International Journal of Automotive Technology, Vol. 6, No. 1, pp. 53–63 (2005)

1229–9138/2005/019–08

A FUZZY NEURAL NETWORK-BASED DECISION OF ROAD IMAGE QUALITY FOR THE EXTRACTION OF LANE-RELATED INFORMATION

U.-K. YI[1], J. W. LEE[2)*] and K. R. BAEK[3]

[1]Department of Digital Animation, Busan Kyungsang College, Busan 611-701, Korea
[2]Department of Industrial Engineering, Automotive Research Center, Chonnam National University, Gwangju 500-757, Korea
[3]Department of Electronics Engineering, Research Institute of Computer Information and Communication, Pusan National University, Busan 609-735, Korea

(Received 18 February 2004; Revised 31 May 2004)

ABSTRACT–We propose a fuzzy neural network (FNN) theory capable of deciding the quality of a road image prior to extracting lane-related information. The accuracy of lane-related information obtained by image processing depends on the quality of the raw images, which can be classified as good or bad according to how visible the lane marks on the images are. Enhancing the accuracy of the information by an image-processing algorithm is limited due to noise corruption which makes image processing difficult. The FNN, on the other hand, decides whether road images are good or bad with respect to the degree of noise corruption. A cumulative distribution function (CDF), a function of edge histogram, is utilized to extract input parameters from the FNN according to the fact that the shape of the CDF is deeply correlated to the road image quality. A suitability analysis shows that this deep correlation exists between the parameters and the image quality. The input pattern vector of the FNN consists of nine parameters in which eight parameters are from the CDF and one is from the intensity distribution of raw images. Experimental results showed that the proposed FNN system was quite successful. We carried out simulations with real images taken in various lighting and weather conditions, and obtained successful decision-making about 99% of the time.

KEY WORDS : Fuzzy-neural network, Cumulative distribution function, Suitability analysis, Image quality, Image processing

1. INTRODUCTION

There have been many attempts to develop lane departure warning or prevention systems to prevent lane departure due to driver inattention. Such lane departure warning or prevention systems rely on the lane-related information extracted by image processing, which has been increasingly used in automotive engineering (Ozawa, 1999; Bertozzi *et al.*, 2000; Aoli, 1998; Lee *et al.*, 2000).

In this paper, the target roads are paved with asphalt or cement, and have painted lane marks that are brighter than the background of the lane marks. Extracting lane-related information such as the location and orientation of lane marks becomes the matter of concern. However, it is difficult to extract reliable information because a great deal of random noise factors, which are unpredictable, are included in road images. The lane-related information extracted by image processing is also sensitive to weather or lighting conditions. Sometimes it is impossible for human to visually distinguish lane marks due to noise corruption. Contrary to our expectations, the information extracted from noise corrupted images is too inaccurate and therefore using it for practical applications is too risky for safe driving.

If the quality of a road image is known prior to the extraction of lane-related information, it is possible to avoid the extraction of unreliable information by discarding bad quality images. Here, the image quality is concerned with the visibility of lane marks. If the lane marks on a road image are clearly visible, we can conclude that the image is good. With respect to bad images, the lane marks are nearly invisible. However, it is not easy to find quantitative measures to determine good and bad images. We have inevitably relied on the human eyesight based on experience when determining been requested to.

**Corresponding author.* e-mail: joonlee@chonnam.ac.kr

In this research, this determination is essential for making a practical system for the lane departure warning and prevention, and it is also very important to maintain safe driving. However, it is not easy to consider every unpredictable situation which may happen in the real environment such as lighting, shadowing and occlusion of lane marks. Even though a lot of research has been conducted to overcome noise problems, research concerning the judgment of image quality has been insufficient. We can classify the research related to solving such noise-related problems into two branches: one is the development a robust image processing algorithm under the premise that a lot of noise exists, the other is related to scene analysis like an image quality decision. Most research has focused on the former, while the latter has received little attention (Takahashi *et al.*, 1999; Kreucher and Lakshmanan, 1999).

Takahashi *et al.* (Takahashi *et al.*, 1999) used a parameter space constructed by edge points to detect robust lane information by using RVP-I (Real-time Voting Processor-I) from images captured in rainy and shadowy environments on highways. Kreucher and Lakshmanan (Kreucher and Lakshmanan, 1999) detected the characteristics of lane marks in the frequency domain and had success in detecting reliable lane information under the conditions of varying lighting and lane occlusions. However, there are still problems with respect to noise such as pseudo-lane marks or apparent boundaries, reflection of sunlight and ambiguous boundaries, which make system performance undesirable.

In this paper, we focus on deciding whether or not raw images are good enough for the reliable extraction of lane-related information prior to the extraction. Such decisions are essentially required to make a lane departure warning or prevention system practical. The extraction of lane-related information and its applications are beyond the scope of this paper.

We use a cumulative distributed function (CDF), which accumulates the edge magnitude along the edge orientation of the input image to determine the quality of a road image (Lee *et al.*, 2001). When we carefully look at the shape of the CDF we can decide whether the input image is good enough or not to extract lane-related information. To realize this by computer, inferring the possibility of reliable extraction of lane-related information is required by the feature values of the CDF. There are several methods of inference: the brute-force method, the statistical method like the Bayesian theory (Duda and Hart, 1973), and the fuzzy or neural network approach. The brute-force method has too many case numbers to express rules and the Bayesian method needs a priori probability. A priori probability can be obtained from a sample set of characteristics. However, it is not only difficult to get precise priori probability but it also requires a lot of knowledge about the sample set (Duda and Hart, 1973). Therefore, there seems to be a limit to using a decision-making algorithm for the quality of road images. To solve this kind of problem, it is necessary to add an intelligence which can cope with various and dynamic road environments.

Fuzzy and neural networks can be proper theories for this decision. Fuzzy theories can express organized knowledge and manage ambiguous information easily. However they do not have learning mechanisms and it takes a long time to tune the system until its performance is satisfactory (Lin and Lee, 1996). Neural networks have the abilities of learning, parallel processing, fault-tolerance and tuning an arbitrary input-output relationship, but the information is stored in weights in a distributed network. Therefore, it is difficult to express the knowledge in a linguistic sense (Horikawa *et al.*, 1992). As we have seen, fuzzy and neural networks are mutually complementary. Recently, there has been a lot of research on fuzzy neural networks which has fused the two systems by taking only merits from each. Moreover, research has shown that the fused systems can satisfactorily solve many problems (Lin and Lee, 1996; Horikawa *et al.*, 1992). The diagnosis for faults based on FNN has been especially popular because FNN can provide very effective mapping methods with various learning algorithms when the given data is strongly nonlinear. Another reason for the wide acceptance popularity of FNN is that it can carry out efficient interpolations even when the type of given data has never been treated before by the system (Maki and Laparo, 1997).

In this paper, we decide whether the quality of a road image is good or not based on the result of FNN which is a combined form of a fuzzy and neural system, easily making human linguistic quantity descriptions measurable and making a neural network capable of learning and generalizing the human activity. Input to the implemented FNN here is composed of 8 parameters taken from the CDF and one parameter from intensity values. It is shown that the feature parameters are closely related to the prediction of lane-related information through the analysis of the correlation between parameters and input images. The experiment was carried out in a case by case fashion with the 5, 7 and 9 inputs to realize real time processing and efficient decision-making. The experiment also tested the usefulness of the decision for the quality of road image.

2. QUALITY DETERMINATION SYSTEM OF THE ROAD IMAGES

In order to determine road image quality we need to figure out if we can possibly detect information such as the position of lane marks or the direction of a lane in

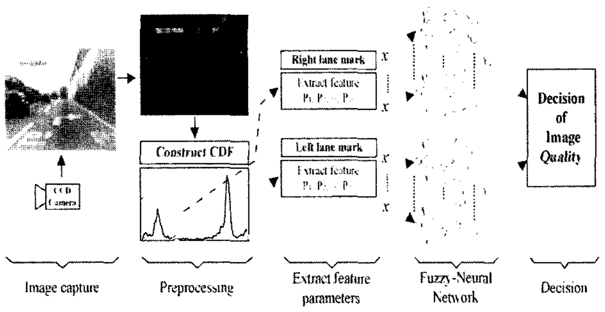


Figure 1. Structure of the system.

advance of image processing from the input images captured by a CCD camera mounted on a vehicle. Figure 1 shows the structure of the system.

As shown in Figure 1, an input road image has a great amount of pixel information. We cannot use all the pixels for the input stage of a fuzzy neural network inferring system because this can cause excessively complicated inferring system structure, increase the time required for calculation, and decrease performance due to the poor expression of features. Therefore, pre-processing is needed to simplify the system by extracting the feature parameters for the decision-making.

In order to preprocess, we need to construct a CDF based on the following two facts: 1) lane marks are painted in a brighter color than background colors: 2) the lane direction changes very smoothly and lanes are locally straight and parallel (Lee *et al.*, 2001). The CDF in particular implies the information related to lane direction. Therefore, we can obtain useful information for the decision of road image quality from the CDF. Eventually, the extracted features from the CDF are used as the input for a fuzzy neural network inferring system. Here, FNN takes the roll of a mapping-function in order to decide if a raw image is good or bad. FNN is trained to make this decision by learning. An output of FNN ranging from '1' to '0' determines whether the reliable extraction of lane information from an input image is possible or not. An FNN output of '0' means the input image is bad, whereas an FNN output of '1' means the input image is good.

3. STRUCTURE AND LEARNING OF FNN

3.1. Structure of FNN

A fuzzy neural network is a fuzzy system that is trained by a learning algorithm derived from the neural network theory. The configuration of the proposed FNN is shown in Figure 2 (Horikawa *et al.*, 1992). The FNN realizes a simplified fuzzy inference in which the consequences are described with singletons. The back propagation (BP) algorithm can be applied for adjusting the weights in the

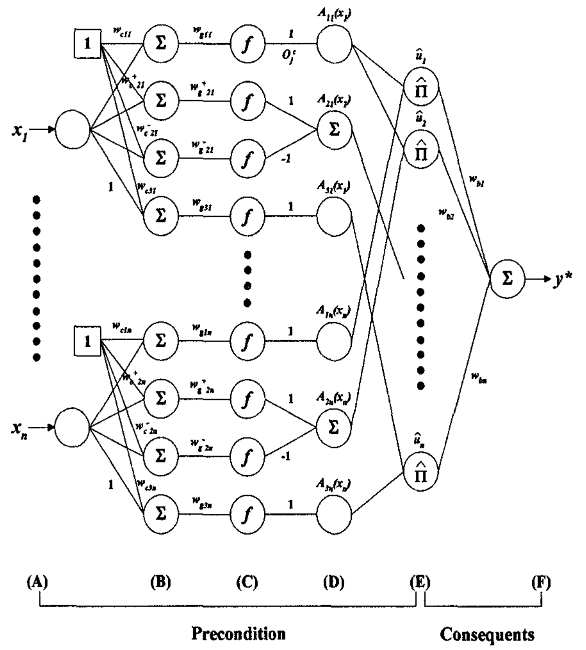


Figure 2. Structure of FNN.

neural networks. The input of FNN to determine the image quality consists of ten feature parameters derived from the CDF. There are three fuzzy variables: – "good", "shady", and "bad" – and there is one output.

In Figure 2, the unit $\boxed{1}$ is a bias unit with constant value '1', and the unit with the symbol '*f*' uses a sigmoid function that has the ability to approximate a certain nonlinear function because the sigmoid function asymmetrically adjusts the shape of membership functions (Lin and Lee, 1996; Horikawa *et al.*, 1992). Hence, using connection weights w_c and w_g, the output of a unit in (C)-layer O_j^c is given by

$$O_j^c = \frac{1}{1 + \exp\{-w_g(x_j + w_c)\}}, \tag{1}$$

where w_c and w_g determine the central positions and gradients of the sigmoid membership functions from the units in (C)-layer, respectively.

A simplified fuzzy rule is expressed as the following fuzzy implication:

R^i: *IF* x_1 is A_{i1} *AND* ... *AND* x_n is A_{in}
THEN y_i is w_{bi} (i=1, 2, ..., n)

$$y^* = \frac{\sum_{i=1}^{n} u_i w_{bi}}{\sum_{i=1}^{n} u_i} = \sum_{i=1}^{n} \hat{u}_i w_{bi}, \tag{2}$$

where R^i is the i-th fuzzy rule, x_1, ..., x_n are inputs, A_{i1}, ..., A_{in} are fuzzy variables, y_i is the output of the i-th fuzzy

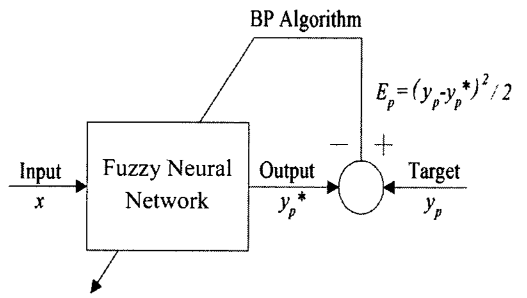


Figure 3. Learning of FNN.

rule, w_{bi} is a constant, and n is the number of fuzzy rules. In addition, u_i is the truth value of R^i and $\hat{u}_i$ is the normalized truth value so that the sum of $\hat{u}_i$ is unity. y^* is the inferred value. The consequence part consists of layers (E) through (F). The inferred value is given as the output of the unit in layer (F), which is the sum of the products of $\hat{u}_i$ and w_{bi}.

3.2. Learning of FNN

The FNN tunes the membership functions on the premises and identifies the fuzzy rules by adjusting the connection weights through the BP algorithm as shown in Figure 3. The connection weights are initialized so that the membership functions on the premises are appropriately allocated to the universe of discourse. The FNN has no rules at the beginning of the learning.

When learning data is given to the FNN, we first define a cost function, which measures the system's performance error by :

$$E_p = \frac{1}{2}(y_p - y_p^*)^2, \tag{3}$$

where y_p is the target value of the p-th learning data, y_p^* is the inferred value of the FNN about y_p.

Then according to the gradient-descent method, the weights are updated by:

$$\begin{aligned}\Delta w_{bi} &= -\eta\frac{\partial E_p}{\partial w_{bi}}\\ &= -\eta\frac{\partial E_p}{\partial y^*}\frac{\partial y^*}{\partial I^F}\frac{\partial I^F}{\partial w_{bi}}\\ &= \eta(y_p - y_p^*)\cdot 1\cdot \hat{u}_i,\end{aligned} \tag{4}$$

where η is a learning rate. And I^F is the sum of the unit in layer (F) as follows:

$$y^* = I^F$$

$$I^F = \sum_{i=1}^{n} w_{bi}\hat{u}_i. \tag{5}$$

Similarly, the updated rate Δw_g, Δw_c of the connection weights w_c, w_g can be obtained by the same method. The updated rate Δw_{g11} is presented as follows:

$$\begin{aligned}\Delta w_{g11} &= -\eta\frac{\partial E_p}{\partial w_{g11}}\\ &= -\eta\frac{\partial E_p}{\partial y^*}\frac{\partial y^*}{\partial I^F}\sum_{k=1}^{19{,}683}\left(\frac{\partial I^F}{\partial \hat{u}_k}\cdot\frac{\partial \hat{u}_k}{\partial I_k^F}\cdot\frac{\partial I_k^E}{\partial A_{11}}\right)\cdot\frac{\partial A_{11}}{\partial w_{g11}}\\ &= \eta(y_p - y_p^*)\cdot 1\cdot\sum_{l=1}^{3}\sum_{m=1}^{3}\sum_{n=1}^{3}\sum_{o=1}^{3}\sum_{p=1}^{3}\sum_{q=1}^{3}\sum_{r=1}^{3}\sum_{s=1}^{3}\\ &\quad\left(w_{bi}\frac{1-\hat{u}_j}{\sum_{i=1}^{19{,}683}u_i}A_{l2}A_{m3}A_{n4}A_{o5}A_{p6}A_{q7}A_{r8}A_{s9}\right)\cdot(x_1 + w_{c11})\\ &\quad\cdot A_{11}(1-A_{11}),\end{aligned} \tag{6}$$

where j is $3^7(l-1)+3^6(m-1)+3^5(n-1)+3^4(o-1)+3^3(p-1)+3^2(q-1)+3^1(r-1)+3^0(s-1)+1$ and I_k^E is the summation of k-th unit in layer (E).

The updated rate Δw_{c11} is presented as follows:

$$\begin{aligned}\Delta w_{c11} &= -\eta\frac{\partial E_p}{\partial w_{c11}}\\ &= \eta(y_p - y_p^*)\cdot 1\cdot\sum_{l=1}^{3}\sum_{m=1}^{3}\sum_{n=1}^{3}\sum_{o=1}^{3}\sum_{p=1}^{3}\sum_{q=1}^{3}\sum_{r=1}^{3}\sum_{s=1}^{3}\\ &\quad\left(w_{bi}\frac{1-\hat{u}_j}{\sum_{i=1}^{19{,}683}u_i}A_{l2}A_{m3}A_{n4}A_{o5}A_{p6}A_{q7}A_{r8}A_{s9}\right)\cdot w_{g11}\\ &\quad\cdot A_{11}(1-A_{11}).\end{aligned} \tag{7}$$

4. EXTRACTION OF FEATURE PARAMETERS

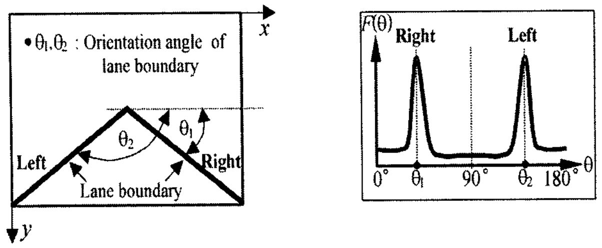
4.1. Constructing the CDF

Extracting the feature parameters of the input to FNN is performed on a CDF, which has been constructed by using edge-related information (Gonzalez and Woods, 1992) as follows:

$$F(\theta) = \sum_{n(\theta)}\nabla f(x, y), \tag{8}$$

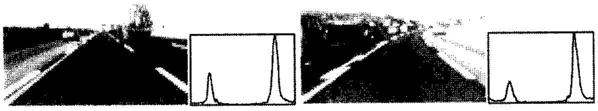
where θ is the orientation of an edge, $\nabla f(x, y)$ is the magnitude of an edge and $n(\theta)$ is the number of pixels with the orientation of θ which is expressed in terms of 1°. Detailed information with respect to the CDF is given by (Lee *et al.*, 2001).

The CDF is the cumulative histogram of the edge magnitude of pixels with same edge orientation. In a road

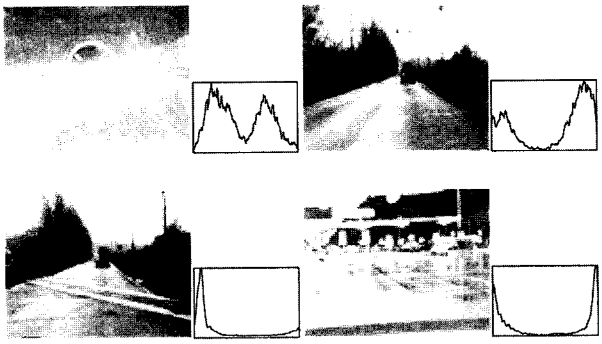


(a) Orientation angle of lane boundary (b) CDF

Figure 4. Lane boundary and CDF.



(a) Images with good visibility of lane marks

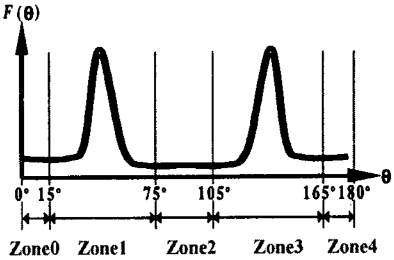


(b) Images with poor visibility of lane marks

Figure 5. Typical road images and their CDF.

image, the pixels from lane boundaries have a larger edge magnitude than other pixels, and almost the same orientation. Therefore, the CDF has a rather large value in the direction corresponding to the lane boundary. As shown in Figure 4(a), suppose that the direction of the right lane boundary corresponds to θ_1 and the left lane boundary corresponds to θ_2. If the CDF is defined in a range of from 0° to 180° then, we have the CDF as shown in Figure 4(b). We can easily see the relationship between the CDF and lane boundary from this figure.

Figure 5 shows typical images and their CDFs for determination of road image quality. It shows CDF with a large value around the direction of lane boundaries because lane boundaries have continuity in orientation without sudden change. The CDF contains much information that can be used for making quality decisions. We can decide if the image can be used for extracting lane-related information or not by analyzing CDF since it describes the orientation of the lane boundary of the input image quite well.



(a)

Zone	Range
Zone0	0~14°
Zone1	15~75°
Zone2	76~104°
Zone3	105~165°
Zone4	166~180°

(b)

Figure 6. Division of the CDF.

4.2. Extracting Feature Parameters

We define the feature parameters used as the input to fuzzy neural network system heuristically in a probability-distributed form by considering the CDF shape. There are ten parameters: nine of them are taken from the CDF, and one is from the intensity distribution of the input images. The CDF was divided into five zones as shown in Figure 6 and nine parameters P_1~P_9 were obtained by analyzing the shape of the CDF in each zone. The CDF has symmetry along an axis. Since the lane is parallel, the shape of the CDF maintains the property of the symmetry for 90° when the vehicle is traveling in the center of the lane. Therefore, we use zone0 to zone2 for extracting the parameters of the right-side lane boundary and zone2 to zone4 for extracting the parameters of the left-side lane mark. The following parameters P_1~P_9 with respect to right-side lane boundary were extracted in the zones of zone0 to zone2. If the value of each of the parameters P_1~P_{10} is close to 0, this means that extracting the lane-related information is possible. However, if the value of each of the parameters P_1~P_{10} is close to 1, this means that extracting the lane-related information is difficult.

We get the feature parameter P_1 by the relative relationship between zone0 and zone1 which is defined as Equation (9).

$$P_1 = 1 - \frac{1}{2}\left\{\frac{(\mu_1 + \sigma_1) - (\mu_0 + \sigma_0)}{(\mu_1 + \sigma_1) + (\mu_0 + \sigma_0)} + 1\right\}, \tag{9}$$

where μ is the mean of the CDF, σ is the standard deviation, and the subscripts, '0' and '1', stand for the zone number of the CDF.

Zone0, which is not expected to have edge information related to lane marks, and zone1, which is expected to have edge information related to lane marks, are compared to each other. If zone0 has a larger value than zone1, this means that the input image may have poor quality. For example, the track of a worn-out road surface, the cross road of a railway, an access road to highway tollgates, and roads with ambiguous lane marks, are all cases where strong edge information can be detected at the zone0. In such cases, we expect there would be no edge information.

As shown in Figure 7, however, in the case of multiple lane detections, the CDF is shaped with multiple peaks (Local Maximum Point, LMP). In Figure 7, P_1 approaches '1', which is a sign of poor quality of the raw image. To compensate for this problem we define additional parameters, P_2 as in Equation (10) and P_3 as in Equation (11). Unlike P_1, P_2 and P_3 give desired values even with multiple lane detections only if the subject lane has enough strong edge information.

$$P_2=1-\frac{1}{2}\left\{\frac{u_1+u_0}{u_1+u_0}+1\right\}, \tag{10}$$

where

$$u_o=\frac{\sum_{\theta\in\Re_0}F(\theta)}{\|\Re_0\|},\ \Re_0=\{\theta|F(\theta)>\mu_1,\ 0\le\theta\le 14\}.$$

$$u_1=\frac{\sum_{\theta\in\Re_1}F(\theta)}{\|\Re_1\|},\ \Re_1=\{\theta|F(\theta)>\mu_1,\ 15\le\theta\le 75\}.$$

$$P_3=1-\frac{1}{2}\left\{\frac{Si_1-Si_0}{Si_1+Si_0}+1\right\}, \tag{11}$$

where

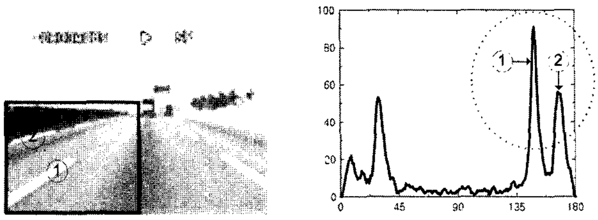
$$Si_0=\frac{\sum_{\theta\in\Re_1'}F(\theta)}{\|\Re_0'\|},\Re_0'=\{\theta|F(\theta)>\mu_1+\sigma_1,\ 0\le\theta\le 14\}$$

$$Si_1=\frac{\sum_{\theta\in\Re_1'}F(\theta)}{\|\Re_1'\|},\Re_1'=\{\theta|F(\theta)>\mu_1+\sigma_1,15\le\theta\le 75\},$$

in which $\|\ \|$ represents the number of elements of a set.

Feature parameter P_4 is obtained from relative relationship among zone1, zone2 and zone3. It is defined as follows:

$$P_4=\frac{u_1+u_3-u_2}{u_1+u_3+u_2}, \tag{12}$$



(a) Input image (b) CDF

Figure 7. Road image with multiple lane detection and its CDF.

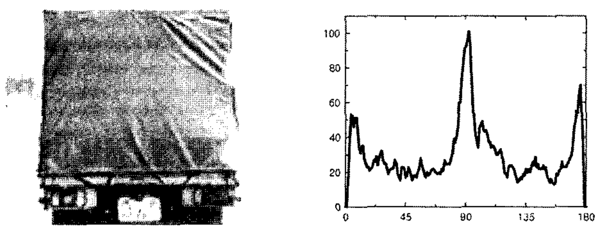
where

$$u_2=\frac{u'+u''}{2}$$

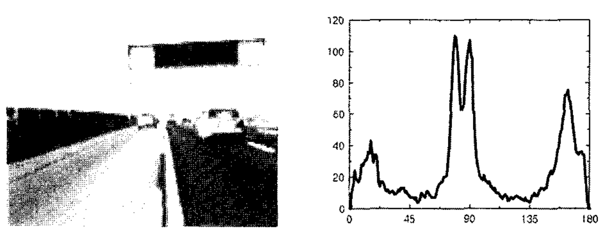
$$u'=\frac{\sum_{\theta\in\Re'}F(\theta)}{\|\Re'\|},\Re'=\{\theta|F(\theta)>\mu_1,76\le\theta\le 90\}$$

$$u''=\frac{\sum_{\theta\in\Re''}F(\theta)}{\|\Re''\|},\Re''=\{\theta|F(\theta)>\mu_3,91\le\theta\le 104\}.$$

P_4 is defined in order to determine whether the value of the CDF of zone2 is bigger than that of zone1 or zone3, which happens when the lane mark is occluded by a vehicle in front as shown in Figure 8(a), or when there is a mark similar to the lane marks at the part around the center of lane. A similar situation could also happen when the centerline of a car body is almost aligned with the lane boundary as shown in Figure 8(b). In the latter case, the CDF shape is very similar to the former case where the lane is occluded by a vehicle in front.

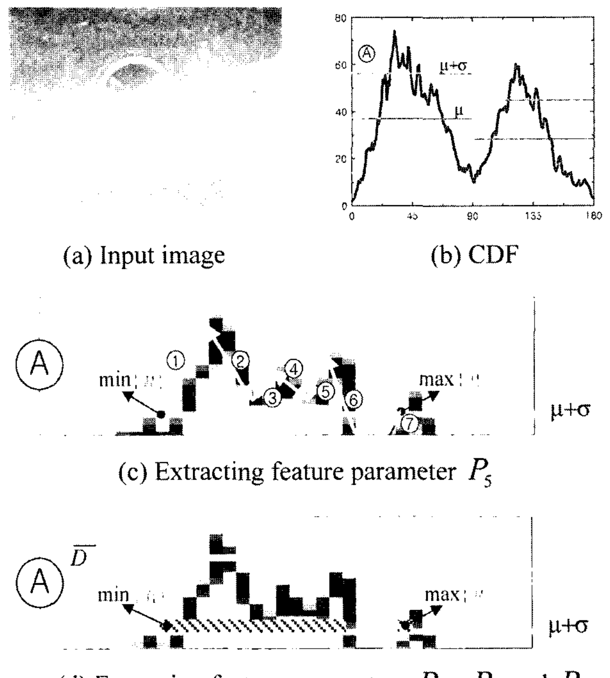


(a) Road image with occlusion and its CDF



(b) Road image with lane change and its CDF

Figure 8. Road images with occlusion and lane change and their CDF.



(a) Input image (b) CDF

(c) Extracting feature parameter P_5

(d) Extracting feature parameters P_6, P_7 and P_9

Figure 9. Extracting feature parameters.

Therefore, it is rather difficult to distinguish each of these with the parameter P_4. Consequently, we eliminate this latter situation from construction of the learning data of FNN because this latter situation not only rarely occurs, but is also easily noticed in advance as lane-changing.

Feature parameters $P_5 \sim P_9$ are parameters representing noise figures of a raw image by analyzing the shape of the CDF at zone1 or zone3. Figure 9(a) shows an image with somewhat high noise and Figure 9(b) is the CDF of the image. Figure 9(c) is a zoomed-out picture of part Ⓐ of Figure 9(b). Figure 9(c) shows that the curve of the function is not very even because of noise. P_5 represents evenness of the function and is defined as follows:

$$P_5 = \frac{Freq_{updown}}{\max\{\Re\} - \min\{\Re\} + 1}, \tag{13}$$

where

$$\Re = \{\theta | F(\theta) > \mu_1 + \sigma_1,\ 15 \le \theta \le 75\}$$
$$\max\{\Re\} = \max_{\theta} \{\Re\}$$
$$\min\{\Re\} = \min_{\theta} \{\Re\}.$$

In Equation (13), $Freq_{updown}$ is the number of fluctuations of the function between $\min\{\Re\}$ and $\max\{\Re\}$. It is the same as the number of arrows in Figure 9(c). Therefore, P_5 cannot be zero, but it is regarded as good if it is near zero.

Feature parameter P_6 is defined in Equation (14) on the supposition that there will be many points crossing the line of $\mu+\sigma$ between $\min\{\Re\}$ and $\max\{\Re\}$ when the input image has poor quality.

$$P_6 = 1 - \frac{\|\Re\|}{\max\{\Re\} - \min\{\Re\} + 1}, \tag{14}$$

where $\|\Re\|$ is the number of elements of the set, the part of the oblique line in Figure 9(d).

If there are many points crossing the line of $\mu+\sigma$ between $\min\{\Re\}$ and $\max\{\Re\}$, this means that there is a large possibility of the existence of other noisy objects in the image besides the lane marks. P_6 is the parameter for expressing this situation.

Feature parameter P_7 is defined in Equation (15) on the supposition that the poor input image makes a wide gap between $\min\{\Re\}$ and $\max\{\Re\}$.

$$P_7 = \frac{\mathrm{mix}\{\Re\} - \min\{\Re\} + 1}{w}, \tag{15}$$

where w is the range of zone1 which is 61 obtained from 75-15+1.

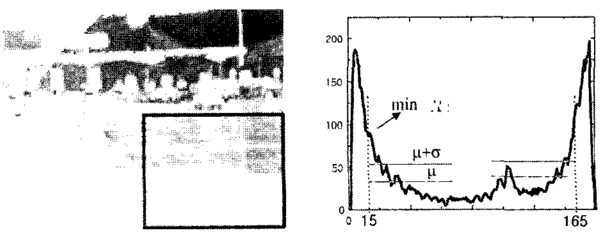
As shown in Figure 9(d), the wider the gap between $\min\{\Re\}$ and $\max\{\Re\}$, the poorer the road image; and the narrower the gap, the sharper the CDF, which makes it easy to distinguish the lane marks.

Feature parameter P_8 is defined in Equation (16) on the supposition that if $\min\{\Re\}$ is below 15°, then a large value of the CDF exists in zone0 in which there is no edge information with respect to a lane mark. In such a situation, discrimination of lane marks is difficult.

$$P_8 = \begin{cases} 1, & if \min\{\Re\} - 15 \le 1 \\ 0, & otherwise \end{cases}. \tag{16}$$

In Figure 10(a) which presents a tollgate entry image, we can see that there is a lot of noise. Figure 10(b) shows that $\min\{\Re\}$ exists in zone0.

Feature parameter P_9 is defined in Equation (17), on the supposition that if the input image is poor, there is a small difference between the average μ and the maximum value of CDF (denoted by $\overline{D}$ in Figure 9(d)).



(a) Input image (b) CDF

Figure 10. Tollgate entry image and its CDF.

$$P_9 = \frac{\mu_1}{\bar{D}}, \tag{17}$$

where $\bar{D}$ is taken by the average of the largest five values of the CDF in zone1.

On the supposition that it is relatively difficult to discriminate between lane marks and road surface when the intensity is saturated, the feature parameter P_{10} is derived from the intensity distribution of input road images and is defined as

$$P_{10} = \frac{\frac{1}{n}\sum_{i=1}^{n} f(x, y)}{255}, \tag{18}$$

where $f(x, y)$ presents the intensity of the input image, and n is the number of pixels within the region of interest which is explained in detail by (Lee, 2002).

4.3. Correlation Evaluation of Feature Parameters

To evaluate the effectiveness of the feature parameters as the input to FNN, we applied 400 road images with the following various conditions: corrupted road-surfaces (for example, worn paint marks), marks covered by dust or mud, heavy shadows, letters and arrow marks on the road surface, various weather conditions, illumination change (for example, darkness), and various types of road, like narrow, wide, curved, straight, inclined, declin-

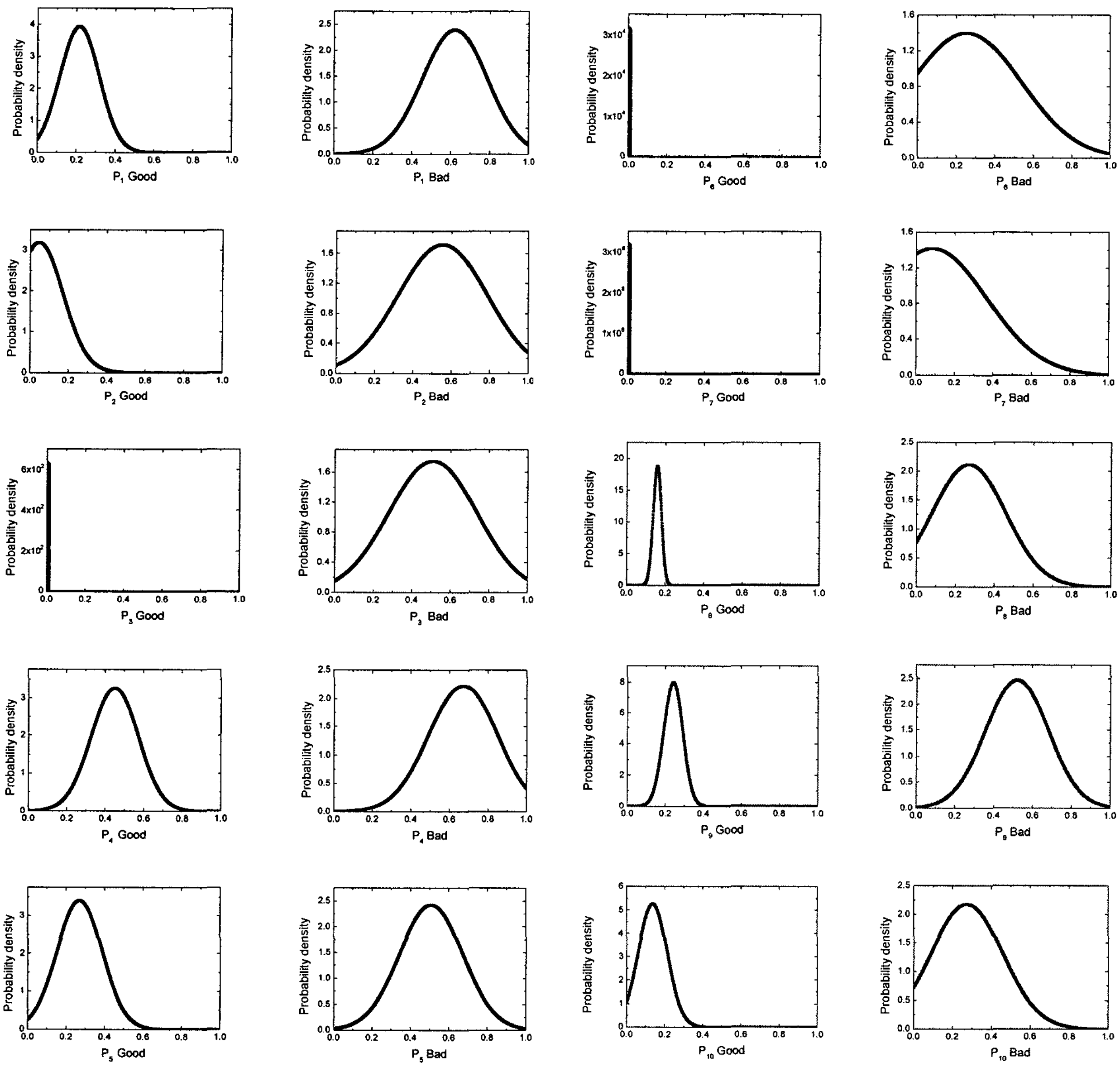


Figure 11. Probability distribution of feature parameters.

ed, tunnel, etc. The determination of image quality from input images depended on human visual judgment. The sample images were viewed by 3 or 4 people who judged the image quality based on the lane marks in the images. The image quality results and the correlation relationship of feature parameters P_1~P_{10} are presented in Figure 11.

Through the distributions of feature parameters P_1~P_{10} as shown in Figure 11, we confirmed that these distributions could be used to make the distinction between good and bad road images. Therefore, reliable information can be supplied to us by determination of image quality using the feature parameters P_1~P_{10} derived from the CDF and the intensity distribution.

5. EXPERIMENTAL RESULTS

5.1. Learning Result of FNN

If the number of input to FNN is increased, the connection weights are also geometrically increased, which eventually leads to an increasing difficulty in learning and calculation time. Therefore, we implemented the FNN with three types of input, considering real-time processing, judging capability, and the cost of implementing hardware for an application system of lane-related information in the future. Each of the three types is shown in Table 1.

As shown in Table 1, structure 1 of the FNN has five inputs which are the feature parameters P_5~P_9 derived from the shape of the CDF in zone1 or zone3, in which the possibility of the existence of edge information related to lane marks is high. Structure 2 has seven inputs which are the same parameters as structure 1 plus the feature parameter P_4 which discriminates occluded lanes and P_{10} derived from the intensity distribution of the input images. Structure 3 has nine inputs composed of nine parameters of the ten parameters, P_1~P_{10}, in which P_8 is excluded because P_1~P_3 play the role of P_8.

The input images from which the FNN learns consists of 200 frames of selected images of various road images, composed of good images (32.7%), shady images (43.7%), and bad images (23.6%). This classification was carried out by human visual judgment. The learning error was evaluated by Equation (19). The error is the accumulative summation of the difference between inferred values and target values. For each structure shown in Table 1, the resulting errors were 0.0824225, 0.0821424, and 0.0866539, respectively.

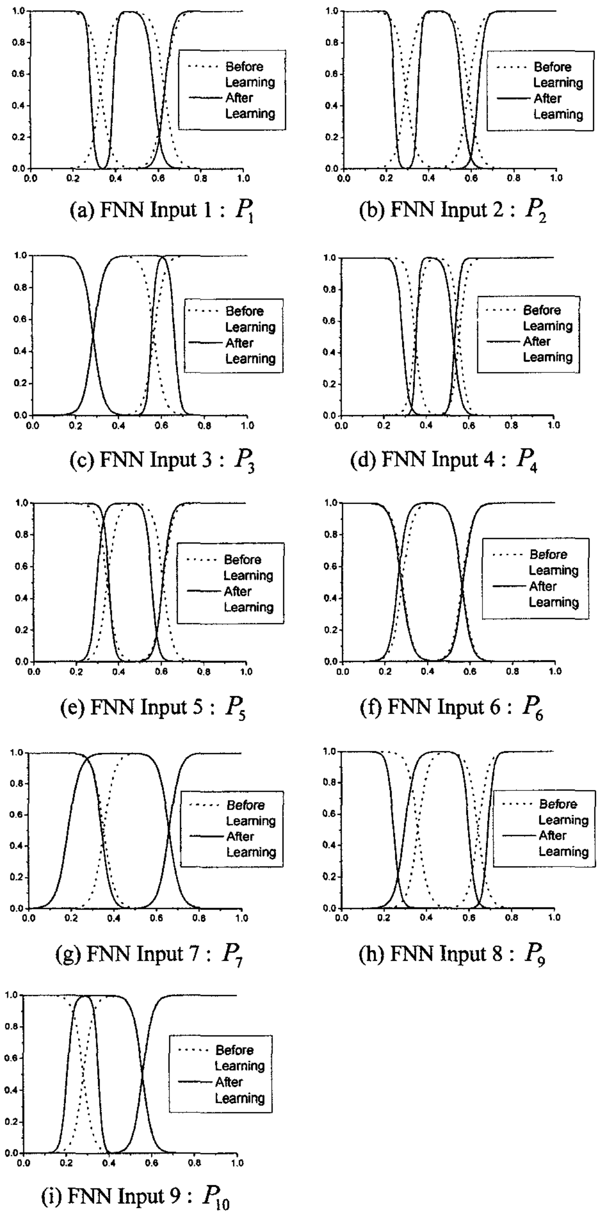
$$E=\sum_p E_p, \qquad (19)$$

where p is the number of input patterns used for learning.

Figure 12 represents the learning result of FNN in the case of structure 3 of the nine inputs. The membership function of fuzzy variables by initial connection weights is represented by the dotted line, and the membership function after learning is represented by the solid line. The connection weights of consequent of Figure 2 are

Table 1. Input number and structure of FNN.

Structure of FNN	Input number of FNN	Feature parameters
Case 1	5	P_5~P_9
Case 2	7	P_4~P_{10}
Case 3	9	P_1~P_7, P_9, P_{10}



(a) FNN Input 1 : P_1 (b) FNN Input 2 : P_2 (c) FNN Input 3 : P_3 (d) FNN Input 4 : P_4 (e) FNN Input 5 : P_5 (f) FNN Input 6 : P_6 (g) FNN Input 7 : P_7 (h) FNN Input 8 : P_9 (i) FNN Input 9 : P_{10}

Figure 12. Learning results of FNN.

Table 2. Experimental results of the determination of image quality.

Experimental image "Good" : 4,287 frame						
Input number of FNN	Normal decision of FNN		Fault decision of FNN			
	Good		Shade		Bad	
	Frame number	Decision rate	Frame number	Decision rate	Frame number	Decision rate
5	3,875	90.4%	176	4.1%	236	5.5%
7	3,905	91.1%	210	4.9%	172	4.0%
9	4,248	99.1%	39	0.9%	0	0.0%
Experimental image "Shade" : 2,768 frame						
Input number of FNN	Normal decision of FNN		Fault decision of FNN			
	Shade		Good		Bad	
	Frame number	Decision rate	Frame number	Decision rate	Frame number	Decision rate
5	2,358	85.2%	183	6.6%	227	8.2%
7	2,596	93.8%	103	3.7%	69	2.5%
9	2,751	99.4%	17	0.6%	0	0.0%
Experimental image "Bad" : 1,676 frame						
Input number of FNN	Normal decision of FNN		Fault decision of FNN			
	Bad		Good		Shade	
	Frame number	Decision rate	Frame number	Decision rate	Frame number	Decision rate
5	1,502	89.6%	72	4.3%	102	6.1%
7	1,582	94.4%	37	2.2%	57	3.4%
9	1,676	100.0%	0	0.0%	0	0.0%

initially set to zero and then, learning is carried out.

5.2. Image Quality Determination Results

A number of experiments have been conducted to determine road image quality. In this experiment, we did not use the images used in the learning of FNN. The total number of images used in this experiment was 8,732 which were classified as follows: good images 49.1%, shady images 31.7%, and bad images 19.2%. For each type of structure shown in Table 1, the results of the tests are shown in Table 2.

Through these experiments, we obtained the good results of 88.4% in structure 1 with five input parameters, 93.1% in structure 2 with seven input parameters, and 99.5% in structure 3 with nine input parameters. Therefore, we concluded that the judging ability of the FNN increased according to the expansion of the number of input parameters. These results also prove that the feature parameters defined by the CDF and intensity distribution are strongly related to image quality. However, the complexity of structure increases as the number of input factors to FNN are increases. Therefore, structure 3 with nine parameters requires a lot of time to be learned.

In the cases of 5 and 7 input parameters, we were given erroneous decisions. For example, images that were judged as bad by human visual function were determined to be shady or good images by the FNN, and images that were judged as shady and good were determined to be bad images by the FNN. This was due to the insufficiency in characterizing the various shapes of the CDF which were derived from real road images by 5 and 7 input parameters that were selected to reduce learning and calculation time. However, in the case of 9 input parameters, we obtained 100% discrimination ability for bad images. This means that these parameters give enough information for determining image quality. As a mapping function for the determination of image quality, the FNN was effective and displayed intelligent performance ability.

6. CONCLUSION

In this paper, we presented a FNN to determine image quality using the feature parameters taken by the CDF. A FNN is a fuzzy system that is trained by a learning algorithm derived from the neural network theory. The learning ability of a neural network can cope with various and dynamic road environments.

Considering real time processing and effective estimation, we designed models of three types and tested these models in this experiment. The results are shown in this paper. These models have the same number of fuzzy variables and output parameters, but are different in the number of input parameters. For each model, numbers of input parameters were 5, 7, and 9, respectively. In addition, there were three fuzzy variables and one output parameter.

The total number of the feature parameters used for the input of the FNN was 10. Nine among them could be obtained from the CDF and the remaining one from the intensity distribution of input images. We could confirm that the derived feature parameters were strongly related to image quality by the experiment, and that the feature parameters were factors that recognized whether road images were good or not, through correlation analysis.

From the experiment with various road images, we obtained a determination ability of over 99%. This means that the FNN presented in this paper was effective and displayed intelligent performance ability. Furthermore, we concluded that the judging ability of the FNN also increased according to the expansion of the input numbers.

In the future, research on the practical application of the results derived from this study must conduct and be applied to the creation of a lane departure warning and prevention system. The system proposed in this paper could not only be applied to image processing of road environments but also to various pattern classifications or recognition systems.

ACKNOWLEDGEMENT–This work was supported by grant no. R05-2004-000-16067-0 from the Korea Science & Engineering Foundation.

REFERENCES

Aoki, M. (1998). Image processing in ITS. *Proc. IEEE Intelligent Vehicles '98*, Germany, 1–4.

Bertozzi, M. Broggi, A. and Fascioli, A. (2000). Vision-based intelligent vehicles: State of the art and perspectives. *Robotics and Autonomous Systems* **32**, 1–16.

Duda, R. O. and Hart, P. E. (1973). *Pattern Classification and Scene Analysis*. Jone Wiley & Sons. New York.

Gonzalez, R. G. and Woods, R. E. (1992). *Digital Image Processing*. Addison-Wesley. Reading. Massachusetts.

Horikawa, S. Furuhashi, T. and Uchikawa, Y. (1992). On fuzzy modeling using fuzzy neural networks with the back-propagation algorithm. *IEEE Trans. Neural Networks* **3, 5,** 801–806.

Lee, J. W. Kim, K. S. Jeong, S. S. and Jeon, Y. W. (2000). Lane departure warning system: Its logic and on-board equipment (20005331). *Proc. JSAE*, Japan, 9-11.

Kreucher, C. and Lakshmanan, S. (1999). A frequency domain approach to lane detection on roadway images. *Proc. 1999 Int. Conf. on Image Processing* **2**, 31–35.

Lee, J. W. (2002). A machine vision system for lane-departure detection. *CVIU* **86, 1,** 52–78.

Lee, J. W., Yi, U. K. and Baek, K. R. (2001). A cumulative distribution function of edge direction for road-lane detection. *IEICE Trans. Information and Systems* **E84-D, 9,** 1206–1216.

Lin, C. T. and Lee, C. S. G. (1996). *Neural Fuzzy Systems*. Prentice Hall. New Jersey.

Maki, Y. and Laparo, K. A. (1997). A neural-network approach to fault detection and diagnosis in industrial process. *IEEE Trans. on Control Systems* **5, 6,** 529–541.

Ozawa, S. (1999). Image processing for intelligent transport systems. *IEICE Trans. Information and Systems* **E82-D**, **3**, 629–636.

Takahashi, A. Ninomiya, Y. Ohta, M. and Tange, K. (1999). A robust lane detection using real-time voting processor. *Proc. IEEE/IEEJ/JSAI Int. Conf. on Intelligent Transportation Systems*, 577–580.