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Recognition of traffic signs based on their colour and shape features extracted using human vision models

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Abstract

Colour and shape are basic characteristics of traffic signs which are used both by the driver and to develop artificial traffic sign recognition systems. However, these sign features have not been represented robustly in the earlier developed recognition systems, especially in disturbed viewing conditions. In this study, this information is represented by using a human vision colour appearance model and by further developing existing behaviour model of visions. Colour appearance model CIECAM97 has been applied to extract colour information and to segment and classify traffic signs. Whilst shape features are extracted by the development of FOSTS model, the extension of behaviour model of visions. Recognition rate is very high for signs under artificial transformations that imitate possible real world sign distortion (up to 50% for noise level, 50 m for distances to signs, and 5° for perspective disturbances) for still images. For British traffic signs ($n = 98$) obtained under various viewing conditions, the recognition rate is up to 95%.

Keywords: Transformation invariant recognition; Traffic signs recognition; Feature extraction

1. Introduction

Colour and shape are dominant visual features of traffic signs with distinguish characteristics and are key information for drivers to process when driving along the road. Therefore to develop a driver assistant system for recognition of traffic signs, this information should be utilised effectively and efficiently even in the knowledge that colour and shape vary with the change of lighting conditions and viewing angles.

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 [1]. However, most colour-based techniques in computer vision run into problems if

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the illumination source varies not only in intensity but also in colour as well. This is because that the spectral composition, and therefore the colour, of daylight change depending on weather conditions, e.g., sky with/without clouds, time of the day, and night when all sorts of artificial lights are surrounded [1]. Many authors therefore have developed various techniques to make use of the colour information of traffic signs. Tominaga [2] developed clustering method in a colour space, whilst Ohlander et al. [3] used a recursive region splitting method to achieve colour segmentation. The colour spaces they applied are HSI (Hue, Saturation, Intensity), and L*a*b* space. These colour spaces normally limit to only one lighting condition, which is D65. Hence, the range of each colour attribute, such as hue, will be narrowed down due to the fact that weather condition changes with colour temperatures ranging from 5000 to 7000 K.

Shape is another powerful visual feature for recognition of signs [4–10]. However, when signs appear in cluttered scenes, many objects may appear similar to the road signs. Also, when the viewing angles are different, the signs will appear differently with some degree of distortion, sometimes with torn corners and occluded parts. Furthermore, signs vary in scale: getting bigger as a vehicle moves toward them, and vary in size: appearing relatively small with about 40–50 pixels wide at the most. Another difficulty is linked to the way the signs are captured by the acquisition system. It is stated that all road signs will be seen with a non-zero angle between the optical axis of each camera and the normal vector to the sign surface [11]. This angle should be as high as 30°, depending on the distance between the sign and the cameras. Piccioloi and Campani [12] concentrated on geometrical reasoning for the detection of triangular and circular signs. For the triangular shapes, they segmented them using the horizontal or having a slope of the ranges $[60 - \varepsilon, 60 + \varepsilon]$, $[-60 - \varepsilon, -60 + \varepsilon]$ degrees, where ε is the deviation from 60 calculated from samples. Hough Transform was applied to detect the circles. However, only two types of shape were studied. Miura et al. [4] extracted sign candidates using white circular regions by using binarization with *area filtering*, which only keeps white regions whose areas are within a predetermined range. Due to the dust of the road, the white regions sometimes may not be the areas with higher intensity values, which will result in lots of false candidates. More recently, Escalera et al. [13] has developed a driver support system which employs a genetic algorithm for detection of sign state and a neural network for achieving the classification. But the neural network needs to be re-trained whenever a new case is included, which is very time consuming.

Due to the adaptation to the environment, human can correctly identify traffic signs invariant of lighting conditions and viewing angles. Therefore invariant features can be extracted using vision models. In this study, two vision models have been applied and developed. One model is CIECAM97 for measuring colour appearance invariant of lighting conditions and is utilised to extract colour features. The other vision model, foveal system for traffic signs (FOSTS), is developed based on behaviour model of visions (BMV) model imitating some mechanisms of the real visual system for perceiving shapes [14–16].

CIECAM97 is a standard colour appearance model recommended by CIE (International Colour Commission on Illumination) in 1997 for measuring colour appearance under various viewing conditions [17,18]. This model can estimate a colour appearance as accurate as an average observer. It takes weather conditions into account and simulates human's perception for perceiving colours under various viewing conditions and for different media, such as reflection colours, transmissive colours, etc. For human perception, the most common terms used for colour or colour appearance are lightness, chroma, and hue that can be predicted using the model. The input parameters are viewing conditions, including lighting source, reference white, and the background.

The BMV model is initially developed on the base of biologically plausible algorithms of space-variant representation [19] of images and of specific viewing trajectory formation. It has demonstrated the ability to recognise complex grey-level images invariantly with respect to shift, plain rotation, and in a certain extent to scale. BMV model has been developed in several directions differing in the extent of biological plausibility, computational algorithms, architecture, etc [14,15]. One of the extensively developed directions in this field is the development of foveal visual systems for traffic sign recognition that are considered as the most prospective in solution of computational problems in real world images processing. Like other foveal systems [20] it imitate the changes of visual acuity from the fovea to the retinal periphery and attention mechanisms during detailed process of choosing image fragments. A main computational advantage of the foveal systems is an essential reduction of information that should be processed at a higher level of resolution [19] and is transformation invariant.

In this study, two steps are applied to recognise a traffic sign in an image. The first step is to set up a database containing all the standard signs. Then features of colour and shape are extracted from those signs. The query images are normally segments from the pictures taken from real road driving conditions, which forms the second step. The features from a query image either match one image features in the database or none at all.

In the following sections, new algorithms and models will be presented for colour and shape representation, context feature description, leading to traffic signs recognition. Section 2 gives detailed description of image segmentation to segment sign-to-be sub-images from the rest of scene. Feature extraction based on vision models will be given in Section 3. Whilst Sections 4 and 5 detail experimental recognition and Section 6 gives conclusions.

2. Extraction of colour information

2.1. Segmentation

Segmentation is to cut sub-images containing possible signs from the rest of scene. To recognise a traffic sign, a picture taken from the real road during driving condition should be segmented first as there might be more than one sign in an image. A typical such image has size about 1680×1680 pixels while a typical standard sign in the database is 400×400 pixels. Because the image has different colour distribution combinations depending on the weather condition when the photo is taken, colour appearance model CIECAM97 is applied to perform this task.

First, the colour ranges have to be found. The colours used in the traffic signs are commonly red, blue, black, and white. Images taken from real world are processed to find the range of colour vectors under different viewing conditions. A representative set of traffic signs has been classified visually according to the viewing and environmental conditions, such as cloudy, sunny, and rainy. Based on the images in each group, the parameters for each viewing condition were found from [1] (e.g., direct sun light having colour temperature 5335 K and light from overcast sky having colour temperature 6500 K) for the application of the colour appearance model. Test images taken under real viewing conditions are transformed from RGB space to CIE XYZ values and then to LCH (Lightness, Chroma, Hue) space using the model of CIECAM97. For the lightness values, they are similar for red, blue signs and background. Therefore only measures of Hue and Chroma are used for segmentation. Tables 1 and 2 list the hue and chroma ranges for red and blue signs during average day light viewing conditions, and during each weather conditions including sunny, cloudy, and raining viewing conditions.

Based on the range of sign colours, traffic sign-to-be are segmented using quad-tree histogram method from the rest of scenes for further processing. A quad-tree is a simplification of the idea of the split and merge algorithm and the T-pyramid [21]. It will overcome the problem localise changes in the features in an image during

Table 1
The ranges of Hue and Chroma for red and blue signs for average day light viewing conditions

Colour	Hue	Chroma
Red	393–423	57–95
Blue	280–290	57–95
Background	—	7–50

Table 2
The ranges of Hue and Chroma under different weather conditions

Weather conditions	Hue		Chroma	
	Red	Blue	Red	Blue
Sunny day	375–411	287–305	31–43	37–59
Cloudy day	370–413	275–290	25–45	30–65
Rainy day	345–405	280–305	30–50	35–60

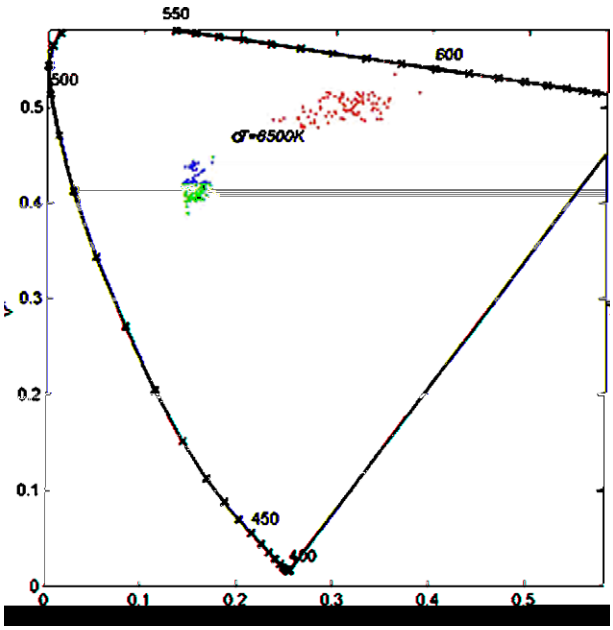

Fig. 1. Traffic signs are plotted on the u'v' diagram together with average daylight colour temperature of 6500 K. The left group of dots represent blue colour while the dots on the right hand side are form red traffic signs.

segmentation, because sometimes, it is difficult to decide whether a particular grid element should be selected for a match, particularly if it contained a strong colour gradient (e.g., it had an edge running through it) [22].

Quad-trees involve recursively dividing the image into quadrants until all elements are homogenous, or until a predefined, "grain," size is reached. A histogram is built for each element in the quad-tree. This means that, in general, the quad-tree method requires more storage than the grid method (and hence longer match times). Unlike the split and merge algorithm which is used for object delineation, the divided areas are not merged again, even if they are adjacent and their area would fit the homogeneity criterion. This ensures no loss of spatial data.

Only blue and red signs are used in this study. Fig. 1 displays these colours plotted on a u'v' chromaticity diagram together with colour temperature of D65 for average daylight source. All sign images with size more than 10×10 pixels (pictures are taken within 100 m distance) have been segmented correctly. Sometimes, some other contents, such as the rear red lights of cars are also segmented. However, these non-sign segments could be rejected during shape classification and recognition stage.

3. Shape feature extraction from traffic signs

The shape features of traffic signs in this study are extracted by the further development of the BMV model, called FOSTS model (foveal system for traffic signs).

3.1. Classification of traffic signs based on external forms

For all signs, both from standard databases and from real world images, preliminary classification is conducted according to the colour, their external form (circle, rectangle, or triangle) by means of histograms of orientations detected at resolution level 3 (RL 3). RL 3 is emulated by Gaussian convolution (kernel size is equal 9). Each sign with a certain external form (regardless of its inner content) has characteristic relationship of horizontally, vertically, and obliquely oriented elements at RL 3. In particular, all oriented elements have nearly equal representations for circle signs contrary to rectangle signs (Fig. 2) that have preferable horizontal and vertical orientations, in another words, more than 50% of all oriented segments. For each external shapes,

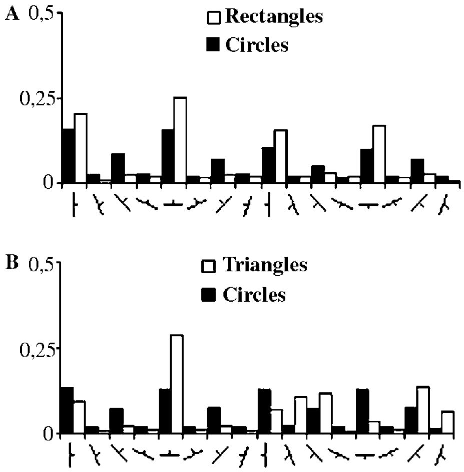

Fig. 2. Averaged histograms of orientations for Russian blue traffic signs in (A) standard database ($n = 66$) and (B) real world images ($n = 19$). Where n indicates the number of sign images used for receiving the averaged histogram and quantitative evaluation of certain oriented elements characteristic to different external form of traffic signs.

quantitative estimations are obtained for classification into particular groups of signs. These estimations are used also for classification of traffic signs segmented from real world images into a certain group according to external forms.

3.2. Representation of shape features

Each image in the FOSTS model is represented by viewing trajectory and specific description of image fragments in the vicinity of each fixation point. The basic features from FOSTS consist of:

(i) an image in each sensor fixation point is described by oriented segments extracted in vicinity of each of 49 sensor nodes;
(ii) the sensor nodes are located at the intersections of 16 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°;
(iv) space-variant representation of image features is emulated by Gaussian convolution with different kernels the sizes of which increase with the distance from the sensor centre. Detailed explanation is given in [8].

To represent shape features using FOSTS, the following vectors are formed. Suppose a formal description of feature vector F is formed by the space-variant sensor.

Suppose a formal description of feature vector is $\overrightarrow{F}$ formed by the space-variant sensor. The description is then based on detected edge orientation α in the vicinity of each of 49 sensor nodes A_i, $i = 0, 1, \ldots, 48$ (as shown in Fig. 3). Let $x_0 = X_0$, $y_0 = Y_0$ be co-ordinates of the central sensor node, then co-ordinates (x_i, y_i) of peripheral sensor node A_i, $i = 1, 2, \ldots, 48$ can be determined as follows:

$$x_i = X_0 + R_l \cos \psi_k, \quad (1)$$

$$y_i = Y_0 + R_l \sin \psi_k, \quad (2)$$

where R_l, $l = 0, 1, 2$ is the radius of lth concentric circle of the sensor ($R_0 = 3$ pixels, $R_1 = 9$, $R_2 = 15$) and $\psi_k = k \cdot 22.5°$, $k = 0, 1, \ldots, 15$ is the angle of the radiating line corresponding to the ith sensor node. Here, R_l simulates a space-variant resolution level. Each sensor node is characterised by edge orientation α that dominates in the node context area (7×7 pixels) and its density ρ as follows:

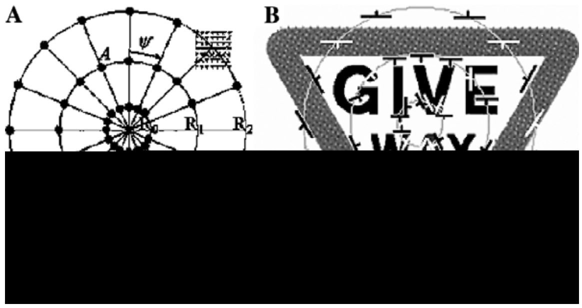

Fig. 3. (A) Schematical representation of sign shape vectors using FOSTS model, context area for a node is indicated by square (B) example of detected edges.

$$\begin{aligned}&\rho(A_i) = \max_{\varphi} \rho_{\varphi}(A_i)\\ &\alpha(A_i) = \varphi \quad \text{if } \rho_{\varphi}(A_i) = \rho(A_i),\end{aligned} \tag{3}$$

where

$$\rho_{\varphi}(A_i) = \rho_{\varphi}(x_i, y_i) = \frac{1}{S(x_i, y_i)} \sum_{m,n} Sg_{\varphi}(Or(m + x_i, n + y_i)), \tag{4}$$

$$Sg_p(x) = \begin{cases} 1 & \text{if } x = p \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

and $Or(x, y)$ is a detected edge orientation (not only dominating one) in the vicinity of the image element with co-ordinates (x, y); $S(x_i, y_i)$ is the square of the context area for ith sensor node equal to 49 pixels; $m, n = -3, \ldots 0, \ldots + 3$; $\varphi = 0, 1, \ldots, 15$.

The resulting feature vector $\overrightarrow{F}(\overrightarrow{\alpha}, \overrightarrow{\rho})$ is therefore formed as Eq. (6):

$$\overrightarrow{F}(\overrightarrow{\alpha}, \overrightarrow{\rho}) = (\alpha(A_0) \cdots \alpha(A_{48}), \rho(A_0) \cdots \rho(A_{48})). \tag{6}$$

Fig. 3 illustrates the procedure of extraction of shape feature vectors.

4. Recognition

To reduce image database size that results in increase of search time for a "traffic sign-to-be" candidate during recognition, the signs (both standard and obtained in real road conditions) have been preliminary classified by colour and shape. Colour classification is performed according to the parameters of sign LCH composition into external colour sign contour (the boundary of the coloured sign) that is determined during colour segmentation (see Section 2.1).

4.1. Determination of sign centre

To apply shape feature for traffic sign recognition, the sign centre, i.e., the location of the sensor of FOSTS model, has to be found from query signs to increase recognition rate. Evidently, such location of the sensor provides the most specific sign description by detailed representation of its internal informative part. It is determined from the centre of mass for colour elements with LCH composition characters from external sign contour. This calculation provides the geometric centre for a sign with necessary accuracy (±3 pixels), the extraction of a "pure" real world sign (without background), and from a normalised sign with size of 40×40 pixels with maximal representation of informative sign parts, i.e., the scale of the FOSTS model to each sign candidate has been adjusted by normalization sign candidate to the size of 40×40 pixels after determination of sign center and extraction of "pure" sign (all procedures are based on external colour sign contour). Fig. 4 schematically demonstrates the determination of sign centre.

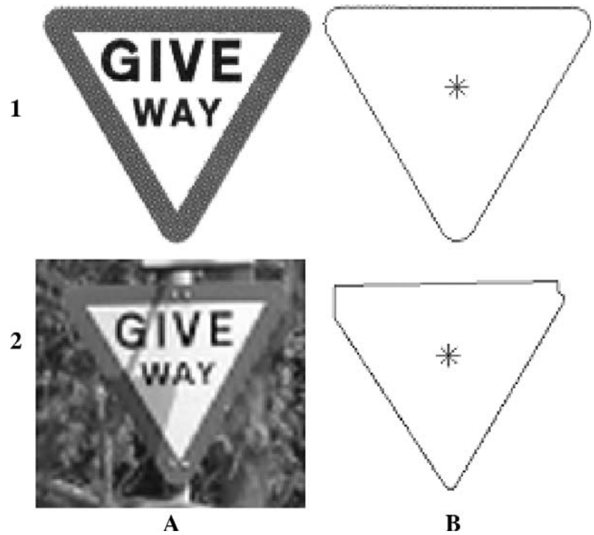

Fig. 4. Determination of the sign centres for images from the standard database (upper row) and a real world picture (lower row). Symbol * indicates location of centre of mass for colour contour elements (column b).

4.2. Recognition

In summary, the recognition is performed in two stages by comparison of the 49-dimensional vectors representing a current image with template vectors stored in the database that has been classified into several colour/shape subgroups.

Stage 1 is based on a compressed context description of each sensor node (see Section 3.1) and has been used for recognition of all current images. Vectors are compared according to Eq. (7):

$$K^b = \sum_{i=0}^{48} \left[Sg\left(O_i^b - O_i^{\mathrm{rw}}\right) \cdot \left(1 - \left|\rho_i^b - \rho_i^{\mathrm{rw}}\right|\right)\right], \quad \text{where } Sg(x) = \begin{cases} 1 & \text{if } x = 0; \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

Here, K^b is the similarity coefficient for two feature vectors (current and template), Or is the dominant segment orientation in the context area of a given sensor node (orientations are determined using Eqs. (1) and (2) and denoted as 0, 1, 2, 3, ..., 15), superscript b stands for template database images, rw stands for the current image; ρ is the density of the dominant orientation in the context area of the given sensor node. A template image from the standard database with maximal K^b is considered as the result of recognition. According to preliminary testing results, a threshold value for K^b is equal to 25.

Stage 2 is based on the full description of each sensor node (see Section 3.1) and is used only for current images with confusing results from Stage 1. In particular, it is performed if difference between K^b of a candidate template image with maximal K^b and the next nearest candidate is less than the tolerance interval (it is empirically determined equalling to 4). In this case, the feature vector of a current traffic sign-to-be image is compared to template vectors for all particular oriented segments (not only with dominant orientation) in the context area of each sensor node. A template image from the standard database with maximal averaged estimation is considered as the result of recognition.

5. Results

5.1. Evaluation of shape transformation invariance

To imitate possible sign transformations in real road conditions and obtain the quantitative estimations of recognition invariance range, several additional sign databases are created for evaluation. Graduated artificial

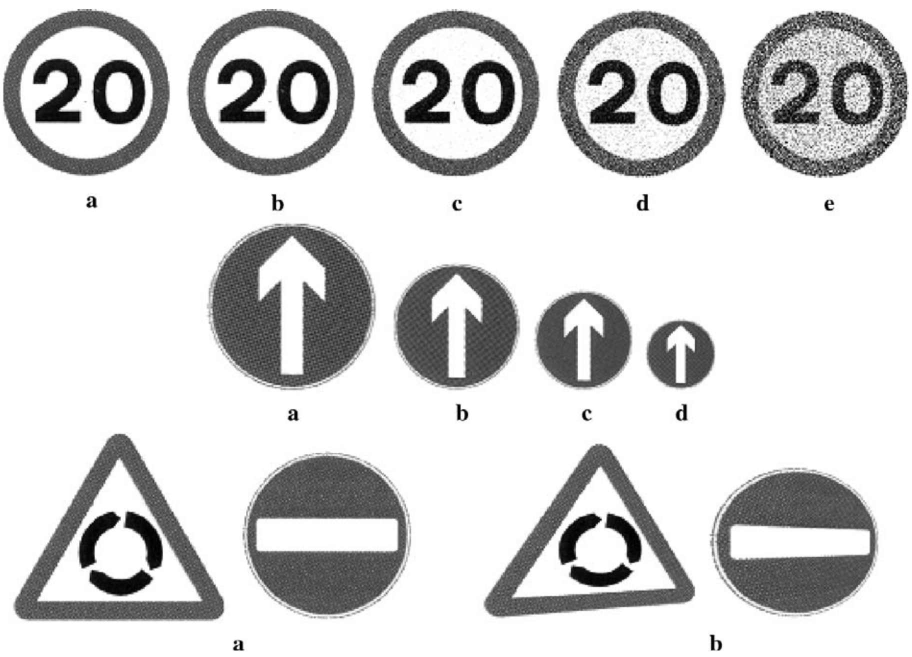

Fig. 5. Examples of an original (a) and transformed (b–e) images. In top row: (b–e), the noise level is equal to 5, 10, 20, and 50%, respectively; in middles row: (b–d) initial image size simulates the distances of 20, 30, and 50 m from sign respectively; in bottom row: (b) image transformations simulate sign viewing from the second road line at the distance of 20 m to the signs.

transformations (noise, scale, and perspective distortions) of traffic sign have been performed. Then, the distorted images are presented for recognition. Only blue circular ($n = 14$), red triangular ($n = 49$), and red circular ($n = 24$) signs have been used in the given experiments.

Noise have been simulated by adding graduated Gauss noise (5, 10, 20, and 50%) to the images from the standard database (Fig. 5, upper line). The scale transformations simulates the decrease of sign size with a distance to the sign in real road conditions, such as, 20 m (initial image size—36×36 pixels), 30 m (initial image size—24×24 pixels), and 50 m (image size—16×16 pixels). Before recognition, initial sign size has been normalized to 40×40 pixels for all images. Perspective sign image transformations have simulated the changes of viewing angles (Fig. 5 low line).

Table 3 gives the averaged results of recognition of noised and scaled traffic sign images. Recognition rate for images with perspective transformations is equal to 1 (= 100% recognition) for red and blue circular signs, and 0.98 for red triangular signs. The obtained results indicate that recognition rate is relatively high for signs with artificial transformations that represent possible sign distortions in the real road conditions (up to 50% for noise level, 50 m of distance to signs, and 5° for perspective disturbances). It is also shown that recognition rate for red triangular signs sharply decreases at the increase of distortion levels.

Table 3
Recognition rate for artificially noised and scaled traffic sign images

Sign subgroups	Transformation						
	Level of noise				Distance to signs		
	5%	10%	20%	50%	20 m	30 m	50 m
Blue circular signs	1	1	1	0.93	1	1	1
Red circular signs	1	1	1	0.87	1	1	0.91
Red triangular signs	1	1	0.98	0.40	0.91	0.96	0.70

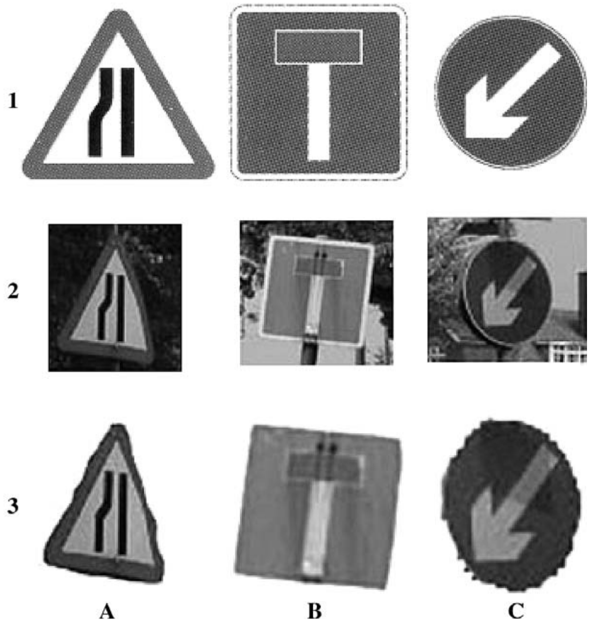

Fig. 6. The examples of recognized (A,B) and non-recognized (C) real world traffic signs. In: (1) the template images from standard database; (2) real world signs after segmentation based on colour; (3) the same signs as in (2) after colour contour determination and size normalisation.

5.2. Evaluation of recognition rates

Ninety-three out of ninety-eight potential traffic sign images are correctly identified, which gives 0.95 success recognition rate (contrary to 0.86 without preliminary classification). Similar results have been obtained for different viewing and environmental conditions (0.96 and 0.94 for sunny and cloudy weather respectively). Recognition time (without low-level processing procedures) varies from 0.2 up to 0.7 seconds per image on a standard Pentium.III PC. The non-identified signs ($n = 5$) are either of low resolution (taken from very far distance, more than 60 m) or have a complex disturbing background. Examples of recognised road signs are shown in Fig. 6B. Fig. 6C demonstrates that a traffic sign with two kinds of distortions (shielding about 35% with perspective disturbance about 10°) is not recognized.

6. Conclusion

Colour and shape features extracted using vision models can perform accurate recognition for traffic signs located at a reasonable distance for still images under various viewing conditions. This approach shows a good performance for a wide variety of traffic signs of different colours, forms, and informative content. The use of the CIECAM97 colour vision model allows the segmentation of the majority of traffic signs from the rest of the scenes. The results on FOSTS indicate that a preliminary separation of traffic signs by shape for each colour (for example, rectangle versus circle for blue traffic sings or triangle versus ring/circle for red ones) can accelerate sign identification. In addition, experimental results demonstrate the importance of sensor fixation points chosen while viewing trajectory formation.

7. Discussion

The algorithms of the FOSTS model provide essential increase of the recognition rate as compared to the former model versions [23,24] (0.95 versus 0.80 and 0.87). It is interestingly noticed, that recognition rate obtained by the FOSTS are similar to that for the human operator in the same real world road conditions (0.96). Apparently, advanced task-oriented modifications of the space-variant sensor, including increase of the sensor size, classification according to colour and shape, determination of context in the vicinity of each sensor node, setting the sensor in the sign centre, etc., allow to receive a detailed feature description for the most informative sign fragments, which results in a higher accuracy of recognition. Furthermore, this description is stable to local image disturbances in a certain range. Overall, the described model-based approach provides an accurate identification of traffic signs located at a moderate distance (up to 60 m) under various viewing conditions.

The invariant recognition to various image transformations in the FOSTS is provided by several model properties and procedures:

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