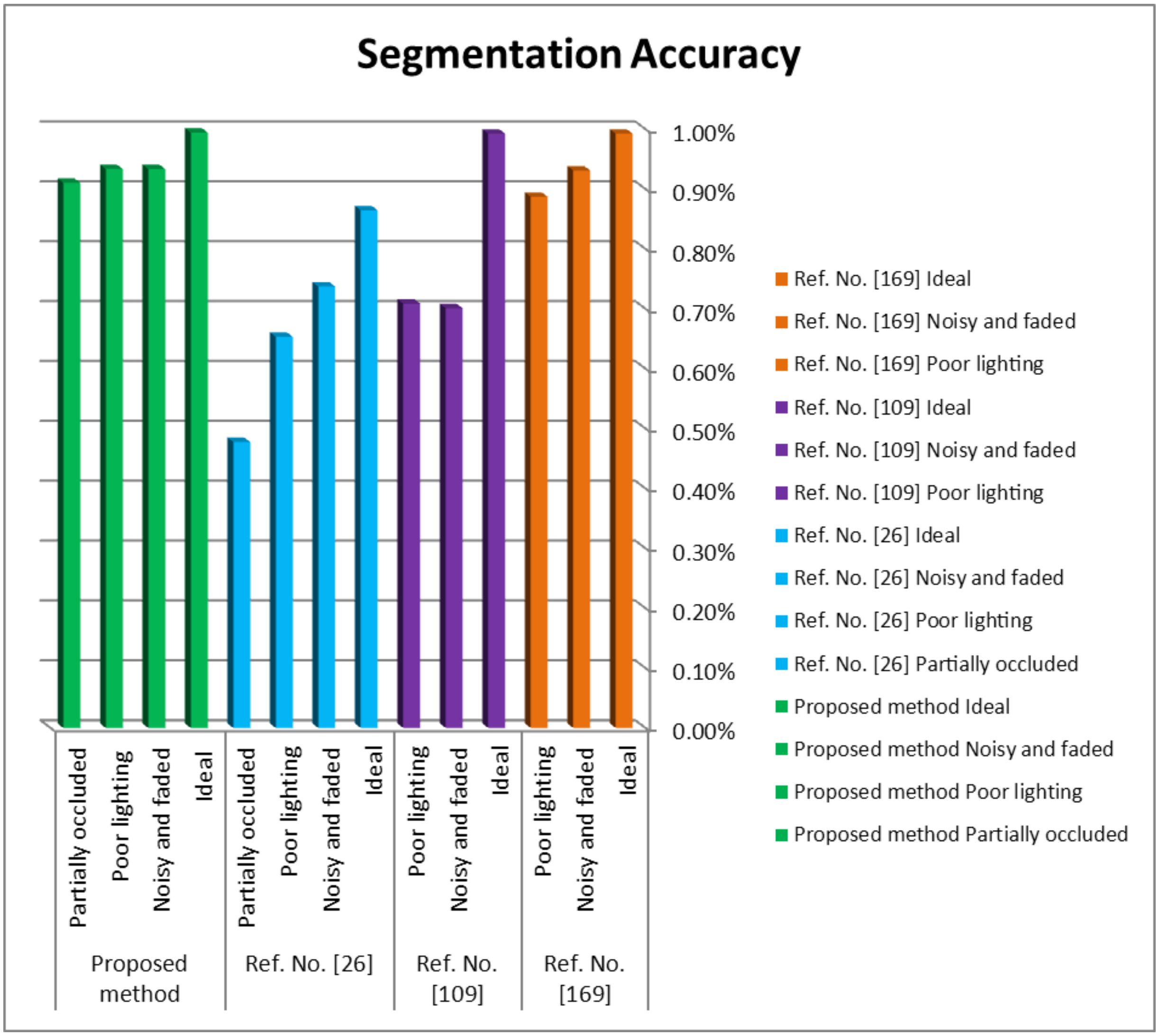


Figure 4.9 Segmentation accuracy rates for different studies

4.7 Conclusion

In this chapter, an efficient and robust road sign segmentation method based on colour information is proposed. Based on invariance properties of hybrid colour spaces and dynamic threshold, we propose an efficient segmentation method. The use of a hybrid colour space improves the robustness and efficiency of road sign segmentation.

Experiments with a large dataset show that the proposed method is particularly robust against severe illumination changes for images taken under various conditions. Compared with previous approaches that use static segmentation algorithms, the proposed method achieves better segmentation results while requiring less computation time. The simplicity and the robustness of the method make it suitable for real-time applications such as onboard driver assistance systems. Moreover, this method has a segmentation accuracy and quality that will help reduce the time of the next several processes in the classification and recognition system. In addition, the resulting blobs are only those close to the road signs in the images. This will improve the efficiency of the classification process and increase the performance to be suitable for real-time recognition systems. This method is tested for road signs with different red colour levels and different road sign shapes.

The proposed method can be integrated as a pre-processing step in a most road sign recognition systems.

Chapter 5 Road Sign Detection Based on Shape Geometric Symmetry

5.1 Introduction

Road sign shape is one of the most distinctive attributes used to recognize different road sign types. Road sign shapes can be the distinguishable attribute from randomly surrounding objects of similar colours. In addition, the road sign shape characteristics are used to classify which category a road sign belongs to; i.e. (circular, rectangular, triangular, diamond, or octagon).

This chapter presents an Automatic Shape Detection based on Shape Geometric Symmetry of the road signs. A new automatic shape geometric symmetry algorithm is proposed. The proposed method is robust against partially occluded road signs, in addition, it can identify and detect different road sign categories. The system consists of two stages: 1) find the DtB features vector for the outer shape of each blob. 2) detect and classify the road sign shape using linear (SVM).

A robust hybrid colour and shape road sign detection system is proposed based on Dynamic Automatic Threshold and Adaptive Geometric Shape Symmetry. Besides this, the proposed shape symmetry algorithm added a significant improvement in detection of a partially occluded sign. Our proposed method was tested on different outdoor images in different poor lighting conditions and partially occluded signs and shows high robustness.

Many problems to be overcome such as: rotation of the signs, the position of the sign that may be partially occluded, and road sign distortion. Besides that, other problems to be overcome are the similarity of shapes to the road sign, and the connected signs (more than one sign connected to each other). Hence, an automatic road sign recognition system must be suitable enough to detect and recognize signs in different environmental conditions, positions, road sign sizes, partial occlusion and, also, must be invariant to scaling, translation and rotation. Occlusions may occur because some objects such as trees, other signs, or vehicles reduce the visibility of the signs, which make the detection system fail. Figure 5.1 shows different problems in road sign images with partial occlusion.

Figure 5.1 Different problems in road sign images with partial occlusion

5.3 Shape Detection Proposed Approach

This chapter proposes a new dynamic shape detection method of road signs in different environmental condition and in partially occluded situations. The proposed algorithm based on both colour and shape features, for colour features we use the segmented results of the dynamic colour segmentation method, and for outer shape detection, we use the DtB features. In addition, to solve the main problem of shape detection for partially occluded situations, we present a dynamic automated shape detection method based on a geometric symmetry of road signs. The methodology of the proposed algorithm is shown in the block diagram of Figure 5.2 including the following three stages:

I. Colour-based segmentation: extracts regions contain road sign colours from the scene using the proposed hybrid segmentation method based on colour thresholding.
II. Geometric symmetry computation: symmetry computations of the segmented blobs are calculated based on the geometric dimensions of the candidate outline shape.
III. Recognition of ROI shape by the distance to the border (DtB) features: by using DtB, the system discards shapes that are not a road sign blob. The outer DtB feature vector is fed into a linear SVM classifier to identify and recognize the outer road sign to its class in the trained database.

The input image contains information about road sign shapes, for example, a red border shape may be a circular, octagonal or triangular sign, while yellow colours would have circular, rectangular, pentagonal, or diamond shapes, and the blue image would have other circular or rectangular shapes. The colour and shape road sign detection algorithm is shown in Figure 5.2.

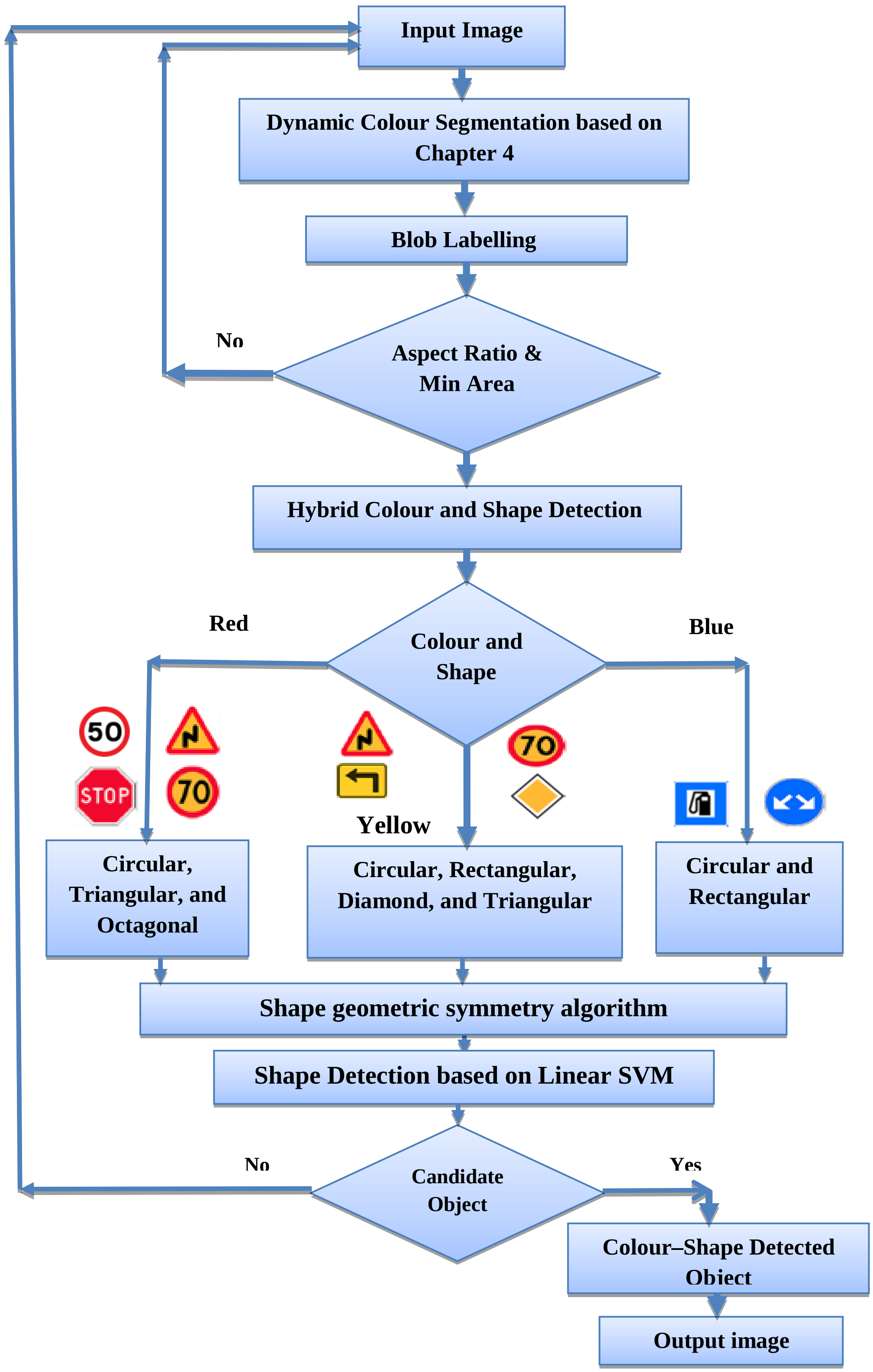


Figure 5.2 Methodology of the proposed shape geometric symmetry algorithms

5.3.1 Dynamic Shape Transformation Algorithm (DSTA)

Unfortunately, the road sign shapes detection process is faced many difficulties. In the environment, there are many objects similar in shape to the road signs such as in mailboxes, windows, cars… etc. Traffic signs in the road may be occluded by other objects, damaged, and disoriented. Because of this, our proposed approach is a hybrid of a colour-shape algorithm. In order to allow invariance localization to size, position, partial occlusion, rotation, scaling, shadow, and the objects of the same colour. Because of these problems we proposed a dynamic colour and shape detection algorithm. Thereafter, the segmented blob contains the road sign is the input to detect road sign shapes presented in the image using our proposed DSTA algorithm. Our DSTA approach starts with normalizing the blob size to be 36 x 36 pixels and to be a perpendicular to the bounding box axes. The resulting road sign model is bounded by a bounding box, if the blob axis is not perpendicular to the bounding box, then some transformations such as (translation, scaling and in the rotation) must be applied until the blob axis is perpendicular to the bounding box axis.

The transform coefficients of our algorithm are: the distance from the middle of the blob to the border of the bounding box (Md), the distance from the left corner of the blob to the border of the bounding box (Ld), and the distance from the right corner of the blob to the border of the bounding box (Rd).

The coefficients left distance (Ld), middle distance (Md), and right distance (Rd) will be used in a transformation process to get the blob in an ideal blob location. Figure 5.3 shows the transformation of the segmented blob sign to the ideal sign.

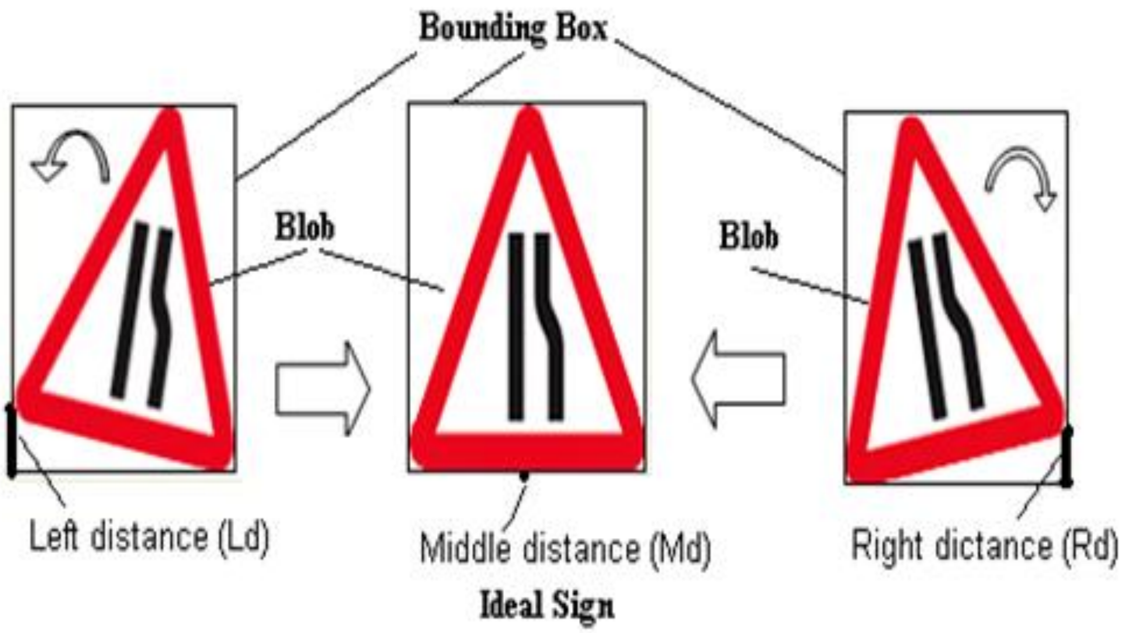


Figure 5.3 The transformation of the segmented blob sign to the ideal sign.

From the graphic example in figure 5.3, this algorithm is a dynamic affine transformation of the actual sign of the ideal sign shape.

This algorithm will be very helpful as a pre-shape geometric symmetry algorithm in the next section.

The steps of the dynamic shape transformation algorithm are:

1. After colour segmentation, many blobs of required colours are found using a thresholding of the colour analysis image, where the number and position of the potential regions are obtained (blobs).
2. The blobs are bounded by the bounding box of the shape.
3. Calculate the middle distance between the blob and the bounding box (Md)
4. While Md # 0 Do

```
{
   Calculate the left distance between the blob and the bounding box (Ld)
   If Ld # 0 then
    {
    Do while (Ld #0) {Rotate the blob by θ = 1degree; calculate Ld}
       Else
     Calculate the right distance between the blob and the bounding box (Rd)
         Do while (Rd #0) {Rotate the blob by θ = -1; calculate Rd}
      }
   Calculate Md
  }
```

5.3.2 Dynamic Shape Geometric Symmetry Algorithm (DSGSA)

The image data by itself is not sufficient for accurate object extraction in the presence of noise, occlusions or assimilation with the background. Many approaches for segmentation recommend incorporating a prior shape constraint to facilitate segmentation [126, 127, 128, 129, and 130], especially if an object is symmetrical, such as road sign shapes (e.g. the outer shape of the road signs). In addition, the shape symmetry is a good visual feature to be used for image identification [122, 123, 124, and 125].

In this research, we present a detection method that can be significantly facilitated by the outer road sign shape symmetry. Our proposed algorithm solved the problem of occluded or partially occluded signs. The partially occluded road signs are still problems that need more research. Our approach uses the concept of geometric symmetry to accomplish the road sign shape detection. This is achieved by the dynamic extraction of the outer road sign boundaries, based on the image black and white, grey levels or colours by applying the process. For example, the outer road sign shape is a geometrical symmetry about the vertical axis as shown in Figure 5.4. The shape symmetry of the road sign can solve many problems such as surrounding noise, shadows, partial occlusions with other signs or objects. The proposed framework is implemented and tested over various images of skew symmetrical road signs and it shows significant improvements over the literature techniques.

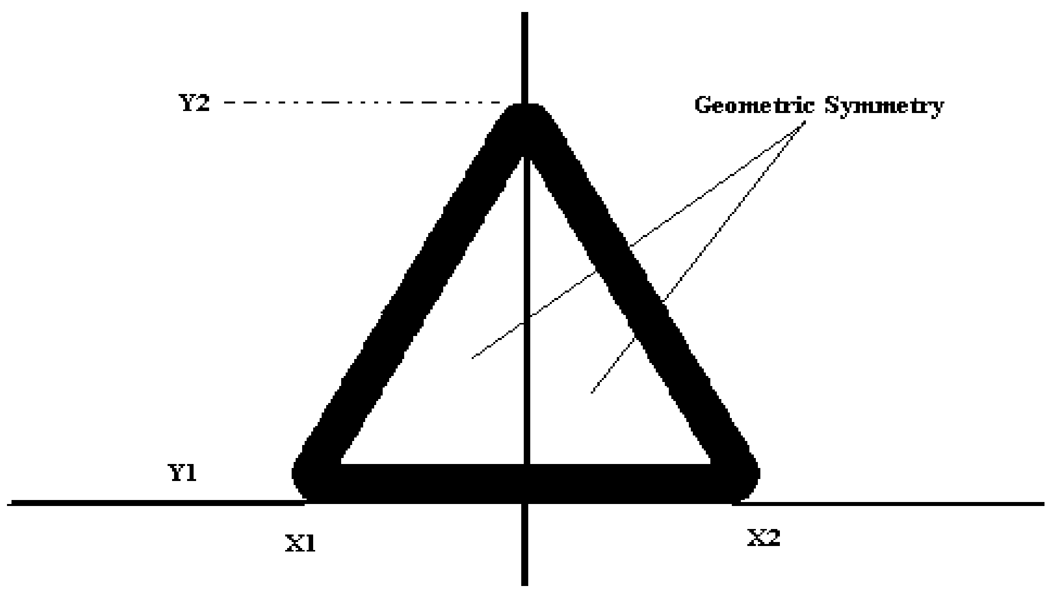


Figure 5.4 Identical geometric symmetry of the outer road sign shape.

The proposed framework is shown in Figure 5.6 and will be used in our research to detect the outer road sign shapes. This step will be very useful in the next steps to achieve the following:

- Reduce the number of training road signs.
- Solve the problem of partially occluded signs.

- Reduce the classification search domain, since the search will be only in the suitable right class shape based on colour and shape.

In order to apply the symmetry algorithm, we use a bounding box of size 36 X 36 pixels as shown in Figure 5.5. Then the blob is normalized in this bounding box relative to the following algorithm:

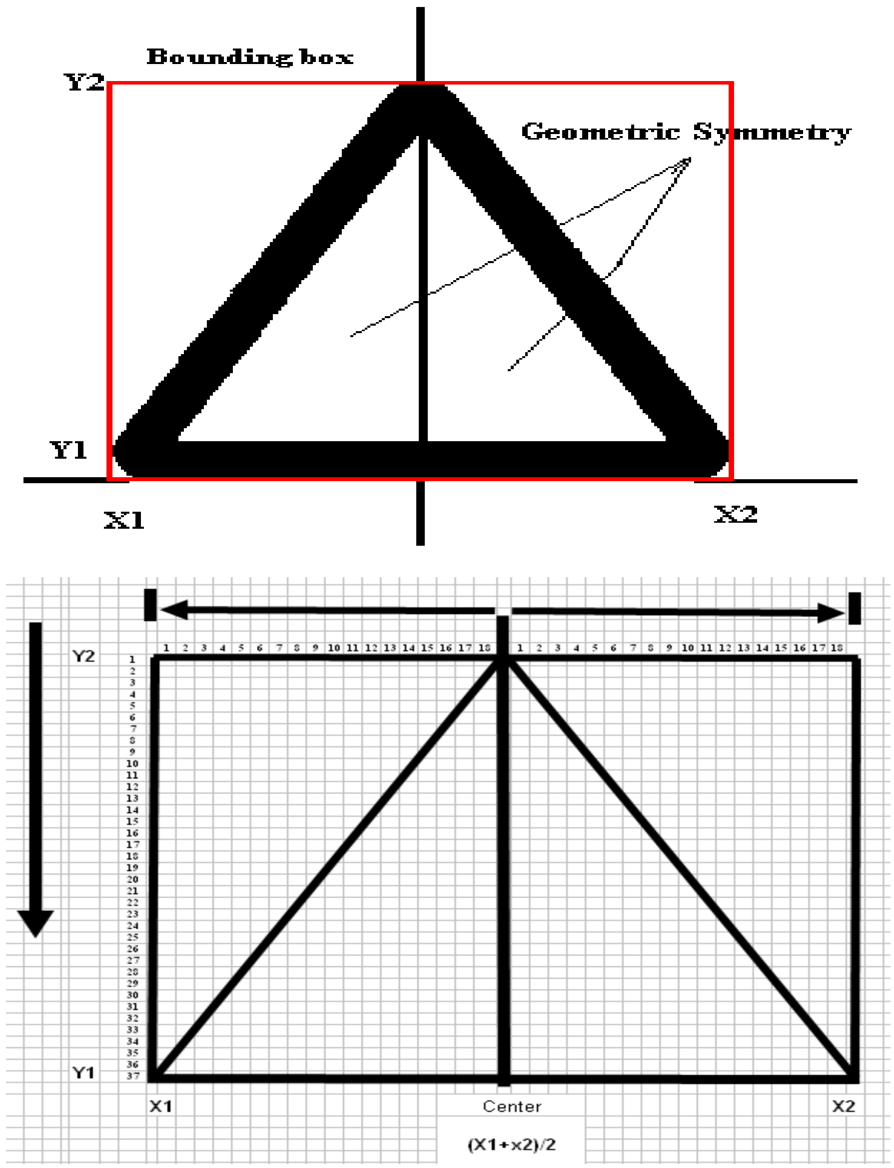


Figure 5.5 Blob normalized in bounding box

The blob image is B and the bounding box centre relative to the horizontal axis is C = (X1+X2)/2, the vertical lines are from Y2 to Y1(vertical pixels from pixel Y2to Y1), and the pixel intensity value is v(x, y).

The proposed symmetry algorithm steps are shown below:

1- Start from the first row ***i*** of the blob where Y2=0

2- Start from the centre, C = (X1+X2)/2 (X1+X2 = 36 pixel the blob size), C is the centre pixel of the bounding box.
Check the colour intensity v(x, y) of the pixels in the left (C-1) and right (C+1) from the centre on the same row.
  If the right pixel (C+1, i) is white and the left (C-1, i) pixel is black
    Fill white colour at the two pixels (left and right)
  Else
  If the right pixel (C+1, i) is black and the left (C-1, i) pixel is white
    Fill white colour at the two pixels (left and right)
  Else
  If the right pixel (C+1, i) is white and the left (C-1, i) pixel is white
  Continue to next pixels on the same row
Else
  If the right pixel (C+1, i) is black and the left (C-1, i) pixel is black
  Continue to next pixels on the same row

3- Go to next row ***i+1*** of the blob

4- Repeat step 2 until ***i***= Y1 end of rows

By using the dynamic symmetry algorithm, any partially occluded distortion in the outer road sign shape will be solved. Also, this will help in the overall algorithm to choose the suitable class for the next classification for the inner road sign shape. As the number of different blobs that result from colour segmentation is large, shape classification will reduce the number of blobs by discarding the non-road sign shape using DtBs feature vector which improves the computation time in the next stage of recognition. Before this step, the blobs of interest are normalized and rotated until to be in an ideal blob model.

Therefore, noisy objects with similar colours and shapes are rejected, because of the two phases shape filtering is done: 1) adaptive dynamic feature selection based on a geometrical symmetry algorithm; 2) and sign shape classification. The overall framework of the proposed methodology is shown in Figure 5.6.

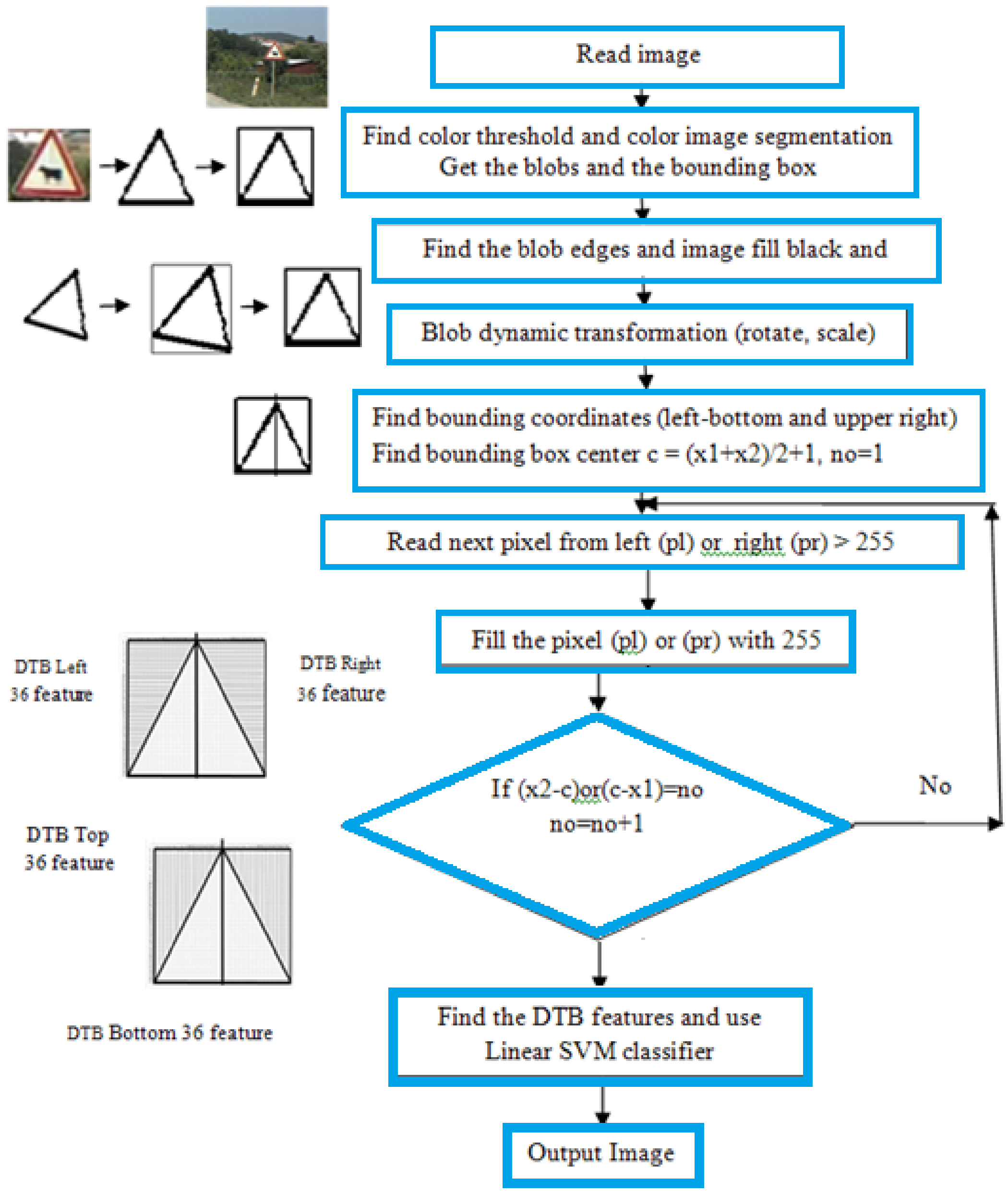


Figure 5.6 Methodology Framework based on dynamic shape transformation algorithm

5.3.3 Shape Classification based on Distance to Border (DtB) features

The blobs that were obtained from the previous steps containing the segmentation, shape transformation and dynamic geometric symmetry are classified by the linear SVM classifier according to their DtB features. In this phase, for every two independent class in the training process, the data are labeled as

$$\{xi, yi\}, \textit{where } i = -1, \ldots, l, yi \in \{-1, 1\}, xi \in \{Rd\}.$$

In this chapter, we use DtBs feature vectors that are mapped into a linear SVMs classifier, as introduced in [26]. DtBs calculate the distances from the blob to the bounding box. Figure 5.7 shows a triangular shape feature vectors D1, D2, D3, and D4 that are the left values, right values, upper values, and bottom values, respectively. Four DtB vectors of 36 components are obtained, and they feed specific SVMs depending on the previous colour extraction because the segmentation colour determines the possible geometric shapes (see Figure 5.5), as mentioned previously. We note that in [26] they consider the octagonal shape as circular and identify it in recognition stage. In our proposed method this problem is solved in shape detection because we use a DtB with 36 components where the difference between the octagonal and circular shapes is easily identified with different DtB vectors for both. That way, the extracted blob feeds to extract four DtB feature vectors, these vectors are fed to linear SVM for classification. A majority voting method is used to obtain the classification.

The proposed method is invariant to scaling, translation, partial occlusion and rotation. First, it is invariant to translation because it extracts the blob from the image based on colour segmentation and it does not matter where the candidate blob is (road signs placed in different positions are presented). Second, the shape detection is also invariant to the rotation whereof the blob normalization process is used to determine the original orientation relative to the blob bounding box. Third, the method is invariant to scale because of the normalization to a size of 36X36 pixels for each blob before extracted the DtB vectors relative to the bounding-box dimensions. Our DtB feature feature vector is = [D1+ D2+ D3+ D4]. Finally, the method is invariant and robust in partial occlusion due to the proposed geometric symmetry method that maintains the occlusion before calculating the DtB vectors. Another advantage of using shape detection is to separate the connected road signs into their category classes for the next classification step. In conclusion, the proposed method significantly improved the road sign detection process for partially occluded road signs.

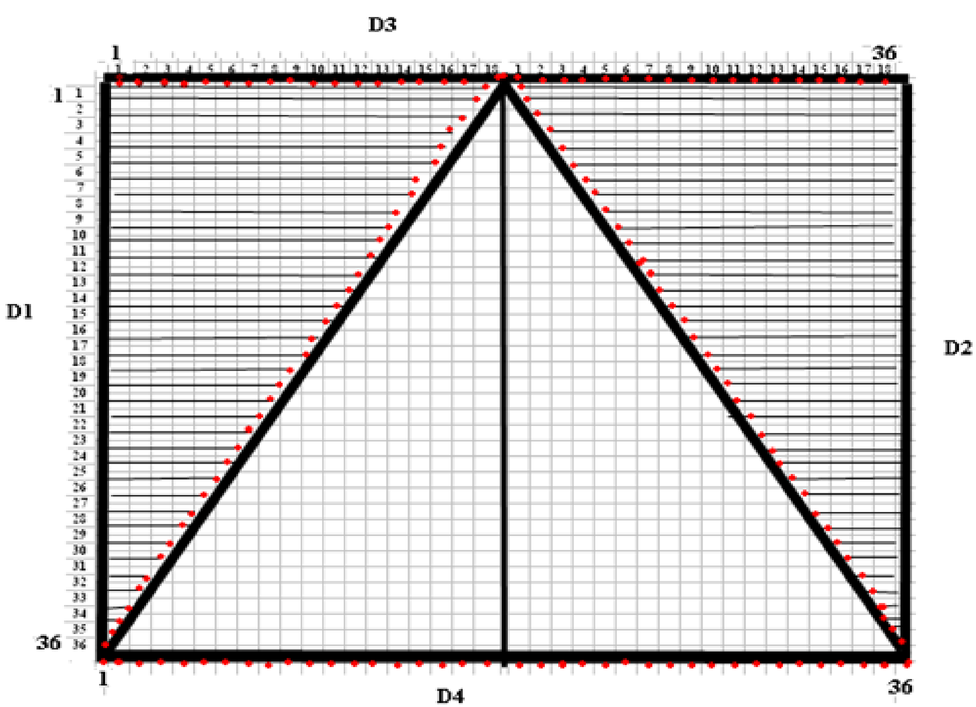


Figure 5.7 Distance to border vectors of 36 components

5.4 Detection Experimental Results

To calculate the performance of our proposed road sign detection algorithm, we used a dataset of 315 images containing 456 road signs of various shapes and types [26]. Many road sign categories in different conditions such as bright sunlight, partially occluded, noisy and poor lighting are used in our experiments. We compared our algorithm with the method of Maldonado et al. [26]. The results of colour segmentation of black and white blobs are used as input for a dynamic shape symmetry algorithm before DtB to obtain the features extraction.

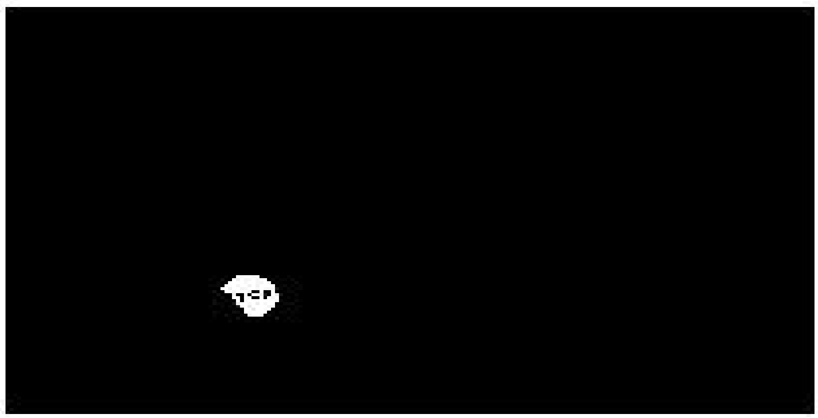
Figure 5.8 shows the original image that contains the partially occluded road sign. The results of the first step of colour segmentation using the proposed method in chapter 4 are shown in Figure 5.9. Figure 5.10 shows the road sign blob in the bounding box where it is clear that it needs to be rotated before applying the proposed symmetry algorithm. The dynamic rotation of the blob is shown in Figure 5.11. The results of the symmetric algorithm and DtB algorithm are shown in Figure 5.12. The proposed algorithm in this chapter will reduce the huge number of training datasets to deal with partially occluded signs, blurred signs, shadow signs and any other effects that make the road sign image appear occluded. The results in this chapter show significant improvements in the segmentation in different environmental conditions. By comparing our results with the benchmark paper especially for the poor lighting images and where the road signs are occluded, the proposed algorithm shows a high-accuracy rate of more than 97% as shown in Table 5.1.

Detection results using the entire data set are summarized in Table 5.1. From the 456 road signs, 435 are correctly detected by the proposed method, which results in a correct detection rate of more than 95% for various road sign shapes and types in different conditions. Furthermore, the proposed method results in normal conditions that provide a correct detection rate of more than 99%, where from 177 road signs, 176 are correctly detected. The method in [26] performed poorly as it correctly detects less than 87% of the ideal road signs and less than 74% for the system overall. In addition, the proposed method showed a significant improvement in the case of partially occluded signs with a detection rate more than 91%. While the detection rate of partially occluded signs in [26] were 47.76% relative to our implementation of the benchmark paper, and it was 44.90% for large occluded and 67.85% for medium occluded size relative to their paper.

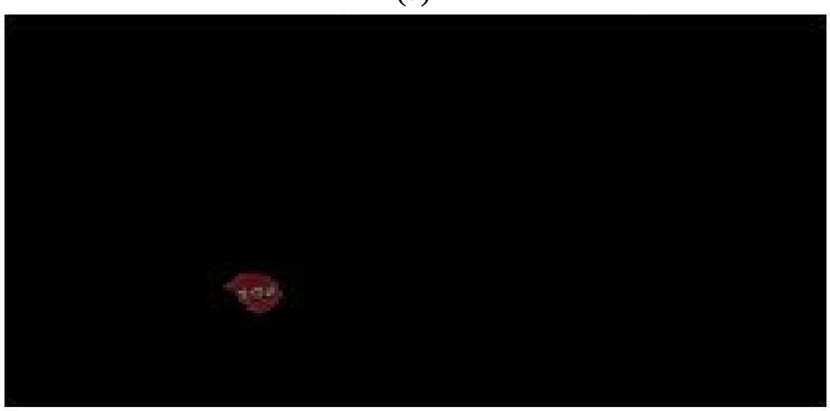
Table 5.1 Proposed detection algorithm results

Original no. of Road Signs	**Different image types and shapes**	**Total no. of correct detected signs of the proposed method**	**Detection Rate of the proposed method**
177	**Ideal**	**176**	**99.43%**
137	**Noisy and faded**	**128**	**93.34%**
75	**Poor**	**70**	**93.33%**
67	**Partially Occluded and other problems**	**61**	**91.05%**
The detection rate of the proposed algorithm			**95.39%**

Figure 5.8 Original image containing a partially occluded road sign.



(a)



(b)

Figure 5.9 Segmentation using the proposed method in chapter 4 for partially occluded road sign (a) Black background and white road sign (b) Capturing the original road sign blob form the original image.

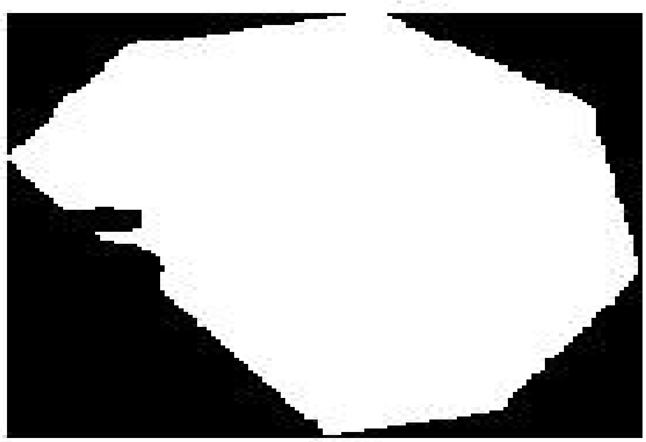


Figure 5.10 Partially occluded road sign blob in the bounding box.

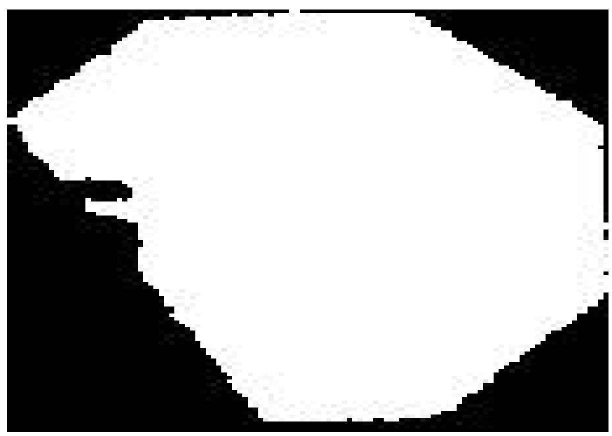


Figure 5.11 When partially occluded, rotate the blob using our proposed algorithm.

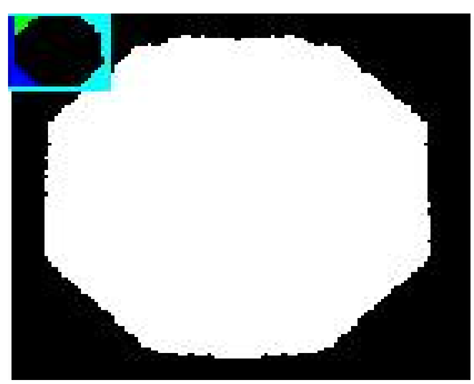


Figure 5.12 Symmetry and DtB of the blob using our proposed algorithm.

The proposed algorithm can detect road sign images in different positions and size as shown in Figures 5.13. Another challenge that can be detected by the proposed algorithm is connected signs, as shown in Figure 5.14.

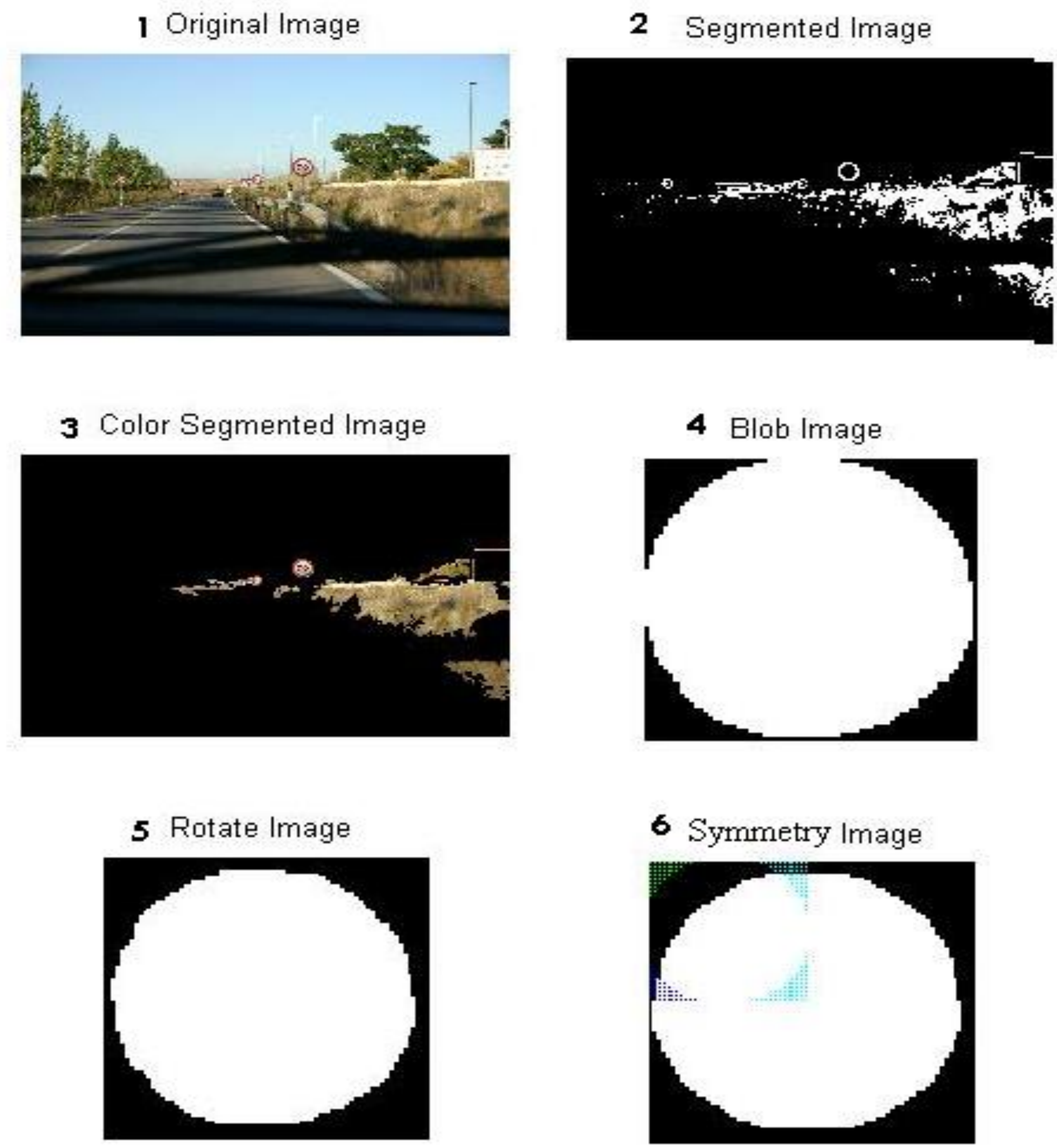


Figure 5.13 Shape detection using our proposed algorithm for size and position problem.

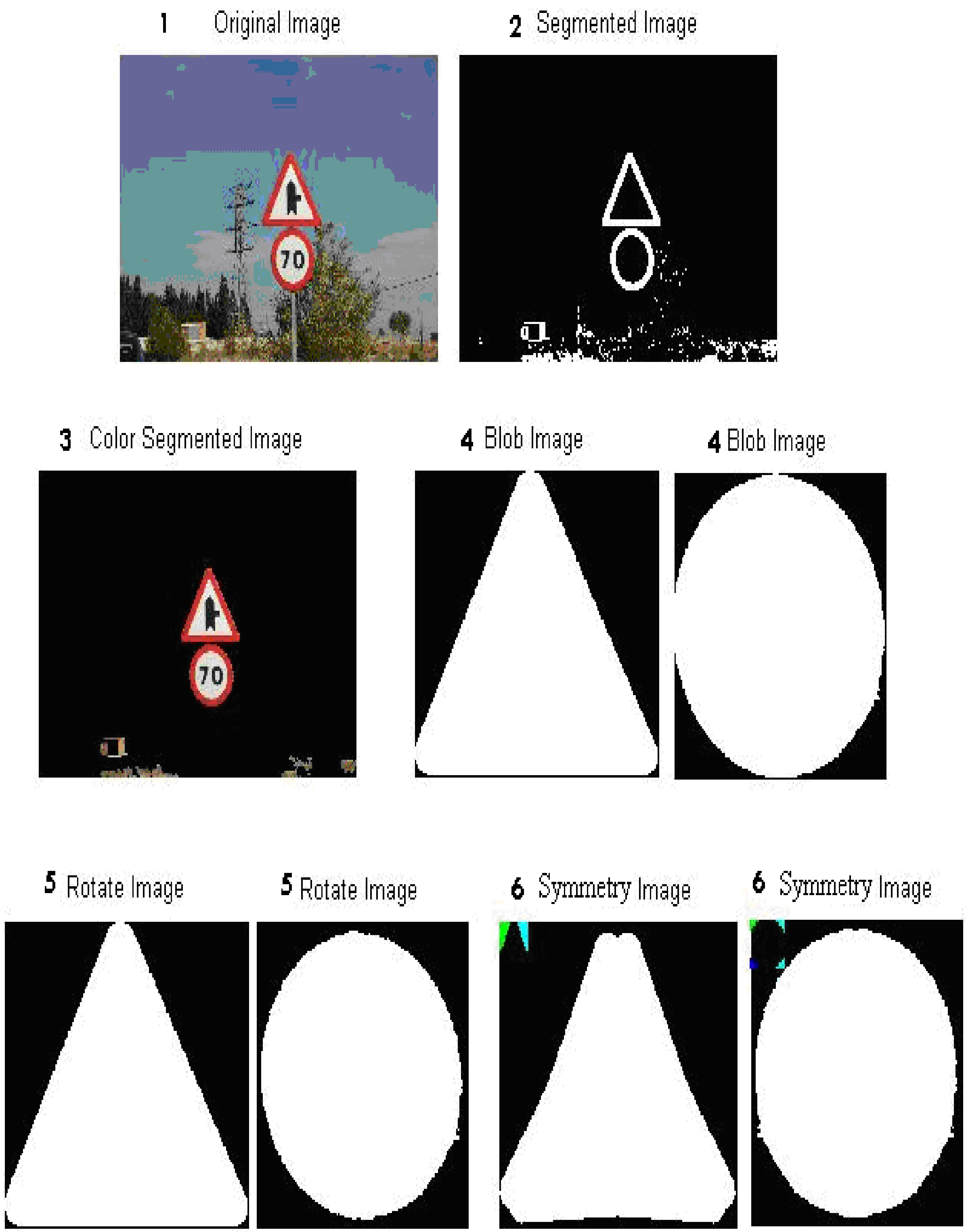


Figure 5.14 Shape detection used our proposed algorithm connected signs.

The proposed method deals with any kind of image, any road sign shape, and in different environmental conditions. Therefore, this method can be applied in any country with any recognition system. Furthermore, this method can be used for any image size and type.

Another experiment was done in an ideal image environment (normal image colours), and the results show excellent results. Also, excellent results are achieved compared with the results of Maldonado et al. in [26] and other studies using other methods, as shown in Table 5.2 and Figure 5.15.

Table 5.2 Detection accuracy rates of our proposed method and the previous methods

Reference	Detection Rate
[26]	86.44%
[48]	80.40%
[88]	91.3%
[110]	88.4%
Proposed method	**95.39%**

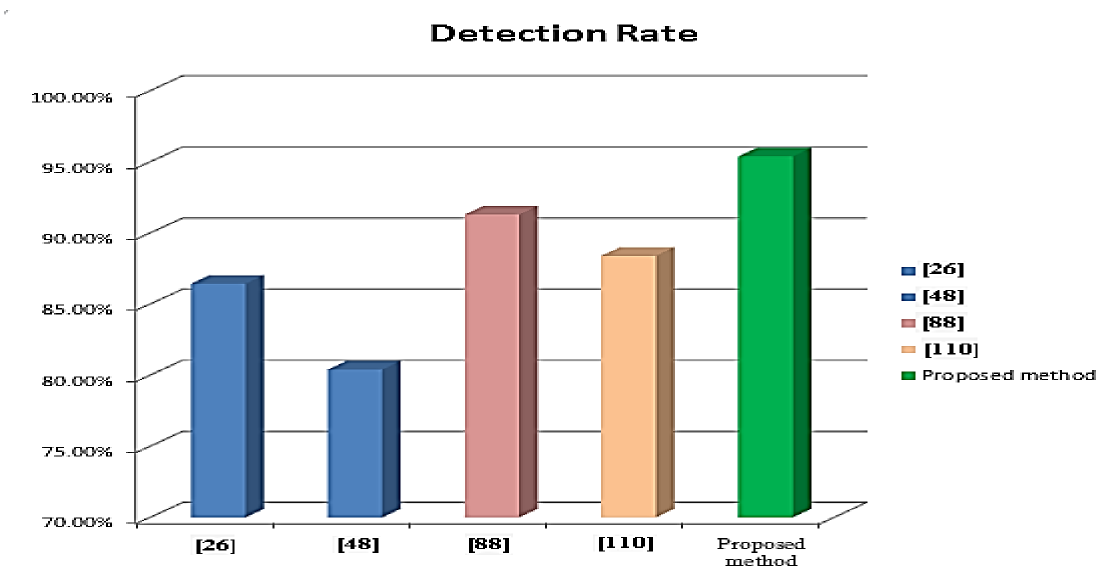


Figure 5.15 Detection accuracy rates of our proposed method comparing different methods

5.6 Summary and Conclusion

In this chapter, an efficient and robust road sign detection algorithm based on colour and shape is proposed. The method is based on a histogram analysis, hybrid colour space, and shape symmetry. Based on invariance properties of colour and shape, we propose an efficient road sign detection method. Experiments show that our detection algorithm is particularly robust against several illumination problems, poor lighting, and partially occluded signs. Comparison with other approaches based on static segmentation algorithms shows that our detection algorithm achieves the best segmentation and detection results. The simplicity and the robustness of the method make it suitable for real-time applications such as self-driving car systems and on driver assistance systems. Moreover, this method shows a shape detection accuracy and quality that will help reduce the time of next few processes in classification and recognition system. In addition, the resulting blobs are only those close to the road signs in the images. This will help in classification time, increase the performance and will be suitable for real-time recognition systems.

The proposed approach is a new dynamic road sign detection method based on shape geometric symmetry method. In addition, this method shows robustness and significant results for different environments, even in poor lighting conditions and partially occluded road signs.

Chapter 6 Feature Extraction and Classification

6.1 Introduction

The basic geometric shapes are the most distinctive attributes used to identify road signs from other objects with similar colours of the signs. In shape detection chapter, the outer shape of the road sign was used to detect the main class that the road sign belongs to, such as: (circular, rectangular, triangular, diamond or octagon). The outer shape detection process will be very helpful since it will filter the segmented objects by detecting the shapes with the same features of the main road sign classes. Furthermore, additional work is needed to extract the features of the inner text or pictogram of the road sign blob. These inner contents are varied relative to the type of pictograms and/or messages that are used to guide the drivers and users of the road. The road sign contents are used to classify the detected blob to the most voted subclasses features in the training dataset.

This chapter presents a new method to classify road sign images based on our proposed algorithm called Dynamic Hybrid Classifier based on Multiclass Features (DHCMF). The multi-class features used are the distance to the border (DtB), HOG, SIFT, and LBP. These features are used in two phases of dependency: the first phase is the outer feature shapes of the road sign based on DtB, and the second phase is based on HOG, LBP and SIFT feature extraction classes. The multi features are fed into our proposed hybrid classifier using adaptive RF, SVM, and utilizing SVM and kNN features.

6.2 Feature Extraction and Classification Proposed Approach

A new robust dynamic multi-feature classification based on a multi-classifier is used to significantly improve the whole process of the road sign recognition system. In this step a SIFT, HOG, and LBP features are calculated from input blob; these features are combined to construct a new feature vector. This feature vector will take advantage of DtB vector to be directed into the suitable branch of the RF tree. Then this vector will be mapped into the hybrid classifiers. The first hybrid classifier contains (RF, and SVM) and the second contains (KNN, and SVM).

The DtB vector is not enough to recognize the road sign subclass. For example, for the circular shape class, there are multi subclasses of inner features depending on the contents of the road sign as shown in Figure 6.1. Because of this, extracting the inner features of the road sign is very important for the road sign recognition system.

Figure 6.1 Sample of multi subclasses in the circle class with different inner content features

The proposed multi features of the inner road sign content is illustrated in Figure 6.2.

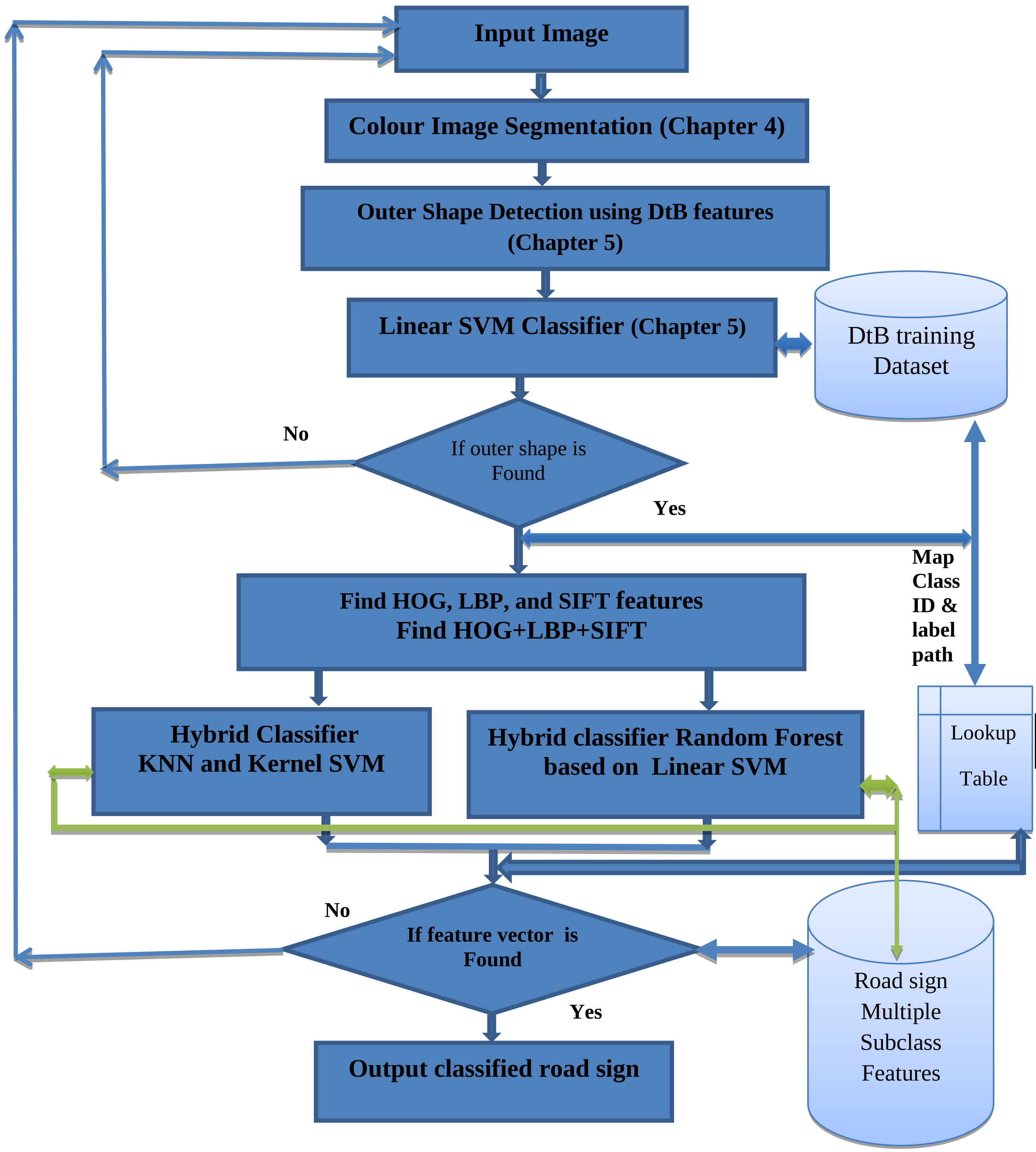


Figure 6.2 Methodology of the proposed hybrid features and hybrid classifier algorithm.

The process of extracting the object of the candidate road sign blob is shown in Figure 6.3, this process is as follows:

1- Fill the regions of the candidate sign blob subimage1 with white pixels to produce subimage2.
2- Extract the inner area (pictogram of the sign) of the blob between subimage1 and subimage2 (inner pictogram is subimage3 = subimage1 XOR subimage2)
3- Extract the inner pictogram of the road sign from the original image relative to the pixel coordinates of the blob and convert it into grey level subimage3.
4- Compute the features of the subimage3 (pictogram) for training and testing.

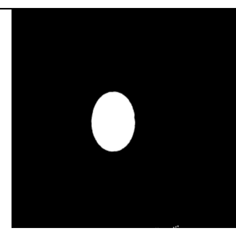
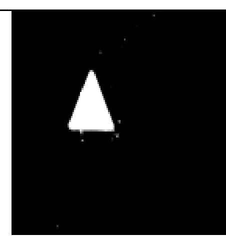
Original image	Region of interest	Filled holes segmentation result	Inner pictogram in grey level with 36x36 pixel blob
			
			

Figure 6.3 Sample of the dedicated inner pictogram in grey level used in feature extraction algorithms.

A new method is proposed by using a lookup table to speed up the overall process especially in the classification phase. The main idea of using the lookup table is to reduce the time of classifiers in searching for the subclass. The lookup table will feed the classifier with the superclass ID where the classifier can search in this subdomain. It is clear that when the classification process focuses on the suitable subdomain, then the classification time will be reduced, the performance will be significantly increased, and the error classification rates will be reduced.

6.3 Lookup Table for DtB features

The distance to border feature extraction used the blobs obtained in Chapter 5, which proposed a dynamic geometric symmetry that is invariant to rotation and scaling. An SVM classifier was used for shape classification. We used linear SVMs fed with a compilation feature vector of four DtB feature vectors (D1, D2, D3, and D4), each with 36 values; we got a new feature vector of 144 feature values, as seen in Figure 6.4.

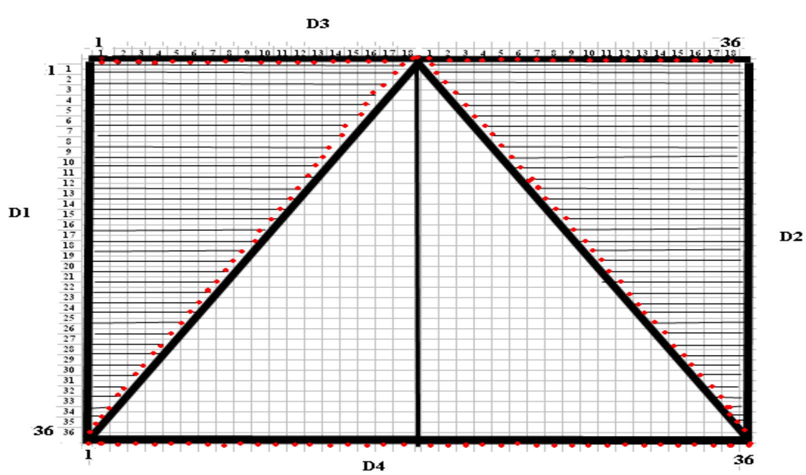
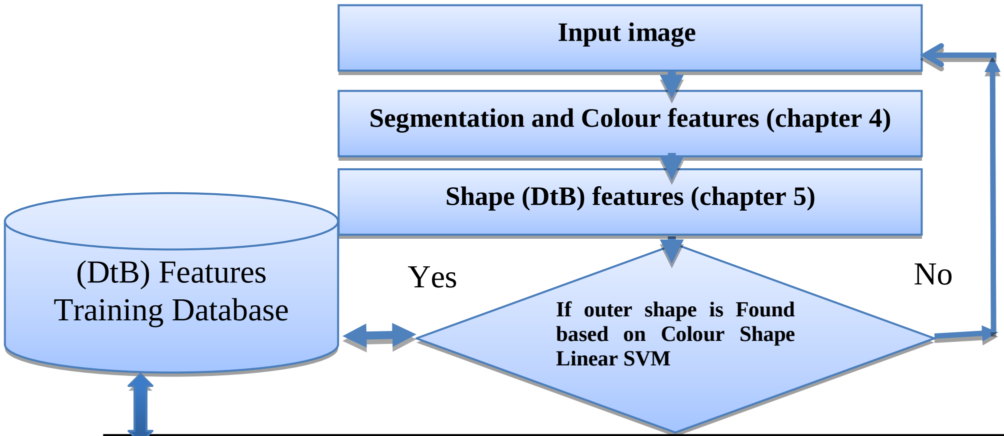


Figure 6.4 DtB new feature vector of 144 feature values joining (D1, D2, D3, and D4).

The main class contains more than one sub-class that are shared with the same colour, outer shape, and DtB feature vector. The methodology of using the speed up lookup table is shown in Figure 6.5.



Lookup Table

Main Class categories		Multi Subclasses in the main class
Colour	Shape (DtB)	Subclasses (inner road contents)
Red	**Circular**	subclass $_1$, subclass $_2$…, subclass $_n$
	Triangular	subclass $_1$, subclass $_2$…, subclass $_n$
	Octagonal	subclass $_1$, subclass $_2$…, subclass $_n$
Yellow	**Circular**	subclass $_1$, subclass $_2$…, subclass $_n$
	Triangular	subclass $_1$, subclass $_2$…, subclass $_n$
	Rectangular	subclass $_1$, subclass $_2$…, subclass $_n$
	Diamond	subclass $_1$, subclass $_2$…, subclass $_n$
Blue	**Circular**	subclass $_1$, subclass $_2$…, subclass $_n$
	Rectangular	subclass $_1$, subclass $_2$…, subclass $_n$

Figure 6.5 The methodology of using a lookup table for inner classification search

Figure 6.6 shows the pre-defined superclass ID based on colour and shape. This pre-defined superclass is updated in the lookup table for the DtB feature vector. This feature vector will be combined as a hybrid vector with HOG, LBP and SIFT feature vectors. In classification process, the lookup table utilizes the hybrid classifier based on FR to identify the proper branch to search for the most voted subclass. This will improve the efficiency and accuracy of the classification process.

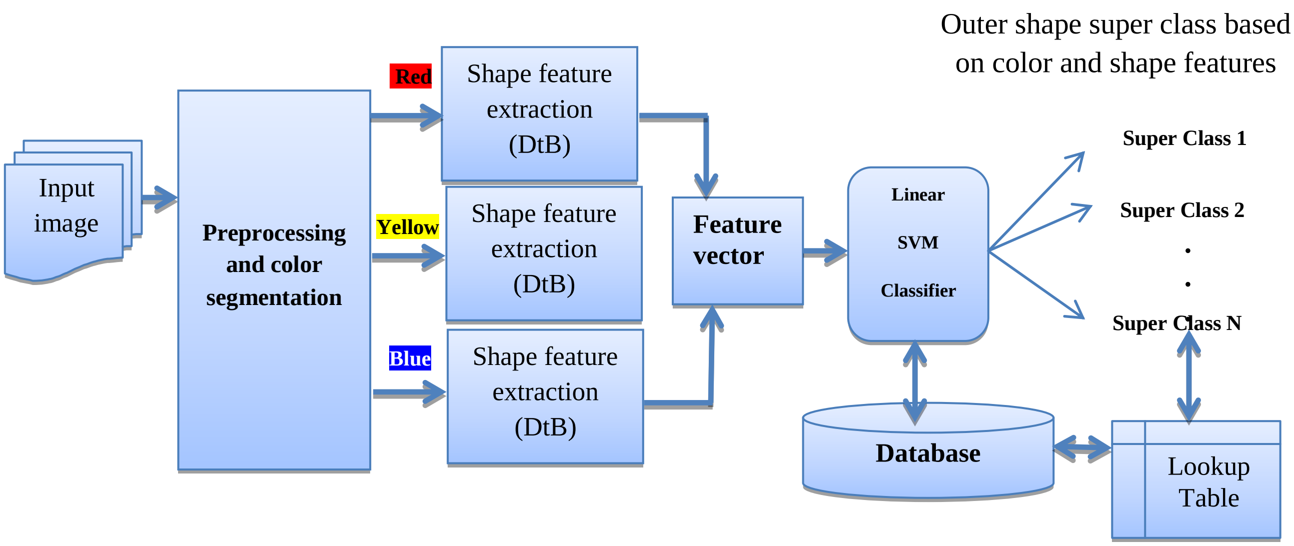


Figure 6.6 Pre-define super class ID methodology

6.4 Hybrid Feature Vector

In our research, the input image will be a candidate grey level road sign blob plus the pre-classified outer shape class that will be mapped from the proposed lookup table. This technique will improve the classification performance and reduce the search domain for the inner shape contents. In addition, it will reduce the dimension of feature vectors, since the image will contain only the candidate road sign blob with a normalized small resolution of (36 pixels X 36 pixels). Therefore, this method will be suitable for any feature extraction method to detect inner pictograms contained in the inner road sign blob. In this section, we propose a novel algorithm of a hybrid feature composed of HOG, LBP, and SIFT feature extraction methods. The algorithm is illustrated below.

Hybrid Feature Extraction Algorithm:

This algorithm will use the concatenated histograms of the feature extraction methods (HOG, LBP, and SIFT) to generate one hybrid feature vector that will be fed into the hybrid classifier. In addition, the three feature vectors are computed based on histograms for blocks and cells as follows:

- Calculating HOG vector features as Vhog

For each input image of size 36 x 36, we compute histogram with 9 pins on cells of 6 x 6 pixels with a non-overlap block size of 2 x 2 cells. Each Vhog feature vector is represented by Vhog = 1296 (6 x 6 x 4 x 9).

- Calculating LBP vector features as Vlbp

For each input image of size 36 x 36, we used a 3 x 3 local window, 12 x 12 cells for the block size and use uniform patterns to reduce the bins of the histogram of each block from 256 to 59 [168]. The LBP feature vector was Vlbp = 708 (12 x 59).

- Calculating SIFT vector features as Vsift

For each input image of size 36 x 36, we used 4x4 gradient windows for a histogram in 8 directions, 9 x 9 cells for the block size and the feature vector is Vsift = 4x4x8 = 128 x 9 x 9 = 10368 dimensional feature vector.

The Hybrid Feature Extraction Algorithm Steps are illustrated below and in Figure 6.7:

Step1: Input candidate road sign blob image and main class ID (Cm_id) (from a lookup table)**.**

Stpe2: Find the feature vectors for**:**

- Calculating HOG vector features as Vhog
- Calculating LBP vector features as Vlbp

- Calculating SIFT vector features as Vsift

Stpe3: Combine Vhog, Vlbp, and Vsift in one comprehensive vector called $V_{hog\text{-}lbp\text{-}sift}$ by concatenating the final histograms of the related feature extraction methods.

Stpe4: Feed the hybrid classifier with the feature vector for classification.

The proposed algorithm

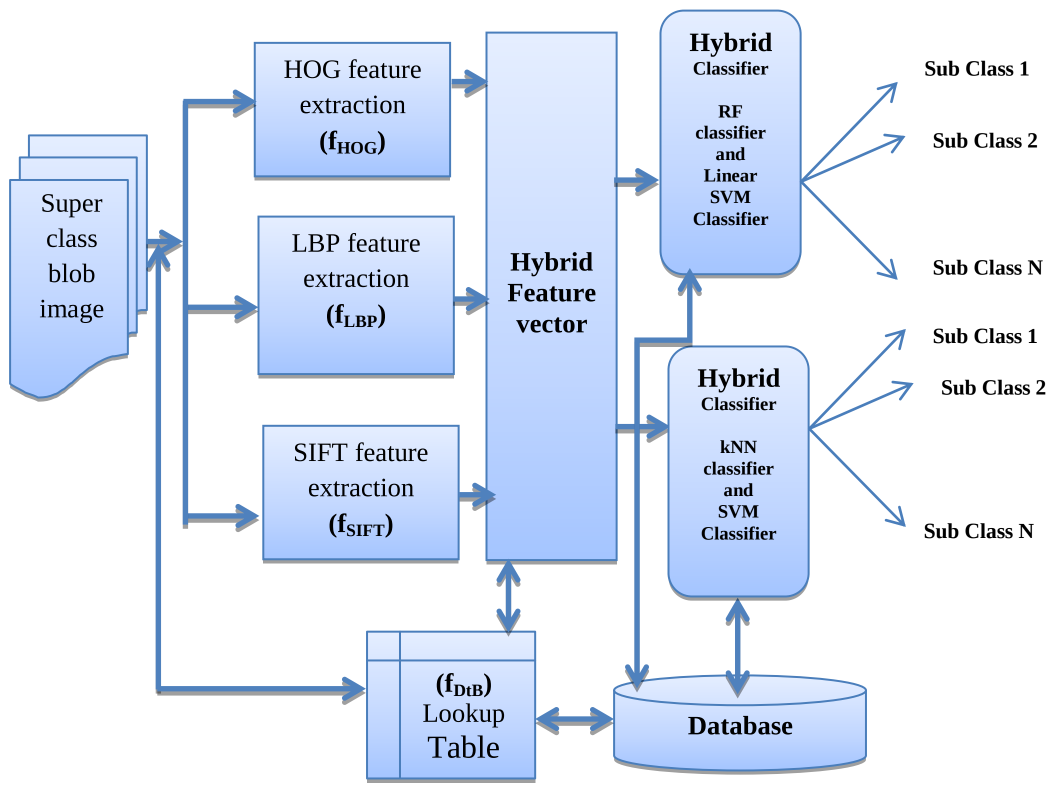


Figure 6.7 Hybrid multi feature methodology

In this Chapter four different techniques of features extraction (HOG, LBP, SIFT and the proposed hybrid feature) are used. In addition, we use a multi-feature as a combination of them. The proposed method significantly improves the classification results throughout the recognition system.

In HOG, LBP and SIFT feature, the candidate blob is represented by a local descriptors vector D.

$$D = [d_{1,} d_{2,} \ldots , d_{m}] \in R^{dxm}$$

where *m* is the local descriptors, *d* is the dimension of each local descriptor and d_i is the local descriptor.

The final multi-feature vector for the image I is based on concatenation of f_{HOG}, $f_{LBP,}$ f_{SIFT}, hybrid of ($f_{HOG\,+}$ f_{LBP+} $f_{SIFT)}$ and the guidance of f_{DtB} from the lookup table will be as follows:

$$f_I = [f^T{}_{HOG,} f^T{}_{LBP,} f^T{}_{SIFT}]$$

6.5 Dynamic Hybrid Classifier

Many studies have used ensemble methods applying the three classifiers by combining the predictions as an ensemble classifier. These predictions combinations can do by the average in regression case or by the majority voting in classification case [143]. In addition, more complex combinations are presented in [147] [148] [149].

In this chapter, we proposed a new dynamic hybrid classifier working as a dynamic selection between two hybrid ensemble classifier phases; the two phases are based on a pre-classified process based on a linear SVM classifier.

6.5.1 Hybrid Classifier based on SVM Utilizing Random Forest Classifier

The first phase is the hybrid classifier by using linear SVM and random forest tree. Each path in the random forest tree contains a binary SVM in the non-leaf node. This method will increase the classification accuracy of the SVM because of the efficient computation of the tree architecture that utilized N-1 linear SVM classifiers to be trained for N classes.

In this, we take advantage of the pre-classification process to feed the next phase with the predicted class to obtain a suitable path in the random forest tree and start with significant prediction path that mapped to the predefined class. By utilizing RF based on a linear SVM classifier only $\log_2 N$ SVMs in a worst-case scenario are needed to be checked for a classifying sample. This will significantly improve the recognition process in finding the true class, especially for a large number of classes. Since by using this method, the classifier will search only in the main shape and colour class and the search will be in the subclasses paths.

The proposed algorithm shows the advantage of the pre-classification process in selecting a suitable path in the forest tree structure. This method does better than random guessing on a new road sign image. In this chapter, we use the random forest tree as an ensemble learning technique in the context of decision trees based on an SVM classifier. The input features must be divided into two groups at each sub-tree node until we reach the leaf node starting from the root node of its path sub-tree; the pseudo code algorithm of using random forest and SVM is shown below:

The proposed method applied recursively by separating the classes into two disjointed groups for each node in the RF subtrees, then start the linear SVM training process to decide where the incoming unknown features should be assigned. To divide the classes into two groups, we use a clustering method and Euclidean Distance in the kernel space to determine the class subtree membership. In addition, RF can manage a multi-class dataset sufficiently, and better accuracy and performance are achieved by using SVM in a hybrid RF-SVM classifier.

Hybrid SVM-Random Forest Classifier Algorithm

1. Input the training classes N and training features D
2. Use linear SVM classifiers in Ensemble SVM.
3. Start by the root node of the RF tree.
   - For each node in the RF sub-tree Do
   - Divide the classes into two disjointed groups (g1, g2).
   - Assign the two classes with the longest distance to each cluster group (left sub-tree, and right sub-tree).
   - Find the class with the smallest distance from each group (g1, g2), and assign it to the corresponding group.
4. Update each subtree and update the lookup table.
5. Repeat steps 3 and 4 until all classes are assigned.
6. Train the linear SVM classifier in each node starting from the root as (positive for left group and negative for the right).
7. Repeat steps 2 to 6 until all nodes are a leaf (one class per group).
8. In testing, to classify an unknown object, a combination of the L individual classifiers outputs the majority voting is calculated.

Our proposed algorithm is also invariant to geometric transformation such as translation, scaling, rotation, and even a partial occlusion. In addition, the proposed algorithm is a rotation invariant because, features based method SIFT, HOG, and the combination of them is also invariant to rotation. Third, the algorithm is scaling invariant, because the DtB feature is normalized to be scaling invariant relative to the bounding box and the blob dimensions. Finally, the method is invariant and robust in partial occlusion due to the proposed geometric symmetry method that maintains the occlusion before calculating the DtB vectors. Besides this, the use of multi-feature properties as a combination of HOG, LBP, and SIFT will significantly improve on the results compared with studies reported in the literature. Another advantage of using shape detection is to separate the connected road signs into their category classes for the next classification step.

6.5.2 Hybrid Classifier based on KNN and SVM

We propose a hybrid classifier algorithm based on combining kNN and SVM classifiers. This classifier helps to improve the accuracy and the computation complexity of the multi-class and multi-feature problems. The proposed multi features hybrid algorithm based KNN and SVM is described as:

Hybrid KNN-SVM Classifier Algorithm

Do

1- Input the training classes N and the training features D

2- For each feature vector:
   - Use the KNN classifier for the input feature vector
   - If class is assigned (labelled) Goto step 4
   - Or else Goto step 3

3- Find the SVM classifier to the input vector.

4- Find the majority voting for the assigned classes.

5- Repeat steps 2 to 5 until all classes are assigned and until all features are trained.

6- In testing, for classifying an unknown object, combine the KNN outputs and the SVM outputs using majority voting.

End

The overall dynamic multi-feature based on a dynamic hybrid classifier is shown in Figure 6.8.

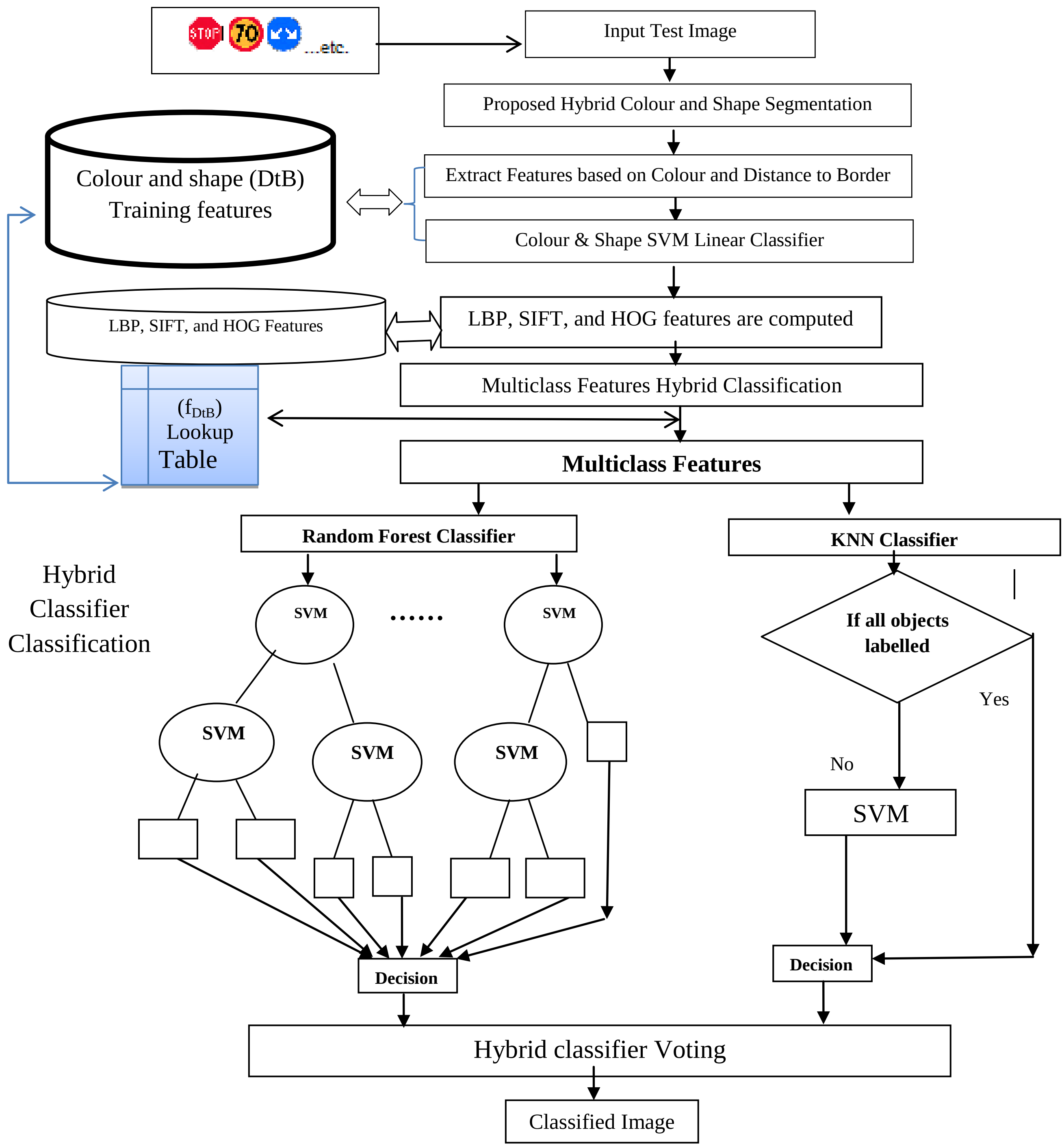


Figure 6.8 Hybrid Classifiers (RF/SVM based decision tree) and SVM/kNN framework

6.6 Experimental Results

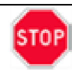
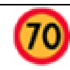
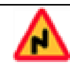
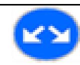
To explore the performance of the proposed road sign recognition algorithm, we used a sample of 315 images from the entire dataset [118]. This sample contains 456 road signs (the image contains more than one sign) of various road sign categories and different environmental conditions. The entire dataset used in this thesis is summarized in Table 6.1.

Table 6.1 Summary of dataset used in testing

Different image types and shapes	Total number of road signs used in testing
Ideal images	177
Noisy and faded images	137
Poor lighting images	75
Partially Occluded and other problem images	67
Total	456

A sample of the testing experimental results using the dataset in Table 6.1 produces super classes classified based on colour and shape features using the lookup table as shown in Table 6.2. In the next phase of extracting the inner pictogram features, many subclasses are produced in each superclass.

Table 6.2 Sample for a number of superclasses and subclasses produced after training process.

Super Class categories		Multi Subclasses in the main super class
Colour	Shape (DtB)	Subclasses (inner road sign contents)
Red	**Circular** 	41
	Triangular 	22
	Octagonal 	1
Yellow	**Circular** 	41
	Triangular 	22
Blue	**Circular** 	14
	Rectangular 	18

Each superclass contains many subclasses. The experimental training and testing results using this dataset are illustrated in the following sections.

To test the robustness of the proposed feature extraction method and the proposed hybrid classifier method on the database illustrated in table 6.1, we compared our system with the benchmark paper in [26]. In addition, we compared our results with another study in [48] that used the same dataset as in [26].

The accuracy of the proposed algorithm in this chapter was measured by using equation (6.1) [164] [165].

$$Accuracy = \frac{(Number\ of\ True\ Positive + Number\ of\ True\ Negative\ )}{(Number\ of\ True\ Positive +\ False\ Positive + False\ Negative + True\ Negative)} \tag{6.1}$$

6.6.1 Experiment-1

To explore the robustness of the proposed classification and feature extraction algorithm on the database illustrated in table 6.1, we first extracted the feature vectors of HOG, SIFT, and LBP features, and then fed the feature vectors into the SVM, RF, and KNN classifiers. Second, the accuracy of the proposed method was calculated and the results are summarized in Table 6.3 and the analysis is shown in Figure 6.9.

Table 6.3 Accuracy of proposed algorithm for different features and classifiers

Classification Methods	Feature Selection Methods		
	LBP	SIFT	HOG
SVM	93%	93.1%	94.5%
RF	90.5%	91.6%	93.1%
kNN	92.3%	92.5%	93.4%

6.6.2 Experiment-2

In this experiment, we try to combine the features as hybrid features that will be fed into the proposed classifiers. The accuracy of different features containing HOG, SIFT, LBP and a hybrid of them is shown in table 6.4 and the analysis is shown in figure 6.10.

Table 6.4 Accuracy of different feature methods and proposed hybrid feature

Classification Methods	Feature Selection Methods			
	LBP	SIFT	HOG	HOG+LBP+SIFT
SVM	93%	93.1%	94.5%	96.8%
RF	90.5%	91.6%	93.1%	94.8%
kNN	92.3%	92.5%	93.4%	95.1%

6.6.3 Experiment-3

In this experiment, we try to combine the classifiers based on a single feature or hybrid features. The result of this experiment will help identify the high accuracy hybrid classifier for the proposed algorithm. The proposed hybrid features to be combined are (SVM+RF) and (KNN+SVM). The comparisons between the single classifiers and hybrid classifiers are illustrated in table 6.5 and the analysis is shown in figure 6.11.

Table 6.5 Comparisons between hybrid classifiers for single feature and hybrid features

Proposed Hybrid Classifier	Feature Selection Methods			
	LBP	SIFT	HOG	HOG+LBP+SIFT
RF + SVM	94.6%	95.1%	96.6%	98.3%
kNN + SVM	93.5%	94.9%	96.1%	98.1%
RF+SVM and kNN + SVM	95.9%	96.7%	97.1%	98.9%

6.7 Results Analysis and Comparisons

To evaluate the proposed method, three experimental results were analysed and a comparison with the benchmark paper [26] and other studies that use the different database are shown in table 6.6. The method of the benchmark paper was re-implemented in this research to ensure comparison accuracy. The results of the other studies were taken from the papers, where the authors presented their results and the database was used in the experiments. In addition, comparisons of recognition accuracies are illustrated in Figures 6.12 and 6.13.

Table 6.6 Comparisons of recognition accuracies by using the same dataset for varying conditions and road sign shapes.

Reference Number	**Experimental Conditions for Different Image Types and Shapes**	**Accuracy**
[170]	Blue Rectangular Red Triangular Red Circular	96.01% 96.30% 94.84%
[26]	Ideal Noisy and faded Poor Partially Occluded	95.3% 85.1% 73.6% 57.3%
[48]	Ideal Noisy and faded Poor Partially Occluded	94.8% 86.1% 76.3% 63.0%
Proposed method for RF + SVM	**Ideal Noisy and faded Poor Partially Occluded**	**99.1% 97.6% 98.4% 91.1%**
Proposed method for kNN + SVM	**Ideal Noisy and faded Poor Partially Occluded**	**98.7% 98.6% 97.4% 92.5%**
Proposed method for The Decision between RF + SVM And kNN + SVM	**Ideal Noisy and faded Poor Partially Occluded**	**99.4% 98.6% 98.4% 92.5%**

Table 6.6 illustrates the results of the three experiments. It is clear that the accuracy shows a significant improvement for the hybrid classifiers compared to a single classifier. In addition, it is also clear that the hybrid features show a significant improvement compared to each single feature. This indicates that the proposed algorithm provides higher accuracy rates than standard systems.

The proposed method can solve several problems. The first problem is related to poor-lighting images, which is solved in the pre-processing and segmentation method. The second problem is the partially occluded road sign; this problem is solved in the second phase of shape detection by using geometric shape detection.

The overall problem is the classification complexity to deal with multi features and a multi-class problem. This problem is solved by the proposed hybrid dynamic multi-feature algorithm using a two-phase hybrid classifier. The results show that using hybrid features based on hybrid classifiers delivers high accuracy rates of 98.6% and 99. 4%.

Classification results using the entire data set are summarized in Table 6.4 and 6.5. From the 456 road signs, 452 are correctly recognized by the proposed method, which results in a correct recognition rate of more than 98% for various road sign shapes and types in different conditions. Furthermore, the results of the proposed method in poor lighting conditions show a correct recognition rate of more than 97%, where 73 of 75 road signs are correctly classified. The methods in [26] and [48] achieve low accuracy rates of 73.6% and 76.3%, respectively.

6.8 Summary and Conclusion

The results show significant improvements in the accuracy by using hybrid features. Additional significant improvements are achieved by using a lookup table since it redirects the classifier to the specific path where the superclass is found. This will reduce the domain of the search in the classification process. The proposed system improves the efficiency and reduces the classification time to be suitable for the real-time environment.

Chapter 7 Conclusion and Future Work

7.1 Introduction

This chapter summarises the main contributions of chapters 4, 5, and 6, by exploring the conclusions and clarifying the importance of our research. In addition, it presents interesting problems for possible future work. Our main aims of this research were to enhance the accuracy of road sign recognition systems, especially for poor lighting and partial occlusion conditions.

. Recently, many Advanced Driver Assistance Systems (ADAS) have been implemented, including those based on computer vision techniques for road sign recognition. ADAS include such innovations as lane departure warning systems and automatic parking systems.

The layout of this chapter is organized as follows: section 7.1 provides the introduction and motivation. Section 7.2 illustrates the research highlights of each contribution in chapters 4, 5, and 6. Finally, Section 7.3 presents insights to guide future studies to emphasize and enhance the functionality and the efficiency for segmentation, detection, and feature extraction and classification algorithms.

7.2 Research Contribution and Conclusions

In Chapter 4, a detailed analysis based on analysing the accuracy and the performance of the proposed colour segmentation methods was presented. In this chapter, we present the following:

1- Three colour spaces were used to propose a hybrid dynamic colour space by combining or selecting the most suitable colour space relative to the illuminations and environmental conditions. By using our proposed algorithm, we solve the problems of illumination, especially in the poor lighting environment conditions.

2- Based on three colour spaces, we presented a dynamic threshold algorithm. This algorithm shows significant improvements in road sign segmentation for different road sign images. The dynamic threshold increases the accuracy of the segmentation method, since it dynamically generates the threshold value that depends on the input image characteristics, illumination conditions, and the level of colour intensity values in the image; for example, some colours are changed with time; under sunlight dark red may become light red. In this case the threshold for the red colour will be different in both cases. Our proposed system solves this problem via the dynamic threshold algorithm.

In Chapter 5, a novel detection algorithm is proposed based on dynamic geometric symmetry using the DtB feature.

1- This algorithm uses the DtB features of the resulting blob from Chapter 4 to identify the candidate road sign image from the scene.

2- The unique characteristics of the road signs motivate us to propose the dynamic geometric symmetry algorithm. This algorithm solves the problem of rotation in the candidate road sign, which increases the accuracy and performance of the overall recognition system. This is done by increasing the correct road signs that can be detected in the DtB method and increases the accuracy of the classification in the final step.

3- An additional contribution is the pre-defined superclass of the road sign categories based on colour and shape. This superclass is fed into a lookup table that is used to increase the accuracy and performance via speeding up the final classification in Chapter 6.

In Chapter 6, we introduced a hybrid feature extraction method and a hybrid classifier technique. The following summarizes the findings:

1- Hybrid feature extraction methods are presented; we use a simple approach to combine the extracted features based on HOG, LBP and SIFT.

2- The histogram of all window cells was calculated and concatenated to generate one feature vector that includes the main key points of interest in the image. This vector uses grey road sign images of resolution 36 pixels x 36 pixels. This size can easily divide into cells and blocks that contains a number of bins used in the feature extraction that significantly improves the performance and accuracy.

3- Another contribution is the hybrid classifier of (RF+SVM) and (KNN + SVM). These two hybrid classifiers use a lookup table to reduce the search domain in all superclasses. Because of this, the classifiers will search in a specific RF path with SVM in each node of the branch. Besides this, the next hybrid classifier will use the guidance of the lookup table to reduce the search domain in all superclasses.

7.2 Future Work

The proposed algorithms open more than one path for further research in this field. The first is to use other hybrid colour spaces in the segmentation process. Another one is to propose new methods for dynamic colour segmentation to enhance the accuracy. Another potential area of future research is feature extraction functionality and efficiency by using other feature extraction methods. The design of suitable hybrid classifiers is a new approach that still needs more research and applications to support it. Another important potential future research work is to develop techniques that allow us to use the proposed algorithms in real-time systems.

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