Vision-Based Roadway Sign Recognition

Gang Yi Jiang, Tae Young Choi, and Suk-Kyo Hong

Abstract : In this paper, a vision-based roadway detection algorithm for an automated vehicle control system, based on roadway sign information on roads, is proposed. First, in order to detect roadway signs, the color scene image is enhanced under hue-invariance. Fuzzy logic is employed to simplify the enhanced color image into a binary image and the binary image is morphologically filtered. Then, an effective algorithm of locating signs based on binary rank order transform (BROT) is utilized to extract signs from the image. This algorithm performs better than those previously presented. Finally, the inner shapes of roadway signs with curving roadway direction information are recognized by neural networks. Experimental results show that the new detection algorithm is simple and robust, and performs well on real sign detection. The results also show that the neural networks used can exactly recognize the inner shapes of signs even for very noisy shapes.

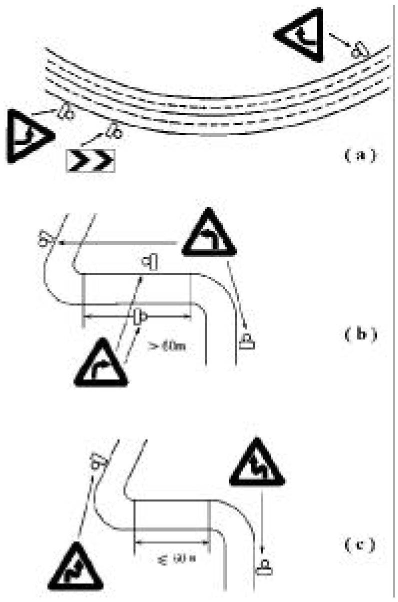
Keywords : roadway direction, roadway sign, fuzzy logic, binary rank order transform

I. Introduction

When a driver travels at relatively high speeds in rural or urban areas, he must pay attention to signs indicating the direction the road ahead will take. Whenever he encounters a curve or turn in the road, it is necessary for him to decelerate his car at once in order to turn smoothly and stay in his lane. However, we often encounter a dangerous moment on turning roadways, because of momentary carelessness. For this reason, the authors take an interest in a vision-based roadway sign detection system.

There are three main tasks in vision-based automatic control of a vehicle; lane detection, obstacle avoidance, and sign recognition. In traffic engineering, in order to indicate turning roadways, some schemes for placing roadway signs have been designed as shown in Fig. 1. Some typical roadway signs are used. One is a warning or indicatory sign showing the direction of a curving roadway or intersection, called a directional sign, and the other is a wedge-shaped supplementary sign, called a guidance sign. The method of lane detection can be used to predict the turn in the road [1,2], and performs well if the roadways are flat and the lanes are clean. This method relies heavily on the presence of painted road markings on the road surface. However, the conditions of flat roadways and clean lanes are not always satisfied, in particular, for rural roadways. Therefore, another approach, using roadway signs, is proposed.
Roadway signs with specific colors, shapes, and structures provide drivers and pedestrians diagrammatic information about routes. Roadway signs are mainly classified into warning, indicatory, regulatory, guidance, and supplementary signs. Some techniques in detection and recognition of roadway signs with RGB color image, which are quite valuable in designing practical systems, have already been reported in our previous work [3,4]. In those methods, a circular pattern vector is used to classify the inner shape of roadway signs. However, the circular pattern vector is of rotation-invariance, so it can not discern two symmetric shapes, for example, the shapes ↲ and ↳. H. Yang et al. proposed a scheme of recognizing roadway-sign-type landmarks using the HSI color model and edge detection [5,6]. But, they did not make sufficient use of color information to detect signs. A. de la Escalera et al. have presented a method to detect road traffic signs by their colors and shapes and to classify signs by the back-propagation neural networks [7]. However, this method used Rangarajan's corner detector [8], the computational complexity of which is quite high, and its classification of signs did not utilize the information of sign shape.
Image processing and computer vision have problems where data and measurements are noisy or uncertain estimates of reality. Fuzzy theory gives mathematical measures to a wide variety of ambiguous phenomena and is a way of handling uncertain information. It has been shown that it is possible and quite effective to develop fuzzy approaches for image processing, such as image segmentation and quantitative analysis [9,10].

In this paper, a new scheme for detecting and recognizing roadway signs is proposed. A color image is pre-processed by fuzzy logic, enhanced under hue-invariance and simplified into a binary image in section 2. A powerful and fast algorithm based on BROTs is used to locate



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Gang Yi Jiang, Tae Young Choi, Suk-Kyo Hong : Division of Electronics Engineering, Ajou University

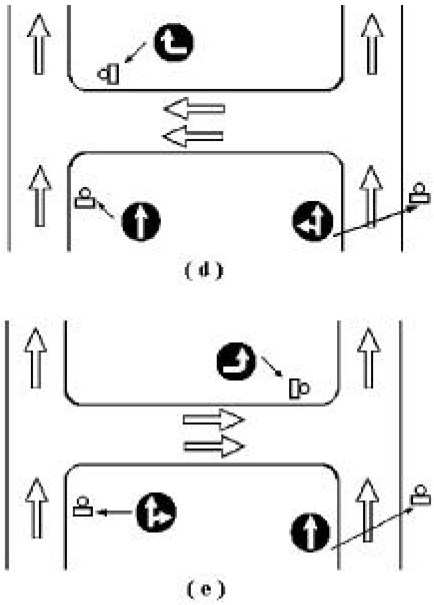


Fig. 1. Some schemes of sign placement at roadway curves and turns.

roadway signs in the binary image in section 3. The extracted signs are identified with neural networks in section 4. Finally, section 5 gives experimental results to test the proposed method.

II. Pre-processing of color image by fuzzy logic

1. Color image enhancement under hue invariance

In general, a roadway sign image in a real outdoor scene is taken with different situations (normal, under-exposed, over-exposed, sunny, rainy, and snowy cases.). To extract roadway sign from an input color image exactly, the input color image needs to be enhanced with hue invariance. Here, we describe a new approach for color image enhancement with hue invariance by using fuzzy set.

In the RGB color model, let v(k)=(r(k),g(k),b(k)) represent a color pixel at point k in the domain D of an image v(k). Then the hue component H(k) of the pixel is defined by Eq. (1).

$$H(k)=\begin{cases}H_o(k), & b(k)\le g(k)\\ 360^\circ - H_o(k), & b(k)>g(k)\end{cases},\qquad (1)$$

where $H_o(k)=\arccos\left\{\frac{0.5(d_{rb}(k)+d_{rg}(k))}{\sqrt{d_{rg}^2(k)+d_{rb}(k)d_{gb}(k)}}\right\}$,

$d_{rb}(k)=r(k)-b(k)$, $d_{rg}(k)=r(k)-g(k)$,

and $d_{gb}(k)=g(k)-b(k)$.

It is obviously true that the hue in Eq. (1) is invariant with an arbitrary constant bias, from the fact that $d_{rg}(k)=r(k)-g(k)=(r(k)-\alpha)-(g(k)-\alpha)$. We will exploit this invariance of hue with a constant bias for a color image enhancement.

Let m_{min} and m_{max} denote the lowest and highest levels of all the three RGB components for a given image that spans the pixel values from 0 to L-1. Color image V can be defined according to fuzzy set theory as: each pixel can be considered as a fuzzy singleton whose membership function ranges from 0 to 1. $V=\bigcap_{k\in D_v}(\mu_V(v(k))=\mu(k)|v(k))$, where $\mu_V(v(k))$ is defined as a fuzzy membership function associated with the color pixel v(k). We define $\mu(k)$, $0\le\mu(k)\le 1$, as

$$\mu(k)=\frac{r_1(k)+g_1(k)+b_1(k)}{3(m_{max}-m_{min})},\qquad (2)$$

$$r_1(k)=r(k)-m_{min},\qquad (3a)$$

$$g_1(k)=g(k)-m_{min},\qquad (3b)$$

$$b_1(k)=b(k)-m_{min}.\qquad (3c)$$

Usually, the S-function is used to enhance images by fuzzy set theory [10]. As a new approach, a Gamma function is used and defined by

$$y(k)=\mu(k)^{1/\gamma}\quad\text{for }\gamma>0,\qquad (4)$$

where it is easy to see that efficient performance with enhanced low-level components in an image can be obtained using $\gamma>1$, whereas high-level components can be enhanced using $\gamma<1$. When it requires a compression for the low-level part of the image, and an expansion for the high-level part, the transfer function can be modified as

$$y(k)=\begin{cases}\frac{1}{2}(2\mu(k))^{1/\gamma}, & 0\le\mu(k)\le\frac{1}{2}\\ \frac{1}{2}+\frac{1}{2}(2\mu(k)-1)^{1/\gamma}, & \frac{1}{2}<\mu(k)\le 1\end{cases}\qquad (5)$$

$$v'(k)=\begin{cases}(\lceil r_1(k)y(k)\rceil,\lceil g_1(k)y(k)\rceil,\lceil b_1(k)y(k)\rceil), & \lceil\rho(k)y(k)\rceil\le L-1\\ (\lceil r_1(k)\phi(k)\rceil,\lceil g_1(k)\phi(k)\rceil,\lceil b_1(k)\phi(k)\rceil), & \lceil\rho(k)y(k)\rceil>L-1\end{cases}\qquad (6)$$

Clearly, when $\gamma=0.5$, the Eq. (5) shows the same effect as the S-function. At final, the enhanced color pixel v'(k) is given by Eq.(6).

where $\rho(k)=\max\{r_1(k),g_1(k),b_1(k)\}$, $\lceil\ \rceil$ denotes an integer operator, for example, $\lceil 3.5\rceil=3$, and $\phi(k)=(L-1)/\rho$.

From Eqs. (1), (2) and (6), it is clear that the proposed method for enhancing the image does not change the hue of the original image, which is quite important for getting objective information from the hue of the color image.

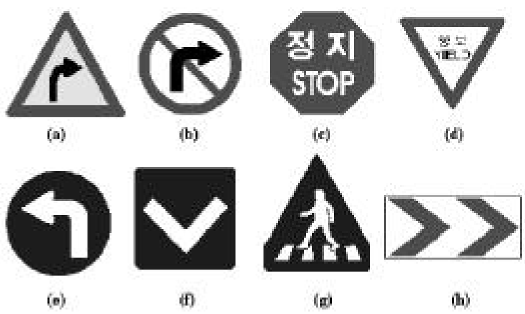


Fig. 2 Some korean traffic signs.

2. Simplifying color image by fuzzy logic

Roadway signs have special colors and outer shapes, which provide important information which must be detected and extracted from the overall scene image. Fig. 2 shows some Korean roadway signs, in which there are two colors to be used, i.e., red and blue, and seven shapes to be applied, that is, up-triangle, down-triangle, circle, octagon, pentagon, square, and rectangle. Our goal is to detect the signs using fuzzy rules on color pixels, that is, to decide whether a pixel is red or blue, and then to extract the signs based on matching their outer shapes to known sign shapes. To accomplish this, the RGB model is changed into the chrominance plane (r',g',b') with $r'+g'+b'=1$, where r', g', and b' are given by

$$r' = \frac{r}{r+g+b}, \tag{7a}$$

$$g' = \frac{g}{r+g+b}, \tag{7b}$$

$$b' = \frac{b}{r+g+b}, \tag{7c}$$

in which, for example, when r' is very close to 1 and both b' and g' are very close to 0, the pixel may be regarded to be red.

The enhanced color image is mapped to the chrominance plane, and fuzzy rules to be utilized to recognize the red pixel are given by the following procedures. For a color pixel v(k), let m(k)=r(k)+g(k)+b(k), m_{mean} be the mean of m(k), th1 be a threshold (th1=0.15 m_{mean}), and th2 be a constant (empirically 0.45). Then, a binary function $\lambda(k)$, containing the information of roadway sign, is given as follows

1) If m(k)<th1 or $r'(k) \le g'(k)$ or $r'(k) \le b'(k)$, then $\lambda(k)=0$;
2) else if $(r'(k)-g'(k)) < |g'(k)-b'(k)|$, then $\lambda(k)=0$;
3) else if (r/g>1.5 and r/b>1.5), then $\lambda(k)=1$;
4) else if $r'(k) \ge th2$, then $\lambda(k)=1$;
5) else $\lambda(k)=0$;

Finally, an image X is obtained by filtering $\lambda(k)$ with a morphological open-close. In the same way, we can also detect out blue pixels.

III. Extracting roadway signs

1. Detecting and locating warning signs

The next step is how to detect signs from the binary image X. First, the warning signs with up-triangle outer shape are utilized to explain how to extract signs based on binary rank order transforms (BROT). A BROT of binary image X by structuring element B, denoted $X \textcircled{\scriptsize P} B$, is defined by [11]

$X \textcircled{\scriptsize P} B = \{a;\ Card(X \cap B_a) \ge G-(G-1)P\}$, (8a) where P=0,1(G-1), ...,1. G=Card(B) is the cardinality of B. And dilation and erosion, the fundamental morphological operators, are defined as follows [12]

$$X \oplus B = \{a;\ \breve{B}_a \cap X \ne \Phi\}, \tag{8b}$$

$$X \ominus B = \{a;\ B_a \subseteq X\}, \tag{8c}$$

where $\breve{B} = \{-b;\ b \in B\}$ and B_a is translated B by a.

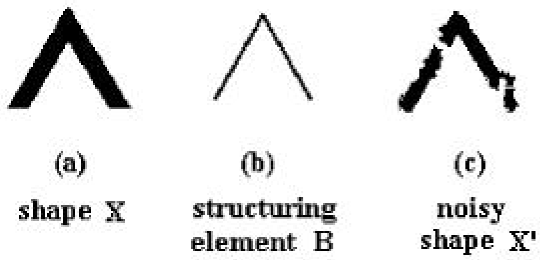


Fig. 3. An example for comparison BROT with erosion $(X' \ominus B)$ is an empty set, but $(X' \textcircled{\scriptsize P} B)$ is close to $(X \textcircled{\scriptsize P} B)$ for suitable P.

BROTs possess many characteristics present in the morphological operators and perform better than the morphological operators in noisy environments because of their tolerance to noise. $X \textcircled{\scriptsize P} B$ is increasing with P, and $(X \textcircled{\scriptsize P} B) \supseteq (X \ominus B)$. Particularly, $X \textcircled{\scriptsize 0} B = X \ominus B$ and $X \textcircled{\scriptsize 1} B = X \oplus \breve{B}$, which imply that the BROT is an extension of the binary morphology. Fig.3 gives a comparison between the BROT and erosion, where X can be well matched with B by BROT and erosion. However, when X is corrupted as X', then $(X' \ominus B)$ is empty set and different from $(X \ominus B)$, while $(X' \textcircled{\scriptsize P} B)$ is close to $(X \textcircled{\scriptsize P} B)$ if a

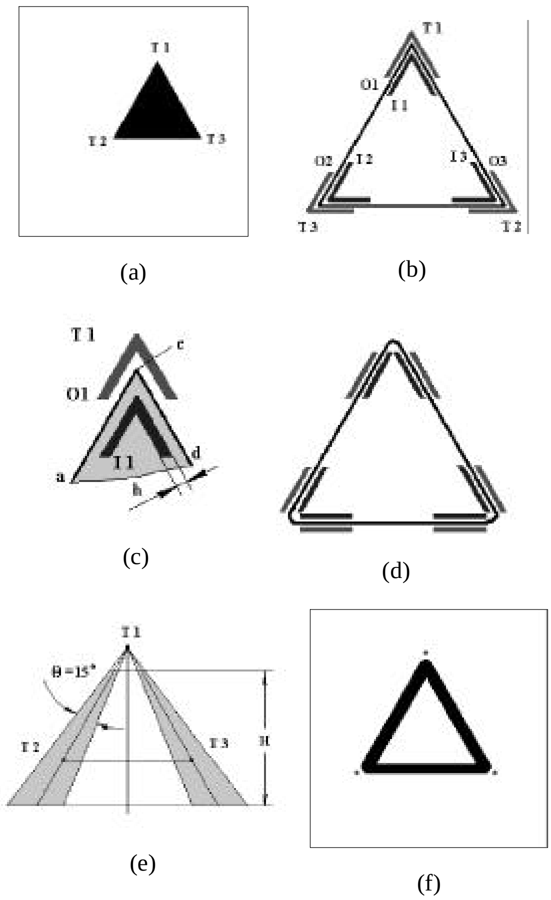


Fig. 4. (a) A binary image, (b) 3 pairs of structuring elements, (c) Matching by BROTs, (d) Modified structuring elements, (e) Search area, (f) A test shape.

suitable P is adopted. So, compared with erosion, BROT provides more effective shape matching in noisy case. BROT is useful for finding some features, for instance, corner points of a shape. To simplify the computation of the BROT, we rewrite Eq.(8a) as follows

$$X \boxdot B = \{ a;\ Card(X \cap B_a) \geq m \} \tag{9}$$

where m = 1,2,...,G.

Fig. 4(a) shows a binary image with a triangle, analogous to the outer shape of warning signs. In order to extract the triangle from the image, a direct and effective method is to locate its three corners. Fig. 4(b) illustrates three corners (T1, T2, T3) and corresponding pairs of masks (Ij—Oj, j=1,2 and 3). As shown in Fig. 4(c), we would like to identify the corner of $\angle acd$. If the pixels on the structuring elements I1 and O1 at a point constitute respectively an angle of $\angle acd$, we judge the point to be a corner point c. Hence, we define a compound BROT, $M_j(X, Ij, Oj)$, which specifies the existence of the pixels on the structuring elements Ij and Oj belonging to an angle, as follows

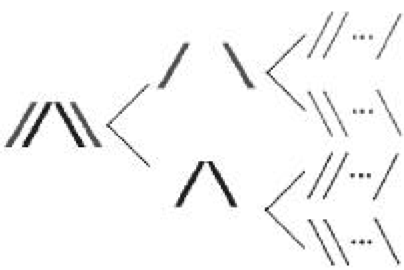
$$M_j(X, Ij, Oj) = (\overline{X} \boxdot Oj) \cap (X \boxdot Ij) \tag{10}$$

where $\overline{X}$ is the complement of X, and j=1,2,3.

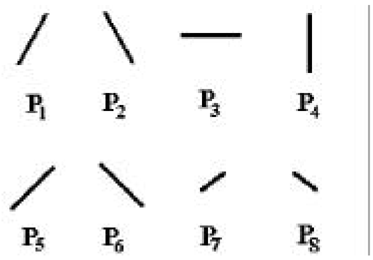
If $M_j(X, Ij, Oj)$ at point k is 1, the point k will be regarded as a candidate for a corner point. Usually there exist several candidates surrounding a corner point. So, a cluster procedure is performed to identify the real corner point k_c, that is, $k_c = \sum k_i / n$ (k_i is a connected neighbor of k_c).

In fact, it is possible for the sharp-angle parts of the structuring elements Ij and Oj (j=1,2,3) to result in some useless or erroneous information; for example, there is an arc on each corner of the outer shapes of warning signs in Fig.2(a). Hence, the structuring elements are modified in Fig.4(d). The sharp-angle parts in the structuring elements are eliminated, which not only reduces the likelihood of producing an error, but also is beneficial to carrying out the detection algorithm quickly, with decomposition of the structuring elements. Fig.5(a) illustrates the decomposition of the structuring elements I1 and O1. The three pairs of masks in Fig. 4(d) can be represented in the combination of three crucial matching patterns P1, P2, and P3 in the Fig. 5(b).

To sum up, we have the following fast algorithm to locate warning signs in a binary image.



(a)



(b)

Fig. 5. (a) Decomposition of Ij and Oj. (b) Crucial matching patterns

1) Calculate $Card(X \cap Pi)$, i=1,2,3, and obtain 3 resultant images, $Card(\overline{X} \cap Pi)$ can be computed by

$$Card(\overline{X} \cap Pi) = Card(Pi) - Card(X \cap Pi).$$

2) Compute $M_j(X, Ij, Oj)$, j=1,2,3, using translation and comparison operations in the resultant images.

3) Cluster the candidates to get three types of corner points (that is, T1, T2, and T3).

4) If there exists any T1-type corner point p1, search its two corresponding corner points (T2-type and T3-type). The search areas are determined by the shadows in Fig. 4(e).

5) If there exist two corner points corresponding to p1 in the search areas, three corner points constitute the outer shape of a warning sign. Otherwise, delete the point p1.

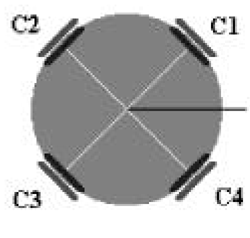
Fig.4(f) shows a test image of an equilateral-triangle, with 150 pixels length in its hemline, and Table 1 shows the results of corner detection using BROTs, where δ_{Tj}, j=1,2,3, is the difference between the locations of the real and estimated corner points.

2. Detecting and locating other signs

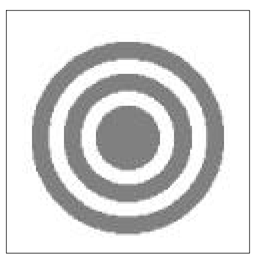
As shown in Fig.2, there are two categories of roadway

Table 1. A test of corner detection of equilateral-triangle with 150 pixels in Fig.4(f).

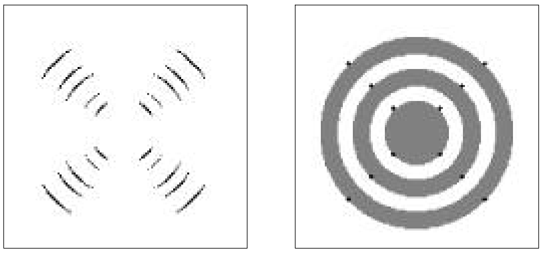
	δ_{T1}	δ_{T2}	δ_{T3}
orignal image	(0,0)	(0,0)	(0,0)
add 15% noise	(0,0)	(0,0)	(0,0)
rotate 7.5 ° right	(-2,0)	(-1,-2)	(2,2)
rotate 7.5 ° left	(-2,0)	(0,2)	(0,-2)



(a)



(b)



(c) (d)

Fig. 6. (a) 4 pairs of structuring elements for circle detection, (b) Homocentric circle and cirques, (c) After BROTs with 4 pairs of structuring elements, (d) Diagonal points obtained after clustering and judging.

signs with a circular outer shape, indicatory signs and prohibition signs. We can utilize Eq.(10) with four pairs of structuring elements, as shown in Fig.6(a), to locate a circle or a cirque. Here, an example of detecting a circle and a cirque is given in Fig.6. Fig.6(b) shows a binary image with homocentric circles and cirques, and Fig.6(c) shows the result after BROTs with 4 pairs of structuring elements. With clustering and judging similar to that in the detection of a warning sign, the diagonal points which locate a circle or cirque are obtained, shown as the black dots in Fig.6(d).

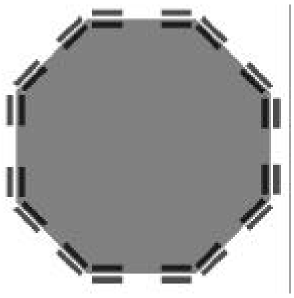


Fig. 7. Eight symmetric pairs of structuring elements.

The structuring elements in Fig.6(a) are also used to find a "stop" sign with the octagon outer shape in Fig.2(c). The "stop" sign is distinguished from indicatory and prohibition signs by its color and distribution. To obtain accurate identification of the "stop" sign, the 8 symmetric pairs of structuring elements in Fig.7 may be applied. Of course, all these processes to locate signs can be performed rapidly by using the crucial matching patterns in Fig.5(b).

Additionally, there is another special sign which provides information about road information, that is, the guidance sign. To locate a guidance sign as shown in Fig.2(h), we can combine the patterns P7 and P8, which are shorter than P5 and P6. Since a guidance sign has a special structure with a double-arrow, we can detect these two arrows by locating their corner points, judge whether or not the object is a guidance sign, and decide its size and outer shape by the corner points.

Compared with the method used to detect a known corner point in [7], the new method performs better and faster, especially in the case of signs with damaged corners.

IV. Sign recognition by neural networks

After detecting a sign, we can extract it from the enhanced color image, obtain its inner shape, and normalize its shape in scale and geometric structure, by its outer shape. The next step is to recognize the sign by its inner shape. Neural networks are a new generation of information processing systems that are deliberately constructed to make use of some of the organization principles that characterize the human brain. Hopfield proposed a class of neural networks, known as Hopfield networks, which started the modern era in neural networks. His work also promoted

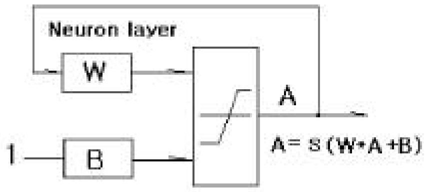
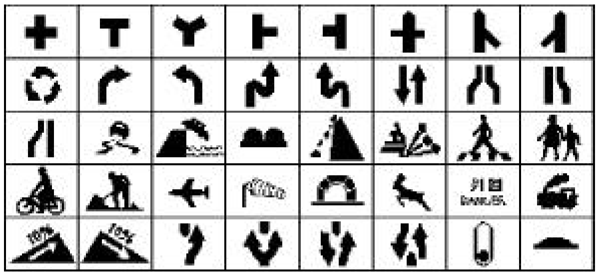
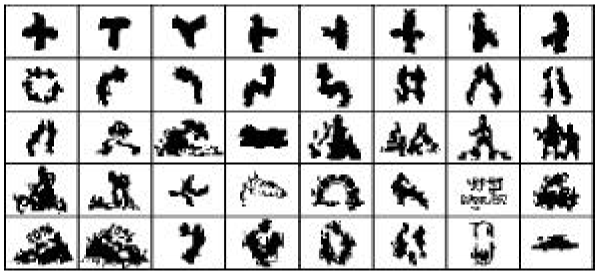


Fig. 8. Architecture of Li's neural networks.



(a)



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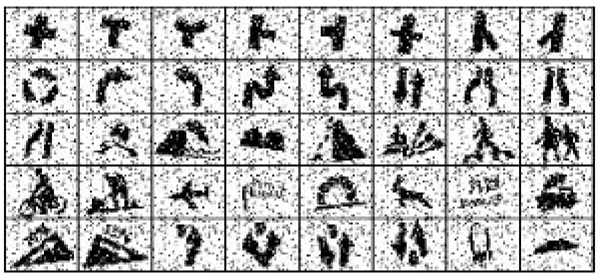


(c)

Fig. 9. (a) Reference inner shapes of signs, (b) One set of noisy shapes, (c) Another set of noisy shapes.

construction of the first analog VSLI neural chip. The Hopfield networks have found many useful applications, especially in associative memory and optimization problems. The discrete Hopfield networks are single-layer feedback networks and have symmetric weights with no self- connections. They can be used to decide whether an input vector is a known pattern stored by networks or an unknown one.

J. H. Li et al. have developed another class of neural networks, described as a system of first-order linear ordinary differential equations which are defined on a closed hypercube [13]. The neural networks retain the basic structure of the Hopfield model and are easier to analyze, synthesize and implement than the Hopfield model. The architecture of the neural networks is shown in Fig.8, where the function s(x) is limiting non-linearity. When the neural networks are used, the output after convergence has to be compared to the M exemplars to decide if it matches an exemplar exactly. If it does, the output is the very exemplar matched with the output pattern. Otherwise, a 'no matched' result occurs.

Figs.9(a) and (b) give the reference inner shapes of 40 Korean warning roadway signs (that is, 40 exemplars) and one of their test sets, respectively, where each inner shape has the size of 45×32. The reference shapes are used to train the neural networks in order to obtain the weight coefficients of the neural networks. The test shapes are quite noisy but are all recognized exactly based on the reference shapes in the corresponding location of Fig.9(a). The results show that the neural networks have classified the test sets accurately. To show the classification effects of the neural networks clearly, Fig.9(c) shows another test set, where the first 20 shapes are rotated clockwise by 7.5° then corrupted by 10% noise, and the other 20 shapes are rotated counterclockwise by 7.5° then corrupted by 10% noise. Again, the results show that the neural networks have accurately recognized the test sets. Fig.10 shows an unknown input and 6 stages of its recognition process in the neural networks, the last state being the stable convergence state, which corresponds to No.11 pattern in Fig.9(a).

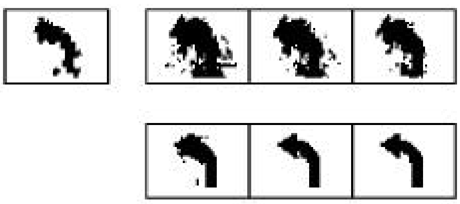
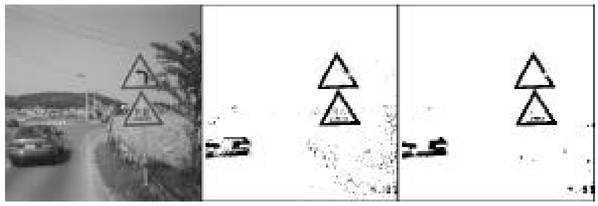


Fig. 10. An unknown shape and its 6 stages in the neural networks.

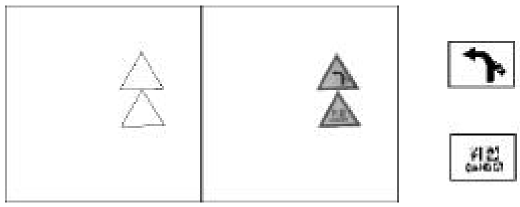
V. Experimental results

As mentioned above, a system to detect roadway direction by recognizing road signs has been developed. First, a real scene image is inputted and enhanced under hue-invariance. Figs.11(a) and (b) show two color images which have very bad contrast, and are under-exposed or over-exposed, respectively. They are enhanced under hue-invariance as shown in Figs.11(c) and (d). The enhanced color image is simplified into a binary image by fuzzy logic, and morphologically filtered as shown in Figs.11(e) and (f). A new, efficient and fast corner detection algorithm using BROTs is employed to locate the signs in Fig.11(f) and extract them from Fig.11(c). Fig.11(g) shows the border of the detected signs and Fig.11(h) gives the detected signs. The extracted inner shapes from Fig.11(h), which have been normalized, is shown in Fig.11(i).

(a) (b) (c)



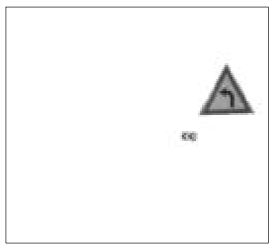
(d) (e) (f)



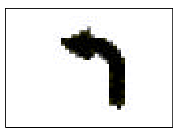
(g) (h) (i)

Fig. 11. (a) Under-exposed image, (b) Over-exposed image, (c) Enhanced image of (a), (d) Enhanced image of (b), (e) Simplified image of (c), (f) Filtered binary image, (g) Border of detected signs, (h) Located signs, (i) Extracted inner shapes.

(a) Scene image



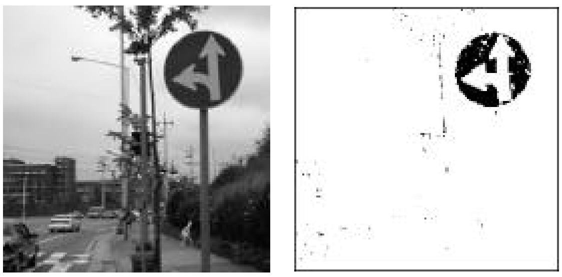
(b) Located signs



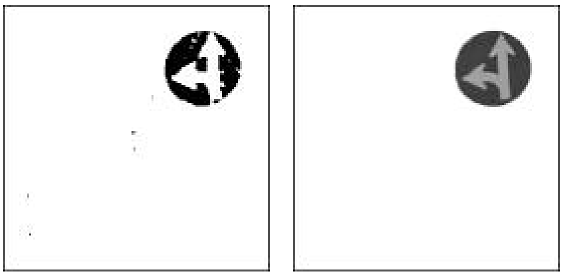
(c) Inner shape

Fig. 12. A guidance sign and warning sign detection.

We can judge the type of sign according to its outer shape and its color. After locating a sign, we can extract it from the enhanced color image, obtain its inner shape and normalize the shape in scale, geometric structure, and translation by the outer shape of the sign. Neural networks have shown great efficacy in pattern recognition. Here, efficient neural networks are adopted to classify the roadway sign because of very good flexibility in a noisy environment. The test results show that the neural networks have accurately classified the test set. The inner shapes of the roadway signs in Fig. 11(i) are easily and exactly recognized by the neural networks to be the 11th and 31st reference shapes. And the information, left-curving roadway and danger, is provided to the driver.



(a) Scene image (b) After transforming



(c) After filtering (d) Located sign

Fig. 13. An example of detecting indicatory sign.

(a) (b)

Fig. 14. (a) Scene image, (b) Located signs.

A guidance sign and warning sign are detected and extracted in Fig.12. The results of locating and recognizing these signs show that the road ahead curves to left. Fig.13 shows the results of detecting an indicatory sign with a circular outer shape. Figs.13(a) is a scene image, after pre-processing, Fig.13(b) and (c) are the simplified image and filtered image, and Figs.13(d) shows the located indicatory sign. Similarly, after extracting the indicatory sign, it is recognized exactly. Fig. 14 also shows the result of detecting the "stop" sign.

Finally, the proposed method is tested by using a test set of 336 road roadway images with different situations, which consist of normal, under-exposed, over-exposed, sunny, rainy, and snowy cases. The rate of detecting and recognizing roadways sign is about 95.2%. It takes 2.65s to detect and recognize roadway signs from a color image. Fig.15 and Fig.16 show 10 typical warning sign images and 10 typical indicatery sign images and their detected signs, respectively. All these signs are recognized correctly.

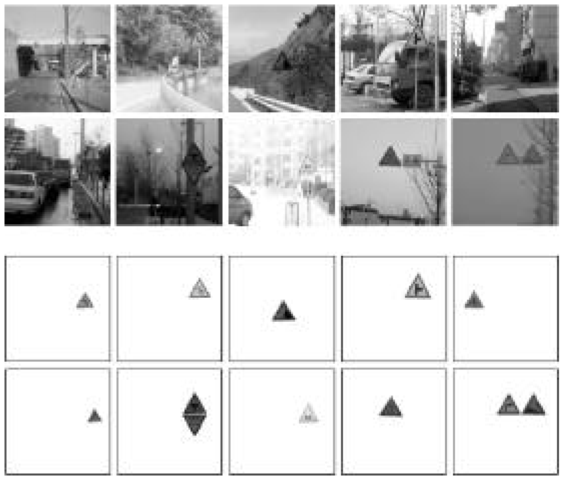


Fig. 15. 10 typical warning sign images and their located signs.

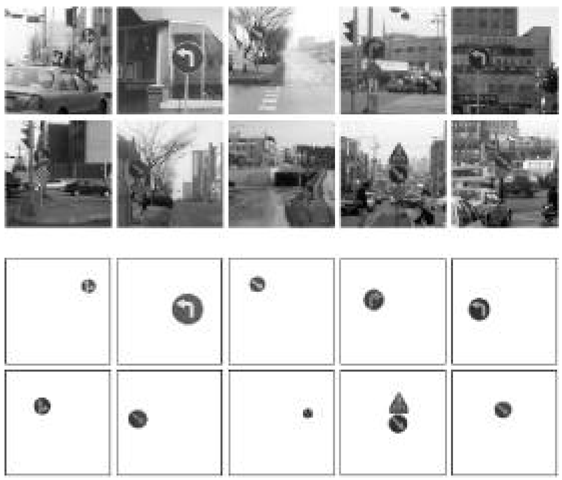


Fig. 16. 10 typical indicatery sign images and their located signs.

In [4], a circular pattern vector is used to recognize the symbol of a roadway sign, however, this algorithm cannot discern the difference between the rotated pairs of roadway signs such types of ↲ and ↳. The proposed method in this paper can classify them well. In [7], some masks are used to detect the corners of a warning sign, which may not perform well because of the arcs of corner of the warning sign and when the corners of sign are corrupted. It uses a gray-scale image of an entire road sign, with the size of 30 ×30 pixels, to recognize roadway sign by a three-layer back-propagation neural networks. It does not exploit the information on the inner part of roadway sign. So, it can only recognize 9 different warning signs (or circular signs), due to very low resolution of input pattern in the back-propagation neural networks. The proposed method in this paper detects roadway signs well by using the modified structure elements and BROTs, and recognizes 40 different roadway signs well by using the feature of inner part of roadway sign.

VI. Conclusions

A roadway detection system for automated vehicle control systems aids safe driving by providing much needed information, telling the driver when to decelerate. We have proposed a new method to detect roadway direction using recognition of signs. The total process of recognizing signs is composed of enhancing the image, detecting and locating signs, deciding the type of signs, extracting the inner shape of each sign, and recognizing the sign by its inner shape. The new method to detect a corner is faster and more than the method used by Escalera. Experimental results show that the new algorithm for detecting signs is very simple and robust because of the use of fuzzy enhancement and BROTs, and the new method can perform object detection well in a real scene. The results also show that the neural networks used can exactly recognize the symbols inside the roadway sign and perform quite perfectly even for very noisy shapes.

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Gang Yi Jiang

Gang Yi Jiang was born in Aug. 23, 1964. He received M.S. degree in Electronics Engineering from Hangzhou University, China, in 1992. He has been with Hangzhou University as an associate professor since 1995. Now he is working toward Ph.D. degree at Ajou University, Korea. His current research interests are in the area of digital signal processing, speech processing, image processing, pattern recognition, computer vision, and intelligent transportation system.

Tae Young Choi

Tae Young Choi was born in Oct. 24 1950. He is with Ajou University since 1983 and is currently a professor in the division of electronics engineering. His research interests are in the area of image processing. morphological signal processing, computer vision, and intelligent transportation system. He received B.S. and M.S. degrees in electronics engineering from Seoul National University in 1974 and 1978, respectively, and D.E.A. and Ph.D. degrees from University of Aix-Marseille III, France, in 1980 and 1982, respectively. In 1999, he was with Georgia Tech. in USA as a visiting professor for one year, there he was doing medical image processing.

Suk-Kyo Hong

Suk-Kyo Hong was born in Aug. 23 1948. He is with Ajou University since 1976 and is currently a professor in the division of electronics engineering. He has received B.S., M.S., and Ph.D degree from Seoul National University in 1971, 1973, and 1981, respectively. He was with R.P.I. in USA as a visiting professor in 1983 and with INRIA in France in 1988. His research interests are in the area of robot control, mobile robot, and intelligent transportation system.