Recognition of Traffic Signs based on Vision Models

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Abstract

This paper presents a new approach to segment and recognise traffic signs via two vision models: the colour appearance model CIECAM97s and Behaviour Model of Vision (BMV). This approach not only takes CIECAM97s into practical application for the first time since it was standardised in 1998, but also improves the accuracy of recognition of traffic signs dramatically, taking into account of changing weather conditions and varying transformations of signs. BMV model has been further developed to a foveal system for traffic signs (FOSTS). Comparison with the other colour spaces in terms of segmentation, including CIELUV and HSI, and RGB colour space is also carried out. The results show that CIECAM97s outperforms over the other three spaces with 94%, 90% and 85% accurate rate for sunny, cloudy and rainy viewing conditions respectively. It also confirms that CIECAM97s does predict the colour appearance similar to the average observer. For recognition stage, FOSTS system gives accuracy rates up to 95%.

Key words: traffic sign segmentation, colour appearance model, CIECAM97s, BMV model, vision model, HSI space, CIELUV space, FOSTS system.

1. Introduction

To recognise traffic signs correctly at the right time and place is very important in ensuring a safe journey for car drivers and their passengers, as well as pedestrians crossing the road. Sometimes, due to the sudden change of viewing conditions, traffic signs are barely visible until it is too late, giving rise to a necessity for the development of an automatic system to assist car drivers in the recognition of traffic signs invariant of variety of transformations of signs and viewing environment. In the past, traffic signs were recognised with quick algorithms because of the limitation of computer power. With the advances of computer technology, especially hardware, the trade-off between processing speed and accuracy should be improved. In this study, two vision models are applied to segment and recognise traffic signs, including a colour appearance model, CIECAM97s for image segmentation of potential traffic signs, and a Behaviour Model of Vision (BMV) to recognise segmented regions.

Based on the appearance of traffics signs, two segmentation approaches become popular, which are colour-based and shape-based. Usually, each approach only works well for a particular group of signs with constrained viewing conditions. For example, most colour-based techniques run into problems if the illumination source varies not only in intensity but also in colour, i.e., colour spectral distribution, as well. This is because the spectral composition, and therefore the colour, of daylight changes depending on weather conditions: e.g., sky with/without clouds, time of the day, e.g., night when all sorts of artificial lights are present [1].

1.1 Traffic Sign Segmentation Based on Colour

Colour is a dominant visual feature and is undoubtedly a key piece of information for drivers to handle. Colour information is widely used in traffic sign recognition systems [2], especially for segmentation of traffic sign images from the rest of a scene. Colour is regulated not only for the traffic sign category (red = stop, yellow = danger, etc.) but also for the tint of the paint that covers the sign, which should correspond, with a tolerance, to a specific wavelength in the visible spectrum. Eight colours: red, orange, yellow, green, blue, violet, brown and achromatic [3], are the most discriminating colours for traffic signs.

Many researchers have developed various techniques in order to make use of the colour information from traffic signs, which includes clustering method in a colour space [4] and a recursive region splitting method to achieve colour segmentation [5]. The colour spaces they have applied are HSI (Hue, Saturation, Intensity), and CIE L*a*b* space. These colour spaces normally are limited to only one lighting condition, which is D65, the average overcast daylight. Hence, the range of each colour attribute, such as hue, will be narrowed down due to the fact that weather conditions only change with colour temperatures ranging from 5000K to 7000K.

Many other researchers focus on a few colours contained in the signs, including 'stop', 'warning', and 'danger' signs [6]. Their system is able to detect 55% of the 'warning' signs within the 55 images. Classification of traffic signs into different colour groups is also attempted [7]. RGB space is the most used space in this application. Additional procedures are also developed to improve the *RGB* performance based on estimation of shape, size and location of primarily segmented areas [8]. Combined approaches are proposed as well, including combination of colour and intensity [9] to determine candidates of traffic signs with white circular and blue rectangular regions. Although this approach does not miss any candidate, it detects many false candidate regions. Applying both RGB and HSI colour spaces in order to detect blue and red regions is another combined method [10], which is able to detect traffic sign of four pre-defined shapes with accuracy up to 90%.

Due to the change of weather conditions and times of the day (for example, in the evening all sorts of artificial lights are present), the colour of the traffic signs, as well as illumination sources, appear different. Therefore, most colour-based techniques for traffic sign segmentation and recognition may not work properly, no existing method being widely accepted [11].

In this study, traffic signs are segmented based on colour contents using a colour appearance model CIECAM97s that is recommended by the CIE (International Committee on Illumination) [12]. After segmentation, the recognition stage is carried out applying a modified Behaviour Model of Vision (BMV) [13] to retrieve the correct sign that matches the sign in the segment from a database of standard traffic signs.

1.2 CIECAM97s colour Appearance Model

CIECAM97s is based on a simplified theory of colour vision for chromatic adaptation together with a uniform colour space [12]. It can predict colour appearance as accurate as an average observer. This colour appearance model is expected to extend traditional colorimetry (e.g., CIEXYZ, and CIELAB) to the prediction of the observed appearance of coloured stimuli under a wide variety of viewing conditions, which is accomplished by taking into account the tristimulus values (X, Y, and Z) of the stimulus, its background, its surround, the adapting stimulus, the luminance level, and other factors such as cognitive discounting the illuminant. The output of colour appearance models includes mathematical correlates for perceptual attributes that are brightness, lightness, colourfulness, chroma, saturation, and hue.

Since it is standardised, the CIECAM97s has not been applied to any practical application. In the present study, this model is investigated on the segmentation of traffic signs. Comparisons with

CIELUV, HSI, and RGB colour spaces are also conducted on the performance of traffic sign segmentation.

1.3 Behaviour Model of Vision (BMV)

BMV model was developed based on biologically plausible algorithms of space-variant image representation and image viewing. It has the ability to recognise complex grey-level images invariantly with respect to shift, plain rotation, and in a certain extent to scale, and has been extensively applied for face recognition. The basic version of the BMV model has been further extended for the task of traffic sign recognition, leading to FOSTS model (Foveal System for Traffic Signs) [14]. FOSTS model provides a compressed and invariant representation of each fragment of signs along the trajectory of viewing using representative space-variant features that are extracted from the fragment by Attention Window (AW). These descriptions have been stored with the images and form a model-specific database of traffic sign images, which needs to be built only once.

2. Methodology

2.1 Camera Calibration

To collect traffic sign images, a high quality Olympus Digital Camera C-3030 Zoom is utilised to capture pictures in the real viewing conditions. Before taking the photos, camera calibration is carried out to ensure the consistency of the camera. Figure 1 illustrates the steps of calibrations.

It starts with the setting the white balance of the camera to D65. The 24 colour patches from the Gretag Macbech Colour Checker are then captured under Verivide Viewing Cabinet with D65 illuminant. After the images are transferred to the computer, which has been calibrated into D65 illuminant by a monitor calibration software (OptiCAL [15]), the images are displayed using MATLAB image processing software which shows the original image format (TIFF in this case). The X, Y, Z tristimulus values of 24 colours from the colour chart are measured by a colour meter CS-100A. After the X, Y, Z values are obtained, the relationships between XZY and RGB values in the image are worked out using linear regression, which is shown in Eq. (1). The measurements for the other viewing illuminant, such as D50, also give similar matrix as in Eq.(1). Therefore Eq. (1) is applied as the camera calibration model to convert the RGB values from an image into XYZ values for all the weather conditions.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.2169 & 0.1068 & 0.048 \\ 0.1671 & 0.2068 & 0.0183 \\ 0.1319 & -0.0249 & 0.3209 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

2.2 Image data collection

The collection of sign images reflects the variety of viewing conditions and the variation of traffic sign sizes caused by differences in distance between traffic signs and driver (the position while taking pictures). The viewing conditions contain two elements: the weather conditions including sunny, cloudy, and rainy conditions, with each group sharing similar level of luminances; and the viewing angles, with complex traffic sign positions as well as multiple signs at a junction.

The distance between the driver (and therefore the car) and the sign determines the size of traffic sign inside an image and is related to the recognition speed. According to The Highway Code [16] from UK, the stopping distance should be more than 10 meters under 30MPH (miles per hour), giving around 5 seconds to brake the car in case of emergency. Therefore, the photos are taken under the distance of 10, 20, 30, 40, and 50 meters respectively for each sign. In total, there are two sets of data are collected, each with 145 and 128 pictures respectively. They are taken under different weather conditions for some representative signs with various colour combinations. The first set of data is utilised to develop the segmentation and recognition systems, whilst the second set of data is applied to evaluate the systems. The first set of data consists of 145 pictures: 52 taken on a sunny day, 60 on a rainy day, and 33 on a cloudy day. All the photos were taken using similar camera settings.

2.3 Image classification according to weather conditions

To apply the colour appearance model, CIECAM97s, a particular set of viewing parameters should be utilised for each of different viewing conditions such as weather conditions or luminance levels. Therefore, image classification should be performed first in order to apply the right sets of parameters.

Most sign photographs are taken in a similar position, leading to an image consisting of three parts from top to the bottom, containing sky, scenes, and the road respectively. If, however, some images miss one or two parts (for example, an image may miss the road when taken uphill), then these images are classified into sunny day condition, which can be verified at the later recognition stage. From this information, image classification can be carried out based on the saturation of sky or the texture of the road. The degree of saturation of the sky (the colour blue in this case) will decide the sunny, cloudy and rainy status, which is determined by using an optimal thresholding method. A sunny sky is clearly distinguishable from cloudy and rainy sky; it is easy to classify a sunny day based on the colour of sky. For cloudy or rainy conditions, another measure has to be enclosed to further the confirmation. This is done by the introduction of texture feature of the road that appears in the third part of the bottom of an image. The texture of the road is measured using fast Fourier Transform (FFT) with the average magnitude (AM) as threshold, which is shown in Eq.(2) [17].

Although a Gabor filter is an alternative approach to represent texture with more comprehensive features, experimental results show that FFT is good enough in this application providing faster processing time.

$$AM = \sum_{j,k} \left| F(j,k) \right| / (N) \tag{2}$$

where $\left| F(j,k) \right|$ is the amplitudes of the spectrum calculated by Eq. (3) and N is the number of frequency components.

$$F(u,v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) \exp\left[-2\pi \left(\frac{mu}{M} + \frac{nv}{N} \right) \right] \tag{3}$$

where f(n,m) is the value of the pixel with coordinates n, m. N, M is the image size, and u, v are frequency components.

2.4 Traffic sign segmentation

After classification, the reference white is obtained by repeatedly measuring a piece of white paper using a colour meter, CS-100A, under each viewing condition. The average of these values are given in Table 1 and applied in the subsequent calculations.

The images taken under real viewing conditions are transformed from RGB space to CIE XYZ values using Eq.(1) and then to LCH (Lightness, Chroma, Hue), the space generated by CIECAM97s. The range of Hue, Chroma, Lightness for each weather condition is therefore obtained, which is shown in Table 2. These values are the mean values ± standard deviations. Only Hue and Chroma are utilised in the segmentation procedure due to the fact that lightness barely change with the change of viewing conditions, which is consistent with the findings from the other researchers [18]. These ranges are applied as thresholds to segment potential traffic sign.

2.5 Recognition of Signs using FOSTS model

Each sign in the FOSTS model is represented by specific description of sign inner content. The basic structure and operations in the FOSTS is illustrated in Figure 2 and consist of:

(i) an image in each sensor fixation point is described by oriented segments extracted in the vicinity of each of 49 sensor nodes;

(ii) the sensor nodes are located at the intersections of sixteen radiating lines and three concentric circles, each with a different radius;

(iii) orientation of segments in the vicinity of each sensor node is determined by means of calculation of the difference between two oriented Gaussian functions with spatially shifted centres having the step of 22.5^{o};

(iv) space-variant representation of image features is emulated by Gaussian convolution with different kernels increasing with the distance from the sensor centre.

Contrary to [13], the input window (IW) size increases to 36 pixels (instead of 16 pixels in the basic BMV) and kernel sizes are changed to process a sign by one fixation of the AW, i.e., they are equal to 5x5 for the central part of the IW, 7x7 for the immediate, and 9x9 for the peripheral part. On the other hand, estimation of oriented elements in the context area of 48 IW nodes (minus the central node) is used to receive a detailed feature description of a sign. The size of context area is varied for different parts of the IW, being equal to 3x3 for 16 nodes located on the central ring of the IW, 5x5 for the immediate one, and 7x7 for the peripheral ring. Each IW node is described by two values, i.e., orientation dominating in its context area (if it is detected in more than 50% of context area points) and by density of oriented elements detected in the context area (Fig. 2, b). Such structure of IW and its location in the sign centre provides maximal representation of oriented elements in informative parts of sign at the first and second resolution levels (up to 90%). An example of oriented elements detected in context area of indicated node of a sign is shown in Fig. 2, b.

3. Experimental Results

3.1 Segmentation

Figure 3 gives an interface for traffic sign segmentation, showing three potential signs segmented from the image. The bottom right of segmented results contain a rear part of a car rather than a sign, which however, will be discarded by the recognition stage (to be discussed later).

To evaluate the results of segmentation, two measures are used. One is the *probability of correct detection,* denoted by P_c, and the other is the *probability of false detection*, denoted by P_f, as calculated in Eqs. (4) and (5) respectively.

$$P_c = \frac{\textbf{number of segmented regions with signs}}{\textbf{number of total signs}} \tag{4}$$

$$P_f = \frac{\textbf{number of segmented regions with no signs}}{\textbf{total number of segmented regions}} \tag{5}$$

To evaluate CIECAM97s model, the second set of data with 128 pictures is applied to avoid duplication when applied performing segmentation, including 48, 53, and 27 pictures taken under sunny, rainy, and cloudy days respectively. Within these images, 142 traffic signs are visible. Among them 53 signs are from sunny days, 32 signs from cloudy days, and 57 signs from rainy days. The results of segmentation are listed in Table 3.

Table 3 illustrates that for the sunny day, 94% signs have been correctly segmented using CIECAM97s model. However, it also gives 23% false segments, i.e., the regions without any signs at all, like the segment at the bottom right in Fig. 3 showing the rear light of a car. Table 3 also demonstrates that the model works better on sunny day than cloudy or rainy days, the last two conditions receive P_c value of 90% and 85% respectively. Although the segmentation process gives some false segments, these segments can be discarded during recognition stages.

3.2 Recognition

The 49-dimension vector for a traffic-sign-to-be image is compared with descriptions of database images of the corresponding subgroup by the formula Eq.(6):

$$K^b = \sum_{i=0}^{i<49} \left[\mathrm{sgn}\left(Or_i^b - Or_i^{rw}\right) \cdot \left(1 - abs\left(\rho_i^b - \rho_i^{rw}\right)\right) \right] \tag{6}$$

$$\mathrm{sgn}(x) = \begin{cases} 1, & if \quad x = 0; \\ 0, & o\mathbf{verwise;} \end{cases}$$

where Or_i^b is dominating orientation extracted from the context area of a given IW node (orientations are determined by the step 22.5° and indicated as 1, 2, 3…., 16), whereas superscript *b* stands for images from a database and *rw* the real world image segmented using colour-based approach. ρ is the density of the dominating oriented segment in the vicinity of the given IW node. Preliminary results have shown that minimal value of resulting K^b is 25; otherwise the region of interest will be considered a false sign to be rejected. Figure 4 illustrates the rejection of falsely segmented regions after segmentation and recognition procedures.

For the data set of 142 signs from 128 pictures, 99% of false positive regions are discarded. Figure 5 demonstrates the interface of the system combining both segmentation and recognition. In the left bottom picture, two regions are segmented (with square boundary). One is the sign with 40 inside a circle, the other is the rear light of a car at the right-hand corner of bottom left picture. After recognition, only the 40mph speed limit sign is framed (top left picture), with a matching sign retrieved from the database (right bottom picture).

4. Comparison with HSI and CIELUV methods

In the literature, nearly all the segmentation approaches apply one of RGB, HIS, and CIELUV spaces to represent a pixel. Comparisons with these three methods are therefore carried out. Because RGB space is device dependent, the comparison will be discussed in the next section.

The HSI (Hue, Saturation, and Intensity) method has been widely used in colour segmentation as it is much closer to human perception [19] than RGB, the space that images are originally formatted. Eq.(7) gives the conversion from RGB to HSI.

$$
\begin{aligned}
H &= \cos^{-1}\left\{\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right\} \quad R \neq G \text{ or } R \neq B \\
S &= Max(R,G,B) - Min(R,G,B) \qquad (7) \\
I &= \frac{(R+G+B)}{3}
\end{aligned}
$$

Another popular space used on colour segmentation is CIELUV, which is recommended by CIE for specifying colour differences and is uniformed as equal scale intervals representing approximately equal perceived differences in the attributes considered. The attributes generated by the space are Hue (H), Chroma (C), and lightness (L), which are calculated by Eq.(8) [20].

$$
\begin{aligned}
&L^* = 116\left(\frac{Y}{Y_0}\right)^{1/3} - 16 \quad , \quad \text{if } Y/Y_0 > 0.008856 \\
&L^* = 903.3 \cdot \left(\frac{Y}{Y_0}\right) \qquad \text{if } Y/Y_0 <= 0.008856 \\
&u^* = 13L^*(u' - u'_0) \\
&v^* = 13L^*(v' - v'_0) \\
&H = \arctan(v^*/u^*) \\
&C = \sqrt{(u^*)^2 + (v^*)^2}
\end{aligned}
\tag{8}
$$

where Y_0, u_0, v_0, are the Y, u, v values for the reference white.

The segmentation procedure using these two spaces is similar to the application of CIECAM97s. Firstly, the colour ranges for each attribute are obtained for each weather condition. Then images are segmented using optimal thresholding method based on these colour ranges. Table 4 lists the comparison results between three colour spaces.

These data show that for each weather condition, CIECAM97s performs best with correct segmentation rate of 94%, 90% and 85% respectively for sunny, cloudy, and rainy conditions. CIELUV performs better than HSI for the cloudy and rainy conditions. Also HSI gives largest percentage of false segmentation with 29%, 37% and 39% respectively for each weather condition. The results also demonstrate that all colour spaces do not perform as well for rainy days as for the other two weather conditions (sunny and cloudy), which is in line with everyday experience, i.e., the visibility is worse on a rainy day than on a sunny or cloudy day for drivers. Figure 6 demonstrates the process of segmentation in a real example carried out by the three colour spaces, which depicts that CIECAM97s gives two correct segments with signs inside. Whereas CIELUV colour space method segments two signs plus a false segment. For the HSI colour space, two signs are segmented correctly in addition to two false segments, which again illustrates that HSI performs worst in traffic sign segmentation task based on colour.

5. Traffic Sign Segmentation Based on RGB

Traffic sign segmentation by RGB space is also performed in comparison with the above discussed methods on a calibrated monitor. The calibration setting is the average daylight of D65. Based on the preliminary evaluation of RGB composition for traffic signs, the ranges of [35, 255], [-20, 20], [15, 230], [5, 85] are determined for signs R-B, G-R, G-R, and B-G respectively. On the other hand, while determining each segmented region as a potential traffic sign, two additional conditions should be taken into account. One is the size of clustered colour blobs that should be no less than 10x10 pixels. The other is the relation of width/height of the segmented region that should be in a range 0.5-1.5.

The same set of testing road sign pictures (n=128) are applied with the implementation of RGB as segmentation method, which is shown in Table 5.

Tables 4 and 5 indicate that probability of correct traffic sign segmentation by RGB is lower than by CIECAM97 for sunny and cloudy weather conditions. Further more, the probability of false positive detection is much higher for the RGB method, illustrating strongly dependence on weather conditions.

6. Conclusions and Discussions

This paper introduces a new approach for recognition of traffic signs based on vision moodels, which utilises the application of the CIECAM97s and FOSTS, developed based on human perception and BMV respectively. The experimental results show that this CIECAM97s model performs very well and can give very accurate segmentation results, with up to 94% accuracy rate for sunny days. When compared with HSI, CIELUV and RGB, the three most popular colour spaces used in colour segmentation research, CIECAM97s over-performs the others. The result not only confirms that the model's prediction is closer to the average observer's visual perception, but also opens up a new approach for colour segmentation while doing image processing. However, when it comes to the calculation, CIECAM97s is more complex than the other colour spaces and needs larger amount of calculations, which will be a problem when processing video images in real time. At the moment, the processing time for segmentation can be reduced to 1.8 seconds and the recognition time is 0.19 second, leading to 2 seconds for processing one frame of image. When processing video images, there are normally eight frames in 1 second, which means the total time (= segmentation time + recognition time) should be 0.25 seconds for one frame of image. Therefore, more work needs to be done to further optimise algorithms for segmentation and recognition in order to meet the demand for real time traffic sign recognition. Although the correct segmentation rate is less than 100% when applying CIECAM97s, the main reason is the size of signs in an image being too small in some scenes. When processing video images, the signs of interest will gradually become larger when the car is approaching to the signs. Hence the correct segmentation rate can be improved dynamically. As for recognition, FOSTS can retrieve the correct signs with 95% accuracy. Some signs, e.g., a speed limit sign covered with leaves, are difficult to recognise its contents.

Acknowledgement

This work is partly support by The Royal Society, UK, under the International Scientific Exchange Scheme and partly sponsored by Russian Foundation for Basic Research, Russia, grant № 05-01-00689. Their support is gratefully acknowledged.

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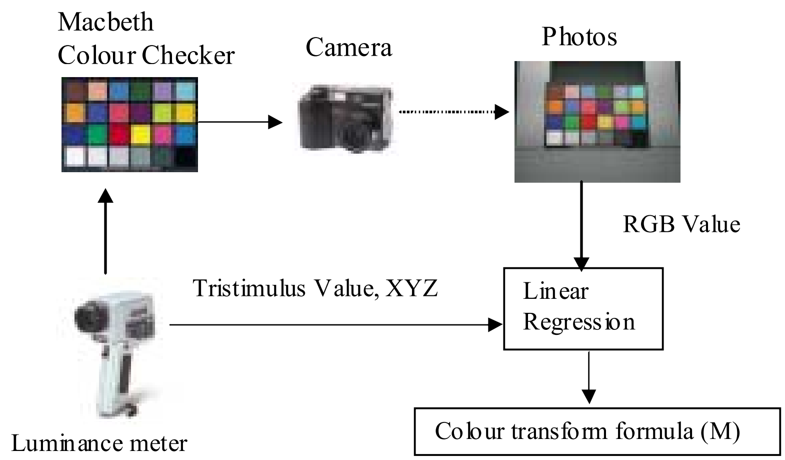
3. Figure

Figure 1. Steps to calibrate a camera.



3. Figure

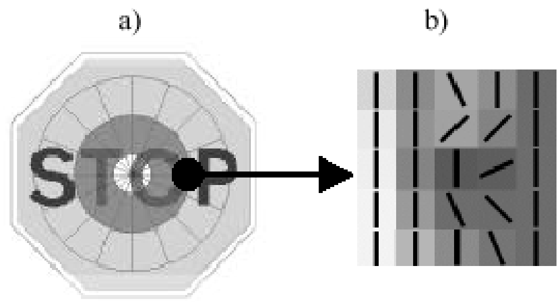
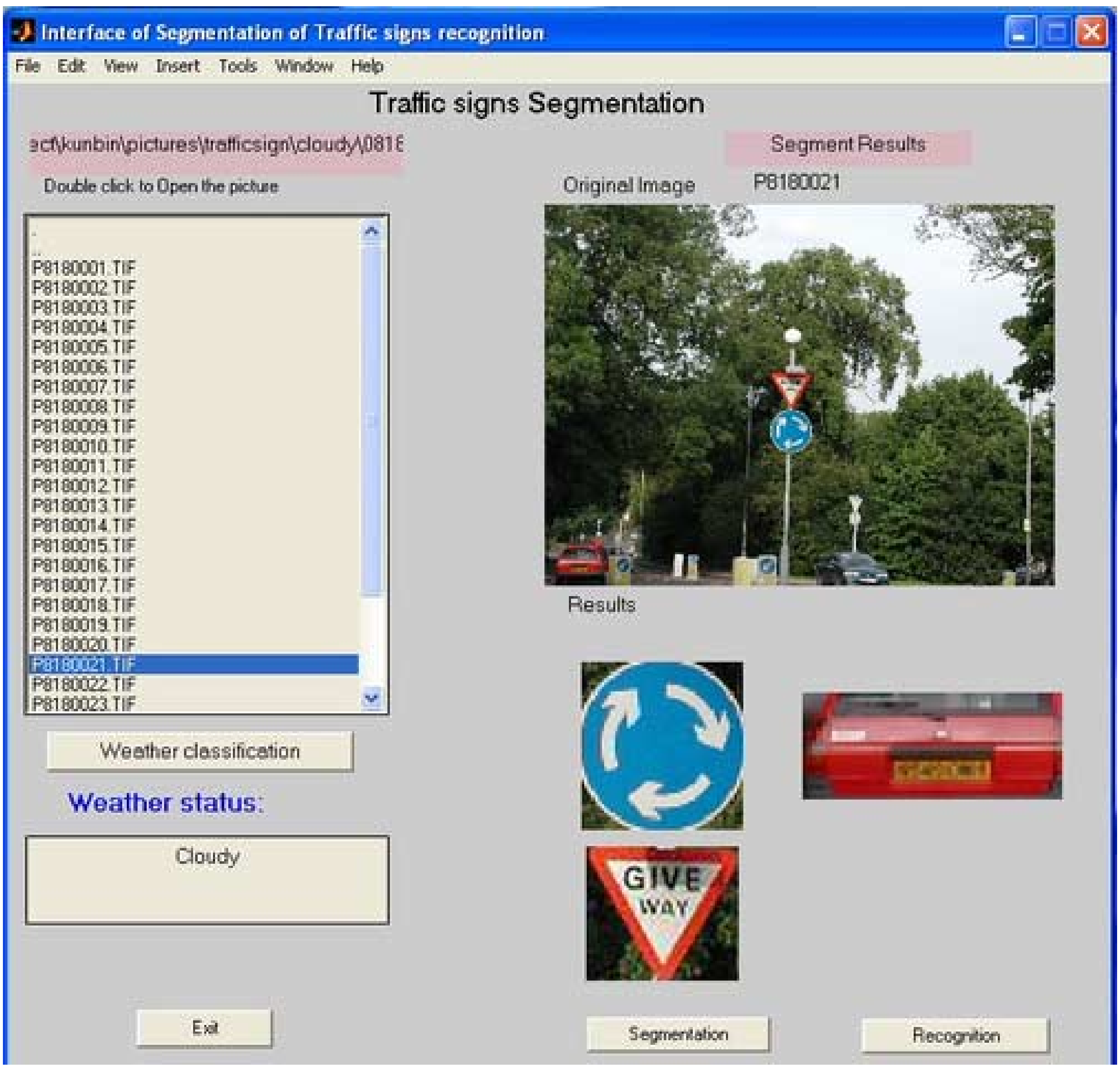


Fig. 2. (a) Schematic of the IW located in the centre of informative part of a sign; (b) estimation of orientation context in each of 49 nodes of input window.

3. Figure
Click here to download high resolution image



3. Figure

Fig. 4. The initial results of segmentation (a) (regions marked by white contours); rejection of false regions after the recognition stage (b).

3. Figure
[Click here to download high resolution image]

4. Tables

Table 1. Parameters used in each viewing conditions during the application of CIECAM97s.

Weather conditions	Reference white		Surrounding parameters				
	x	y	C	FLL	F	N_c	Y_b
sunny	0.3214	0.3228	0.69	1.0	1.0	1.0	20
cloudy	0.3213	0.3386					
rainy	0.3216	0.3386					

4. Tables

Table 2. The range of colour attributes used for segmentation of traffic signs.

Weather conditions	Hue		Chroma	
	Red	Blue	Red	Blue
sunny	375-411	287-305	31-43	37-59
cloudy	370-413	275-290	25-45	30-65
rainy	345-405	280-305	30-50	35-60

4. Tables

Table 3. Segmentation results based on CIECAM97s.

Weather condition	Total signs	Correct segmentation	False segmentation	P_c	P_f
sunny	53	50	15	94%	23%
cloudy	32	29	11	90%	28%
rainy	57	48	18	85%	27%

4. Tables

Table 4. Segmentation results by three colour spaces: CIECAM97, HSI, and CIELUV.

Weather condition	Total signs	Colour space	Results			
			Correct Segmentation	False Segmentation	*Pc*	*Pf*
sunny	53	*HCJ*(CIECAM97s)	50	15	94%	23%
		HSI	46	19	88%	29%
		HCL(CIELUV)	46	17	88%	27%
cloudy	32	*HCJ*(CIECAM97s)	29	11	90%	28%
		HSI	24	14	77%	37%
		HCL(CIELUV)	26	12	82%	32%
rainy	57	*HCJ*(CIECAM97s)	48	18	85%	27%
		HSI	41	26	73%	39%
		HCL(CIELUV)	43	24	76%	36%

4. Tables

Table 5. The results of RGB segmentation

Weather conditions	P_c	P_f
Sunny	88%	86%
Cloudy	83%	68%
Rainy	82%	65%