Dominant Color Transform and Circular Pattern Vector : Applications to Traffic Sign Detection and Symbol Recognition

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Abstract

In this paper, a new traffic sign detection algorithm and a symbol recognition algorithm are proposed. For traffic sign detection, a dominant color transform is introduced, which serves as a tool of highlighting a dominant primary color, while discarding the other two primary colors. For symbol recognition, the curvilinear shape distribution on a circle centered on the centroid of symbol, called a circular pattern vector, is used as a spatial feature of symbol. The circular pattern vector is invariant to scaling, translation, and rotation. As simulation results, the effectiveness of traffic sign detection and recognition algorithms are confirmed, and it is shown that group of circular pattern vectors based on concentric circles is more effective than circular pattern vector of a single circle for a given equivalent number of elements of vectors.

I. Introduction

Traffic signs on road are of artificial and specific shapes which consist of some meaningful inner symbols and some specific outer contours as shown in Fig. 1. They give us diagrammatic information about routes in a very short discernible distance [1] and may be principally distinguishable from the natural and/or man-made background images with computer vision system as human ability, but it is not easily tractable work. Since the human visual perception largely depends on the individual's physical and mental conditions, an automatic traffic sign recognition system will be very helpful as a subsidiary means of drivers or for a remote controlled car.

The key to traffic sign recognition is how to detect correctly the outer contour from a background image and how to identify its inner symbol. In general, segmentation algorithms are based on discontinuity and similarity of gray-level values in an image. The former is related to edge detection [2], while the latter, to regional statistics [3]. In recent years, several image segmentation methods have been developed for gray and color images. Oh and Choi [4] have proposed a hit-and-miss ratio transform (HMRT) modifying the morphological hit and miss transform to find the outer contour of warning sign, but its usage is limited to detecting the upright triangular shapes in gray scale image. Woelker [5], Vlachos and Constantinides [6], etc. have used region-oriented color image segmentation algorithms based on Euclidean distance in RGB or L*a*b* color coordinates. Recently a traffic sign detection and symbol recognition algorithm has reported based on color image [7].

In this paper, refining the concept of [7], we introduce a traffic sign detection algorithm, called a dominant color transform, which is applicable regardless of the shape, color, and the number of signs. And we propose a symbol recognition algorithm invariant for translation, scaling, and rotation, for which we use a circular pattern vector as a spatial feature of symbol.

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II. Traffic Sign Detection

Traffic signs are painted with perceptible colors and located in proper place easily visible and discernible from background. In Korea we have six standard shapes of traffic signs as shown in Fig. 1, whose outer contours are painted with pure primary color such as red and blue, and there are approximately 130 signs : 39 warning signs, 32 regulatory signs, 30 indicatory signs, and 26 supplementary signs.

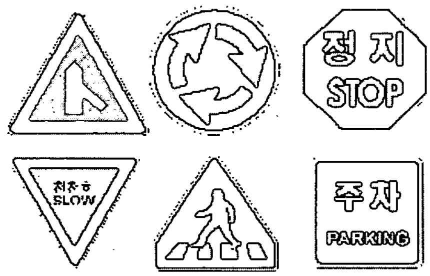

Fig. 1. Six standard shapes of Korean traffic signs.

1. Difference Function of Two Dominant Primary Colors

As we can see on the real roads, generally landscapes around roads are tinged with gray, greenish, or blue-green, while traffic signs have reddish outer contours or the other primary colors as shown in Fig. 1. As an example, Fig. 2(a) shows an image of two warning signs, in which we can easily recognize the existence of two warning signs. The reason is that they are painted with a pure primary color in gray-like background which is composed of three primary colors of similar proportions or not dominated by one primary color. From this point of view, we tried to find an object of a dominant color or dominant color.

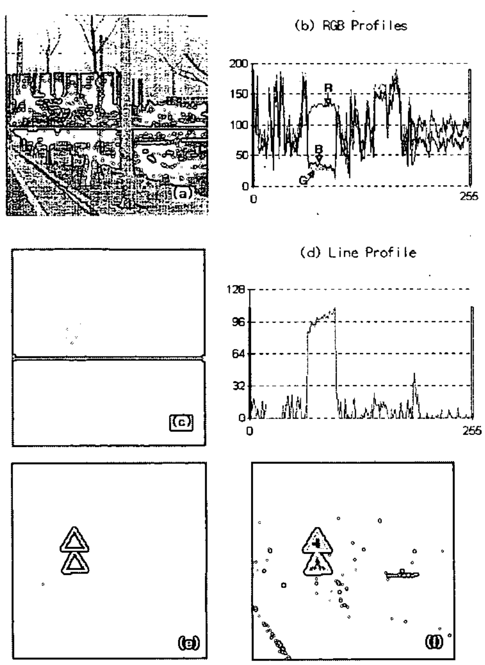

Fig. 2. Dominant color components. (a) Real traffic sign image. (b) RGB profiles of the 142-th line video. (c) Difference image of (a) in Eq.(1). (d) Profile of the 142-th line video of (c). (e) and (f) Thresholded (c) by levels of 60 and 30, respectively.

First of all, we have analyzed road image with respect to three primary color components: red, green, and blue (RGB). Fig. 2(b) shows the 142-th line video profiles of Fig. 2(a) corresponding to RGB colors, where large difference appears in the range of reddish bottom contour of triangular sign. To see this difference, we introduce a function, called a difference function of two dominant primary colors, as

$$d(i)=\max(R(i),G(i),B(i))-\mathrm{med}(R(i),G(i),B(i)) \qquad \textbf{(1)}$$

where R(i), G(i), and B(i) are respectively RGB components of the i-th pixel in an image and max(·) and med(·) represent the maximum and median values of · , respectively.

Fig. 2(c) shows the difference function of two dominant primary colors d(i) in Eq. (1) of Fig. 2(a), and Fig.2(d) shows the 142-th line video of Fig. 2(c), that is, the function d(i) of Fig. 2(b). From Fig. 2(d), we see that it takes smaller values in background than on the outer contour of traffic sign and therefore the traffic sign can be segmented from the background by thresholding the function d(i) with a proper level.

2. Dominant Color Transform for Traffic Sign Detection

Using the difference function d(i) in Eq. (1), we propose an algorithm, called a dominant color transform, which retains only a dominant color component when d(i) is larger than a given threshold. The dominant color transform of the i-th color pixel is defined as

$$D(i)=\begin{cases}(R(i),0,0), & d(i)\ge T_o,\ R(i)=\max(R(i),G(i),B(i))\\(0,G(i),0), & d(i)\ge T_o,\ G(i)=\max(R(i),G(i),B(i))\\(0,0,B(i)), & d(i)\ge T_o,\ B(i)=\max(R(i),G(i),B(i))\\(\phi,\phi,\phi), & \text{otherwise}\end{cases} \qquad \textbf{(2)}$$

where T_o is a threshold level, ϕ is a constant.

In Eq. (2), we see that if $d(i)\ge T_o$, the dominant color transform yields a color pixel retaining a dominant primary color component while discarding the other two primary components, and otherwise, it transforms the color pixel to a gray pixel, for example, black or white depending on ϕ=0 or 255. In other words, if RGB components are very similar to each other, then the dominant color transform yields a constant gray pixel, but in other case, then the most dominant primary color will be left alone and the other minor two primary colors will be discarded. Thus gray pixels will be disappeared by dominant color transform since they have similar levels of RGB components. Therefore the dominant color transform can be used as a specific color image segmentation technique by means of highlighting a dominant primary color and discarding the other two primary colors. Figs. 2(e) and (f) show binary images obtained by thresholding Fig. 2(c) with levels of 60 and 30, respectively. Fig.4(d) shows dominant color transform results for which ϕ =255 in Eq. (2), in which two traffic signs of red triangle and blue pentagon in the third image are also correctly detected like the others.

III. Symbol Recognition Based on Circular Pattern Vector

Assume that the outer contours of traffic signs are detected by a certain method such as the proposed dominant color transform. Since originally the inner symbols are designed with given simple directional graphics and painted with black or white color, approaches to recognizing them may be very similar to character recognition. In general, there are two approaches. One is to compare an object with a given set of templates directly and the other is to compare their features indirectly. The former requires a large amount of data and thus computational load becomes heavy and the latter is much more attractive in speed but it needs robust features to translation, scaling, rotation, and noise. Here we propose an algorithm in the latter category.

1. Circular Pattern Vector Construction

First of all, assume that we have obtained binary symbol sets by thresholding the gray inner symbols. For example, the template binary symbol sets are obtained from the handbook of traffic regulation prescribed by authority and the test binary symbols are obtained from the real road scenes.

Consider the curvilinear shape distribution on a circle as shown in Fig. 3(a). The circle is centered on the centroid of symbol with a given radius proportional to the average distance. Therefore the curvilinear shape distribution on this circle will be invariant under translation and rotation of symbol, and is also able to be invariant under scale change of symbol by normalizing the perimeter of circle to be a constant value since the distribution on the circle is only affected by scale change.

From this, we construct a pattern vector based on the curvilinear shape distribution on a circle, called a circular pattern vector, as follows.

For every binary symbol set S_n

for $n \in N = \{1, 2, \cdots, N\}$,

(1) Find the centroid $(\bar{x}_n, \bar{y}_n)$ and average distance D_n defined as

$$(\bar{x}_n, \bar{y}_n) = \left(\frac{1}{A_n}\sum_{(x,y)\in S_n} x,\ \frac{1}{A_n}\sum_{(x,y)\in S_n} y\right),$$

$$D_n = \frac{1}{A_n}\sum_{(x,y)\in S_n}\sqrt{(x-\bar{x}_n)^2+(y-\bar{y}_n)^2}, \tag{3}$$

where A_n is the number of elements of S_n.

(2) Draw a circle of radius kD_n centered on the centroid (x_{nc}, y_{nc}) (k is a constant).

(3) Read the curvilinear distribution in counter clockwise direction from the horizontal axis and next construct a circular pattern vector C_n such that

$$C_n = (c_{n1}, c_{n2}, \cdots, c_{nK}) \tag{4}$$

where the element c_{nk} is a binary number read out the curvilinear distribution, that is, 1 for dot or 0 for space.

It is easy to see that the averaged distance D_n in Eq.(3) is invariant for any translation and rotation of the symbol S_n.

For invariance to scale change, the number of elements of all the circular pattern vectors C_n's in Eq.(4) are normalized so that they have the same dimension as K. If K is large, it takes so much time in comparing the other pattern vectors with each other and if K is small, the pattern vector can not effectively represent spatial features of symbols. We take an approach to this trade-off for a smaller K by dividing the circular pattern vector C_n into M sub-vectors of equal short length of L, that is, $K = M \times L$ and averaging each sub-vector into an element as the following example.

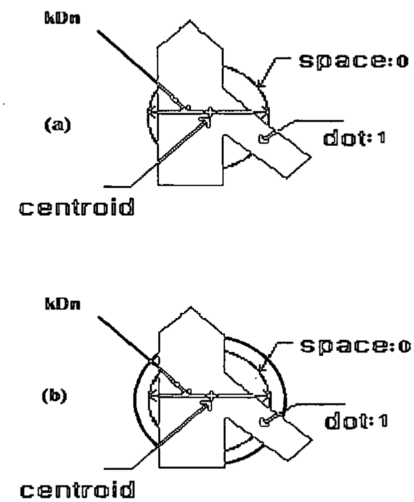

Fig. 3. Curvilinear distributions on concentric circles centered on the centroid. (a) A single circle. (b) Two concentric circles.

For K=30 and L=3, C_n is reduced to an averaged vector $\hat{C}_n$ of length $M = 10$ as

$$\begin{aligned} C_n &= (111111111000000010001101111101001), \\ &= (111, 111, 110, 000, 001, 000, 110, 111, 101, 001), \\ \hat{C}_n &= (1110001110) \end{aligned} \tag{5}$$

where averaging process is to replace three elements of each subblock by one bit corresponding to its majority of 1's and 0's and thus plays a role of low pass filtering or reducing impulse noise.

In addition, we can use a group of circular pattern vectors based on several concentric circles centered on the same centroid of a symbol as shown in Fig. 3(b), which will represent much more spatial features of the symbol.

2. *Symbol Recognition by Minimum Distance between Circular Pattern Vectors*

Now consider how to compare a test circular pattern vector C_X of a test symbol X with a given template circular pattern vector C_n of the template symbol S_n. We use a circularly shifting technique that guarantees the circular vector to be invariant to rotation as follows. Let C_X^r be a circularly shifted C_X by r elements to the right. And let the distance between the same dimensional vectors A and B, denoted $d(A, B)$, be the number of elements in which they differ, that is, the sum of exclusive OR results of each element of A and B. And then we define the minimum distance between C_n and C_X^r for all r in circular shifting range $\mathbb{R}$ as in Eq. (6), denoted $d_C(C_X, C_n)$ and called the circularly shifted distance, which can be used as a measure of a similarity between C_n and C_X.

$$d_C(C_X, C_n) = \min_{r \in \mathbb{R}} d(C_X^r, C_n), \qquad \textbf{(6)}$$

where R is the range of the circular shift as

$$\mathbb{R} = \{-W, -W+1, \cdots, W \mid W = K/2\}, \qquad \textbf{(7)}$$

Then naturally the problem of recognizing X becomes to find the value of n minimizing $d_C(C_X, C_n)$ and thus we can state that the test symbol X belongs to the ith template symbol S_i if the value of n minimizing $d_C(C_X, C_n)$ for all n is i as the following shorthand notation

$$i = \arg\left\{ \min_{n \in N} d_C(C_X, C_n) \right\}. \qquad \textbf{(8)}$$

Now consider the circularly shifted distance of a group of circular pattern vectors based on concentric circles. The circularly shifted distance in this case, called a group circularly shifted distance, is defined as

$$d_C(C_X, C_n) = \min_{r \in \mathbb{R}} \{ d(C_X^r, C_n)\mid_{k_1} + d(C_X^r, C_n)\mid_{k_2} + \cdots \} \qquad \textbf{(9)}$$

where $d(C_X^r, C_n)\mid_{k_i}$ denotes distance between C_n and C_X^r resulting from the radius of k_i times average distance ($k_i D_n$). Thus the group circularly shifted distance denotes a minimum distance that is obtained by adding all the distance simultaneously shifting circularly each circular pattern vector resulting from different radius.

When we use the averaged circular pattern vectors, C_n and C_X in Eqs. (6), (8), and (9) should be replaced by their averaged versions as shown in Eq. (5) of $\hat{C}_n$ and $\hat{C}_X$, respectively and then W in Eq. (7) should be replaced by M/2 since the averaged circular pattern vectors are M-dimensions. And a partial narrow range of the circular shift $\mathbb{R}$ is possible when the test symbol is tilted within a narrow range of an angle and then the time to search the minimum distance is so much reduced.

Ⅳ. Simulation results

To understand the performance of the dominant color transform and the symbol recognition ability of the circular pattern vector, we examine their behaviors on some real color traffic signs on the roads of $256 \times 256 \times 3 \times 8$ bits.

1. *Dominant color transform*

We have tested the performance of the dominant color transform with four real traffic sign images in Fig. 4(a). Figs. 4(b) and (c) represent the negatives of difference functions in Eq. (1) of Fig. 4(a) and their histograms, respectively. Fig. 4(d) shows the final results of the dominant color transform of Fig. 4(a), for which we have used a threshold level slightly below the point of the right most peak in each histogram of Fig. 4(c) and ϕ=255 in Eq. (2). Note that two traffic signs of a red triangle and a blue pentagon in the third image in Fig. 4(a) are also correctly detected like the others including a single sign.

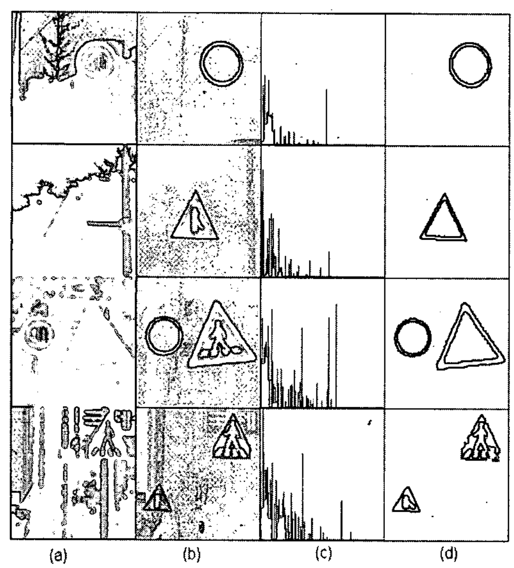

Fig. 4. Dominant color transform. (a) Real images. (b) Negatives of difference images of (a). (c) Histograms of (b). (d) Dominant color transform results of (a).

In fact, there are some problems of how to choose the threshold level and how to know whether a meaningful sign exists or not in the result of the dominant color transform.

Here we do not discuss these problems further since they are of an adaptive and post processing.

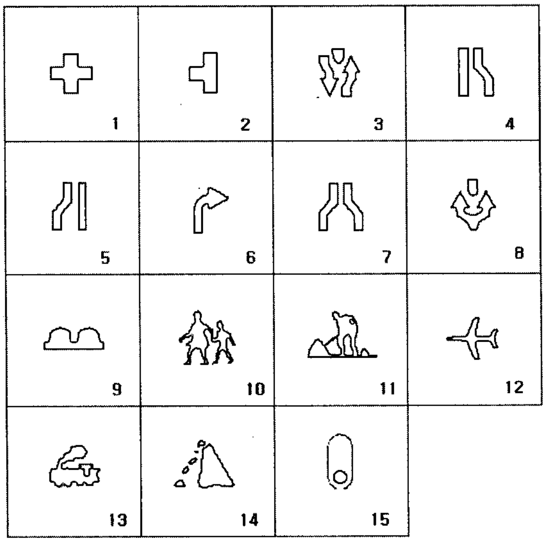

Fig. 5. Template symbols.

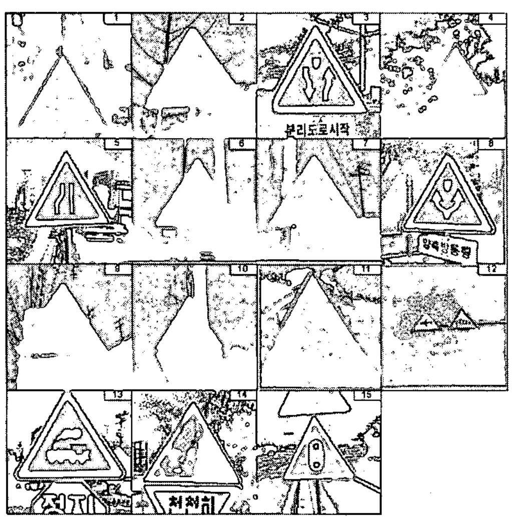

Fig. 6. Real images corresponding to the Fig. 5.

2. *Symbol recognition*

As stated previously, we select 15 template symbols from the handbook of traffic regulation prescribed by authority as shown in Figs. 5 and obtain corresponding real images in Fig. 6. First of all, for each template symbol S_n in Fig. 5, we construct 200-dimensional template circular pattern vectors C_n's (K=200 in Eq. (4)) with respect to four radii kD_n of k=0.9, 1.0, 1.1, and 1.2 and in addition, their corresponding 40-dimensional averaged template circular pattern vectors $\hat{C}_n$'s (M=40 and L=5) as in Eq. (5)). Next, by the dominant color transform we detect the outer contours of traffic signs from Fig. 6 and extract the inner real symbols filtering noise by a morphological open-close operation with 3×3 square structuring element. For these real symbols, in the same manner, the test circular pattern vectors C_{Xn}'s and their averaged versions $\hat{C}_{Xn}$'s are constructed.

With the above circular pattern vectors, we compute the (group) circularly shifted distances between circular pattern vectors of templates and real symbols in Eqs. (6) and (9), for which we use the range of circular shift $\mathbb{R}$ within a range of 36° of a circle, that is, $\pm5\%$ of the number of elements in a circular pattern vector.

Table 1 shows the circularly shifted distances between C_{Xn}'s and C_n's with radius of 0.9 D_n, K=200 in Eq. (4), and $\mathbb{R}=\{r: -10\le r\le 10\}$ in Eq.(7) for $1\le m,n\le 15$, of which the last column of "ratio" denotes the ratio of the diagonal element to the minimum off-diagonal elements in each row. Smaller ratio is more desirable. This concept of ratio is also used in the other Tables. In Table 1, X_4 and X_{12} are all incorrectly recognized by C_5 with a measure of minimum distance defined in Eq. (8). In the similar way, Table 2 shows the circularly shifted distances with radius of 1.2 D_n, K=200, and $\mathbb{R}=\{r: -10\le r\le 10\}$, where X_4 and X_{12} are also incorrectly recognized by C_5 and C_9, respectively.

Table 1. Circularly shifted distances (0.9 D_n, K=200).

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ratio
X_1	22	76	73	53	44	85	95	67	96	73	75	54	73	58	114	0.50
X_2	90	28	83	57	50	95	53	89	92	91	73	102	57	78	98	0.56
X_3	64	86	21	59	74	93	55	45	64	61	95	90	65	80	118	0.47
X_4	68	76	69	33	28	77	45	95	94	87	83	40	85	76	72	1.18
X_5	66	72	93	33	18	65	49	93	92	79	69	64	83	68	74	0.55
X_6	97	103	112	84	69	8	84	112	35	80	42	59	124	59	63	0.23
X_7	101	75	64	66	65	62	30	90	55	70	82	91	98	103	77	0.55
X_8	54	62	41	71	80	101	95	7	90	73	89	96	37	76	152	0.19
X_9	100	100	79	91	94	27	83	87	2	47	67	96	83	98	88	0.07
X_{10}	53	85	60	64	71	86	72	70	59	22	98	87	68	47	113	0.47
X_{11}	78	64	77	73	60	45	85	87	78	101	15	72	81	38	102	0.39
X_{12}	59	79	88	74	39	66	76	86	79	80	68	57	102	85	81	1.46
X_{13}	53	37	50	50	57	94	74	56	109	74	66	89	26	65	127	0.70
X_{14}	44	70	71	83	66	59	107	69	90	61	41	74	71	12	120	0.29
X_{15}	131	127	132	96	87	72	82	158	89	108	96	65	148	113	21	0.32

Table 2. Circularly shifted distances (1.2 D_n, K=200).

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ratio
X_1	17	59	92	68	66	68	77	54	72	77	87	46	88	87	85	0.37
X_2	63	11	90	52	54	50	33	66	96	81	45	78	60	59	59	0.33
X_3	80	72	37	57	55	73	62	75	95	68	54	81	75	70	62	0.69
X_4	76	50	77	15	15	75	32	77	59	78	50	55	71	50	50	1.00
X_5	81	61	72	20	14	52	41	76	68	81	55	60	82	53	43	0.70
X_6	83	47	86	82	74	14	81	74	42	71	67	54	72	75	29	0.48
X_7	89	49	64	56	58	74	27	80	72	75	35	56	52	57	65	0.77
X_8	61	71	70	68	64	54	77	20	74	71	83	42	90	79	63	0.48
X_9	84	100	105	65	73	51	84	79	5	76	64	63	77	56	88	0.10
X_{10}	93	79	84	68	68	72	79	78	76	35	75	56	88	65	49	0.71
X_{11}	94	48	69	51	49	53	30	77	59	88	12	79	49	68	62	0.40
X_{12}	74	78	103	81	63	47	64	81	39	76	60	43	77	50	48	1.10
X_{13}	90	56	73	67	71	79	36	85	81	84	32	79	19	66	98	0.59
X_{14}	87	59	72	50	48	82	63	88	52	59	69	50	80	23	67	0.48
X_{15}	99	73	80	64	56	42	73	76	84	73	75	52	92	47	11	0.26

Table 3 shows the circularly shifted distances between averaged circular pattern vectors $\hat{C}_{Xm}$'s and $\hat{C}_n$'s with M=40, L=5, and $\mathbb{R}=\{r: -2 \le r \le 2\}$ for 0.9 D_n, where X_{13} is incorrectly recognized in addition to X_4 and X_{12} with respect to Table 1, as was expected by decreasing the length of circular pattern vectors 200 by 40. Similarly, Table 4 shows the circularly shifted distances between averaged circular pattern vectors $\hat{C}_{Xm}$'s and $\hat{C}_n$'s with M=40, L=5, and $\mathbb{R}=\{r: -2 \le r \le 2\}$ for 1.2 D_n, where X_{10} is incorrectly recognized in addition to X_4 and X_{12} with respect to Table 2

Table 3. Circularly shifted distances based on averaged circular pattern vectors (0.9 D_n, M=40).

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ratio
X_1	4	16	15	13	10	19	19	13	20	15	18	11	14	11	23	0.40
X_2	18	6	19	13	8	19	9	17	18	21	16	21	12	15	19	0.75
X_3	13	21	6	12	17	18	14	10	13	12	19	18	13	16	22	0.60
X_4	14	18	15	7	6	15	9	19	20	17	16	9	18	15	13	1.17
X_5	15	15	20	6	5	14	8	18	19	16	15	16	17	16	14	0.83
X_6	21	21	24	16	15	2	16	22	9	16	7	14	27	12	12	0.29
X_7	20	16	15	13	12	13	7	17	10	13	16	19	18	21	17	0.70
X_8	10	12	9	15	16	21	19	1	18	15	20	19	6	15	31	0.17
X_9	18	20	15	19	20	7	17	17	0	9	16	21	16	23	19	0.00
X_{10}	12	20	11	13	14	17	15	15	12	3	18	17	12	13	23	0.27
X_{11}	18	12	17	15	12	9	17	17	20	21	4	15	16	7	19	0.57
X_{12}	13	17	18	20	9	14	16	18	15	18	13	12	21	18	14	1.33
X_{13}	11	7	10	10	11	20	14	12	21	16	15	20	7	14	26	1.00
X_{14}	10	14	15	17	18	15	21	13	22	13	8	15	14	3	23	0.38
X_{15}	25	25	26	18	17	14	16	30	17	20	17	12	29	22	4	0.33

Table 4. Circularly shifted distances based on averaged circular pattern vectors (1.2 D_n, M=40).

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ratio
X_1	3	13	20	16	16	14	19	12	15	18	18	18	20	20	18	0.30
X_2	12	2	19	13	11	11	8	13	20	17	9	9	11	11	13	0.25
X_3	16	16	7	11	9	13	12	19	18	15	11	11	15	15	13	0.78
X_4	18	12	15	3	3	15	6	17	14	17	11	11	13	9	9	1.00
X_5	15	13	14	2	0	12	7	16	17	16	14	14	16	10	12	0.00
X_6	18	12	17	15	13	3	16	15	10	15	15	15	17	15	5	0.60
X_7	19	11	14	12	12	16	5	18	15	16	6	6	10	12	14	0.83
X_8	11	15	16	14	16	12	15	6	15	16	16	16	18	16	12	0.75
X_9	16	20	21	17	17	13	18	17	0	15	15	15	17	11	17	0.00
X_{10}	19	17	16	14	12	12	13	16	15	10	14	14	18	14	8	1.25
X_{11}	17	7	16	12	12	12	7	16	15	18	4	4	8	12	16	0.57
X_{12}	14	16	21	19	15	11	12	17	8	15	13	13	15	11	9	1.12
X_{13}	17	11	16	16	16	16	9	20	17	18	6	6	2	14	22	0.33
X_{14}	18	12	15	9	11	17	12	17	12	13	13	13	15	5	15	0.56
X_{15}	20	16	17	13	11	9	14	17	16	15	15	15	19	11	1	0.11

Table 5 shows the group circularly shifted distances based on averaged circular pattern vectors $\hat{C}_{Xm}$'s and $\hat{C}_n$'s with M=40, L=5, and $\mathbb{R}=\{r: -2 \le r \le 2\}$ for radii of 0.9 D_n and 1.2 D_n ($k_1=0.9$, $k_2=1.2$ in Eq. (9)), of which in each row the minimum also occurs on diagonal and thus X_i is correctly recognized by C_i. for $1 \le i \le 15$. Although the equivalent number of elements of the group of circular pattern vectors 80 is less than that of a circular pattern vector 200, the ratios of diagonal to the minimum off-diagonal elements for the fourth and twelfth rows in Table 5 are smaller than those of above all Tables. This is because the group circularly shifted distance stems from wider spatial distribution of symbol than circularly shifted distance. Therefore the performance depends on the compromises between the number of concentric circles and the length of averaged circular pattern vector M.

Table 6 shows the group circularly shifted distances for four radii of 0.9 D_n, 1.0 D_n, 1.1 D_n, and 1.2 D_n based on averaged circular pattern vectors $\hat{C}_{Xm}$'s and $\hat{C}_n$'s with M=20, L=10, and $\mathbb{R}=\{r: -1 \le r \le 1\}$, where the average ratio is similar to that of Table 5.

Consider the computational loads. For each element (circularly shifted distance) of Tables 1-4, we need about 20 $\times$200 times elementary operations of exclusive OR and addition excepting comparison operation. With respect to elementary operations, the ratio of computational loads of Table 6 to Table 5 to Tables 1-4 is 3 : 5 : 50.

Note that the inherent problem of circular pattern vector is immunity in rotation. In other words, it is effective to recognize a rotated symbol but it is not able to discern the difference between rotated pairs of traffic signs such as ⇦, ⇧, and ⇩.

Table 5. Group circularly shifted distances with two concentric circles (0.9, 1.2 D_n) based on averaged circular pattern vectors (M=40) : average ratio = 0.46.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ratio
X_1	7	29	35	25	24	33	30	24	35	31	34	21	34	31	43	0.33
X_2	30	8	36	22	19	28	17	29	38	36	25	36	23	26	34	0.47
X_3	33	35	13	31	30	33	26	30	35	27	34	33	28	33	37	0.50
X_4	32	26	34	10	13	32	17	39	30	34	29	18	33	28	28	0.77
X_5	26	28	34	8	5	26	15	37	32	32	29	26	37	26	28	0.62
X_6	33	31	41	31	28	5	32	42	15	33	24	21	42	25	21	0.33
X_7	39	25	27	25	26	27	12	32	29	29	32	31	30	35	29	0.48
X_8	23	27	27	29	32	37	32	8	33	27	36	27	26	33	43	0.35
X_9	36	40	34	32	33	14	35	35	0	26	25	34	37	32	36	0.00
X_{10}	30	32	28	28	27	30	29	33	28	14	35	28	29	22	30	0.64
X_{11}	35	21	35	27	24	23	24	30	29	39	8	33	26	19	35	0.42
X_{12}	28	34	36	32	21	22	29	37	24	34	27	20	37	28	24	0.95
X_{13}	32	18	26	26	29	38	25	29	36	34	21	32	9	28	46	0.50
X_{14}	30	24	30	28	27	28	35	33	28	26	23	28	29	8	36	0.35
X_{15}	45	41	43	31	32	25	30	48	33	37	32	25	46	31	5	0.20

Table 6. Group circularly shifted distances with four concentric circles (0.9, 1.0, 1.1, 1.2 D_n) based on averaged circular pattern vectors (M=20) : average ratio = 0.48.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	ratio
X_1	12	25	35	38	25	41	42	29	34	36	36	19	40	28	40	0.63
X_2	32	13	37	34	23	35	22	39	36	40	20	37	24	28	30	0.65
X_3	36	41	9	30	33	35	30	29	36	32	38	41	32	32	44	0.31
X_4	41	40	34	9	12	28	17	40	35	39	27	24	31	25	27	0.75
X_5	39	26	34	9	8	24	21	40	39	39	17	34	31	29	27	0.89
X_6	47	38	40	33	28	6	37	46	25	35	29	32	49	35	19	0.32
X_8	47	30	32	23	26	28	13	44	33	33	29	34	29	37	29	0.57
X_9	26	27	25	34	29	39	44	11	36	34	38	31	32	32	50	0.44
X_{10}	41	42	40	35	40	32	41	32	1	23	37	38	37	37	37	0.04
X_{11}	37	46	34	31	32	32	31	42	27	13	41	26	33	33	35	0.50
X_{12}	41	26	34	23	20	22	21	42	35	41	7	38	27	29	33	0.35
X_{13}	37	38	46	37	26	28	37	48	27	37	33	16	43	29	19	0.84
X_{14}	37	24	32	27	28	40	21	32	43	31	25	40	9	29	49	0.43
	29	34	34	23	34	32	33	38	39	31	31	24	31	7	37	0.30
X_{15}	48	43	49	34	33	27	36	57	38	44	36	25	50	32	6	0.24

V. Conclusions

We have introduced a new dominant color transform and a circular pattern vector. An experimental result show that the dominant color transform can be efficiently used for segmentation of the outer contour of traffic signs on the roads and can be applicable to a specific color object detection in color image but it needs further adaptive and post processing to determine a proper threshold and to decide the existence of object.

The circular pattern vector represents a spatial feature of symbol much effective in symbol recognition. Furthermore a group of circular pattern vectors from a lot of concentric circles can improve the performance of pattern recognition better than the circular pattern vector based on a single circle

References

[1] J. L. Pline, *Traffic Engineering Handbook*, 4th ed., Prentice-Hall, 1992.

[2] J. Canny, "A Computational Approach to Edge Detection," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-8, no. 6, pp. 679-698, 1986.

[3] S. W. Zucker, "Region Growing: Childhood and Adolescence," *Computer Graphics and Image Processing*, vol. 5, pp. 382-399, 1976.

[4] J. H. Oh and T. Y. Choi, "A New Hit-and-Miss Ratio Transform and Its Application to Warning Sign Segmentation," *Journal of KITE (Korea Institute of Telematics and Electronics)*, vol. 33-B, no. 3, pp. 546-551, 1996.

[5] W. Woelker, "Image Segmentation Based on Adaptive 3-D Analysis of the CIE-L*a*b* Color Space," *Visual Comm. Image Proc., '96SPIE*, vol.2727, Part 3/3, pp. 1197-1203, 1996.

[6] T. Vlachos and A.G. Constantinides, "A Graph-Theoretic Approach to Color Image Segmentation and Contour Classification," *IEE, 4th IPA'92*, no.354, pp. 298-302, 1992.

[7] J.H. An and T.Y. Choi, "Traffic Sign detection by Dominant Color Transform and Symbol Recognition by Circular Shift of Distributions on Concentric Circles," *Proc. Int. Tech. Conf. Circuits/Systems Comp. Comm., ITC-CSCC'97*, Okinawa, Japan, pp. 287-290, 1997.

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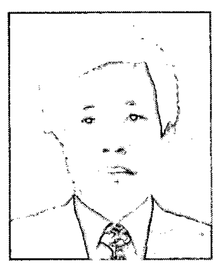

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