칼라스케치 특징점 추출을 위한 퍼지 멤버쉽 함수의 신경회로망 학습

조 성 목*, 조 옥 래**

An Artificial Neural Network Learning Fuzzy Membership Functions for Extracting Color Sketch Features

Sung-Mok Cho*, Ok-Lae Cho**

요 약

본 논문에서는 칼라 영상의 스케치 특징점을 추출하기 위해 퍼지신경회로망을 이용하는 방법에 대하여 설명한다. 이 신경회로망은 스케치 특징점 추출을 위한 퍼지 소속함수를 학습시킴으로써 적절한 국부 임계치를 획득할 수 있도록 구성된다. 제안한 퍼지신경회로망의 입출력 소속함수는 표준영상으로부터 추출된 최적의 특징점 추출결과를 기반으로 구성하여 학습 데이타로 사용된다. 학습에 사용된 퍼지입력변수는 디지털 영상에서의 특징점 추출 시 국부영역 밝기를 잘 반영할 뿐만 아니라 특징점 추출성능이 매우 우수한 특성이 있으며, 이들 입력변수의 소속함수를 신경회로망으로 학습시킴으로써 매우 효과적이고 신속하게 스케치 특징점들을 추출할 수 있다. 실험결과, 소속함수로 학습된 신경회로망으로부터 얻어진 임계치를 사용한 특징점 추출이 다양한 영상에 대하여 매우 우수함을 보였다.

Abstract

This paper describes the technique which utilizes a fuzzy neural network to sketch feature extraction in digital images. We configure an artificial neural network and make it learn fuzzy membership functions to decide a local threshold applying to sketch feature extraction. To do this, we put the learning data which is membership functions generated based on optimal feature map of a few standard images into the artificial neural network. The proposed technique extracts sketch features in an image very effectively and rapidly because the input fuzzy variable have some desirable characteristics for feature extraction such as dependency of local intensity and excellent performance and the proposed fuzzy neural network is learned from their membership functions, We show that the fuzzy neural network has a good performance in extracting sketch features without human intervention.

▶ Keyword : Artificial Neural Network, Membership Function, Sketch Feature, Local Threshold

Ⅰ. 서 론

In case of projection of object space with non-uniform reflection, the features called edges occur at points which have abrupt changes in luminance and in case of projection of object space with uniform reflectance, the features called at points which have local luminance minima call valleys. Feature extraction is a technique used in image pre-processing for image enhancement, for pattern recognition or for motion video transmission by reducing an image to show only its feature details. There have been developed many filters such as Sobel, Kirsh and Robinson filters for the purpose of extracting image features efficiently.[1-3] However, an observer's feeling associated with the features in an image is more sensitive to dark regions than to bright regions, and many filters including the above filters are usually not efficient to extract the significant features as perceived by human beings. In this paper, we show that our gradient represented by the different between the arithmetic mean and the harmonic mean in a 3×3 window generates a feature extraction method which creates feature images clearer than those by other method.[4] This gradient filter has some advantages, for example simple computation, dependence on local intensities and less sensitive to small intensity changes in very dark regions.

Basically, the idea underlying most feature extraction techniques is the computation of a local derivative operator and the selection of a threshold.[2] However, the establishment of a threshold for extracting features may be viewed as an operation that involves in trials and errors test because an optimal threshold depend on image contents. And due to the complexity of the physical objects and of the imaging apparatus, and to multiple sources of noise, the signal to be processed is complex, and the selection of the threshold which we use to extract meaningful intensity discontinuities

is non trivial. Besides, human visual system has visual increment thresholds and converges asymptotically from the De Vries_Rose region to the Weber region as intensity increases[5]. Therefore, a good thresholding technique should match the above mentioned human psychovisual phenomena as closely as possible. In this paper, we introduce fuzzy measures and present their fuzzy membership function for a threshold selection in order to extract features in images. And using the method of trial and error, we tune the membership function of the fuzzy reasoning which evaluates a local threshold for feature configurations. Finally, we put the membership functions which is generated for the learning data into the neural network. We will show that the artificial neural network which is learned by the fuzzy membership functions provide a local threshold for feature extraction in an image without any human interventions.

Ⅱ. Feature Extracting Filters

Several convolutional filters have been emerged to improve the performance of the sketch feature extraction in images. The operators presented by Van Vliet et al. relate closely to the morphological gradient operator[6] and the implementation of these operators is very easy. The nonlinear gradient operator is relatively insensitive to noise and granularity but it extracts ramp edges often existing in real images as thick lines and does not depend on local intensities. The nonlinear gradient operator, NG, is defined as follows:

$$NG(i,j) = f_{\max}(i,j) - f(i,j), \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (1)$$

where fmax(i,j) denotes the maximum intensity and f(i,j) the center-pixel intensity in a window. The Laplacian edge operator produces a zero crossing at an edge location. It detects high frequency details accurately and its implementation is facilitated, but it is generally more sensitive to

noise than other operators. This defect can be overcome to some extent by adopting its nonlinear versions. The nonlinear Laplacian, NL, is defined by the second-order derivatives as follows:

$$NL(i,j) = f_{\max}(i,j) + f_{\min}(i,j) - 2f(i,j), \quad \cdots\cdots\cdots\cdots (2)$$

where fmin(i,j) denotes the minimum intensity in a window. The shifting effect of the edge locations which occurs in the nonlinear gradient operator does not occur in the nonlinear Laplacian because of its second-order derivatives. However, the nonlinear Laplacian does not depend on local intensities and creates several false edges, especially in the areas where the image variance is small, because small intensity perturbations tend to produce false zero-crossings.

The logical Laplacian operator, LL, is defined in a 3×3 window as follows:

$$
\begin{aligned}
LL(i,j) = & L_1[f(i-1,j-1) - f(i,j)] \quad \cdots\cdots\cdots\cdots (3) \\
& + L_2[f(i-1,j) - f(i,j)] \\
& + L_1[f(i-1,j+1) - f(i,j)] \\
& + L_2[f(i,j-1) - f(i,j)] \\
& + L_2[f(i,j+1) - f(i,j)] \\
& + L_1[f(i+1,j-1) - f(i,j)] \\
& + L_2[f(i+1,j) - f(i,j)] \\
& + L_1[f(i+1,j+1) - f(i,j)],
\end{aligned}
$$

where L1(x) and L2(x) are nonlinear accelerated type functions for rejecting small differences and amplifying large differences. The logical Laplacian is less sensitive to noise than any other versions of the Laplacian but it also does not depend on local intensities.

The entropy operator, H, calculates the entropy at a center-pixel in a 3×3 window as follows.

$$H(i,j) = -\sum_{i=-1}^{1}\sum_{j=-1}^{1} p_{i\,j}\log p_{i\,j}/\log 9, \quad \cdots\cdots\cdots\cdots (4)$$

,where

$$p_{i\,j} = f(i,j) \,\Big/ \sum_{i=-1}^{1}\sum_{j=-1}^{1} f(i,j). \quad \cdots\cdots\cdots\cdots (5)$$

The entropy operator extracts the features of dark regions quite well because of its dependence on local intensities. However, the features are extracted as thick lines since it weights all pixels uniformly within the local region. It is noted that the entropy operator needs a large amount of computation due to the logarithmic operation.

On the other hand, an approximation of the visual increment threshold was proposed by Kundu et al[5]. They pointed out that the perceived intensity of a surface depends on its local intensities and classified the visual increment threshold differently according to the De Vries-Rose region, the Weber region and the saturation region as a function of local intensity. The visual increment thresholds in each region were proposed as follows:

$$
\Delta B_T = \begin{cases} K_1\sqrt{B}, & \textit{De Vries}-\textit{Rose region,} \\ K_2 B, & \textit{Weber region,} \\ K_3 B^2, & \textit{saturation region,} \end{cases} \quad \cdots\cdots (6)
$$

,where ΔB_T, B, K1, K2, and K3 denote the visual increment threshold, local intensity and constants of the corresponding regions respectively.

As reviewed in the above, the presently existing convolutional filters possess their shortcomings for extracting sketch features since they either do not consider local intensities or have some problems such as computational time and sensitivities in dark regions. We will show that our filter named DBAH is well appropriate for the effective extraction of sketch features similar to the human psychovisual phenomena.[4] The DBAH convolutional filter calculates the difference between the arithmetic mean and the harmonic mean using the selected two pixel in window. The DBAH filter uses the maximum intensity pixel value $f_{\max}$ and the center-pixel intensity value f_{cen} in a window, which is defined as follows:

$$DBAH(i,j) = \frac{f_{\max} + f(i,j)}{2} - \frac{2f_{\max}f(i,j)}{f_{\max} + f(i,j)} \quad \cdots\cdots\cdots (7)$$

The above DBAH convolutional filter tends to become larger for the greater intensity change. This tendency is the result that the arithmetic mean increases linearly but the harmonic mean approaches to the center pixel intensity with higher rate as the difference between the maximum and center pixel intensities increases. And the DBAH filter is apt to be larger in the dark region for the same intensity change rate. This tendency is the result that the arithmetic mean decreases linearly but the harmonic mean approaches more rapidly and closely to the center pixel intensity for the lower sum of the selected the pixel intensity values. As a result, the DBAH filter tends to become larger for the greater difference between these two intensities and is apt to be higher in the dark region where the sum of these two intensity values is lower. Moreover, it is noted that the DBAH filter is extremely small in the very dark region because both of the intensities are quite small. The advantages of the DBAH filter discussed so far is that the DBAH filter can take into account the intensity change rates, the local intensities and the very dark regions as well in images, which makes it possible to develope an efficient feature extraction technique akin to the human visual system.

Figure 1 shows the output responses of each convolutional filters to an ideal ramp edge and an ideal valley. The nonlinear gradient and entropy filter exibit a possibility of a thick edge extraction and the entropy filter has a small response in the valley. On the other hand, the DBAH extract edges at the bottom of the ramp but responds very well in the valley.
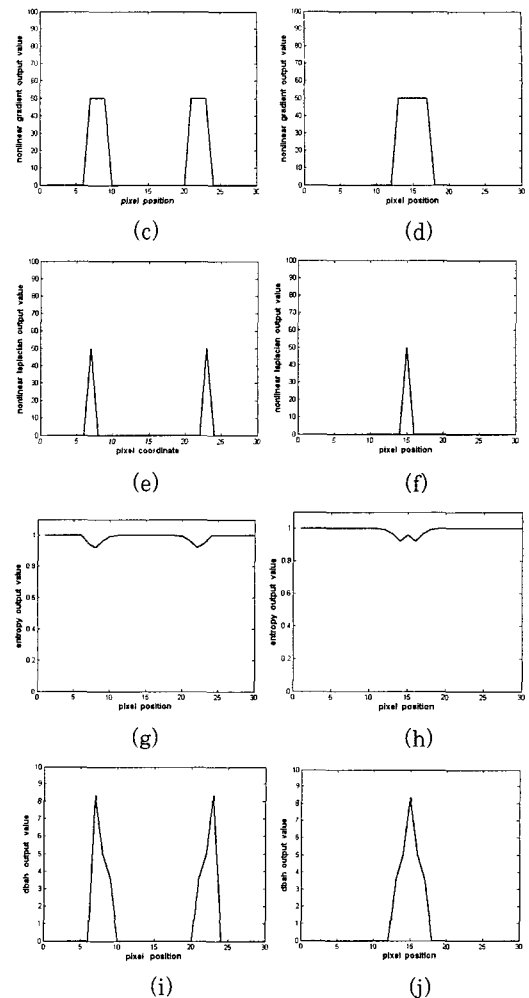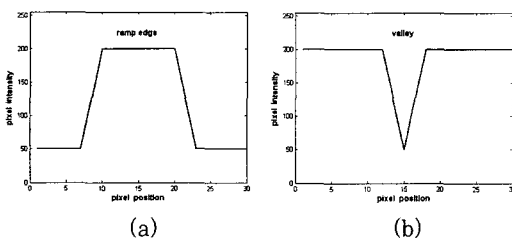
Figure 1. (a) an ideal edge; (b) an ideal valley; (c)-(j) filtered result applying nonlinear gradient, nonlinear laplacian, entropy and DBAH to (a) and (b), respectively.
그림 1. (a) 이상적인 에지; (b) 이상적인 밸리; (c)-(j) 비선형 그레디언트, 비선형 라프라시안, 엔트로피 및 DBAH를 (a)와 (b)에 적용한 결과

Figures 2 (b)-(d) show the transfer characteristic functions of convolutional filters employing to the input which has all possible combination of local intensities and intensity variations in an image (Figure 2(a)); independent of the local intensities (Figure 2(b)), dependent on the local intensities (Figure 2(c), for example entropy convolutional filter) and considered with DBAH (Figure 2(d)). As it is seen in Figure 3, the outputs applying filters

such as nonlinear gradient shows independence of local intensities and the outputs applying the entropy filter could not reveal the reality of images due to extremely high responding value for the small intensity change rates in the very low intensity regions. While the output of the proposed filters as shown in Figure 2(d) agrees quite closely with the perception of human being especially in very dark regions. Therefore, the proposed filters convolutional filter possesses unique advantages over the other convolutional filters for extracting sketch features.
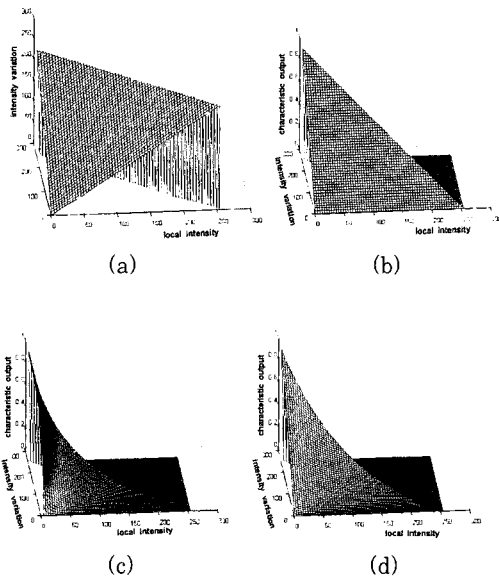

(a)   (b)

(c)   (d)

Figure 2. (a) all possibile combination of local intensities and intensity variations in an image; (b) local intensity independent transfer characteristic function(for example Nonlinear gradient, Nonlinear Laplace convolutional filter); (c) transfer characteristic function of the entropy convolutional filter; (d) transfer characteristic function of the proposed convolutional filters.
그림 2. (a) 영상내의 국부적 밝기와 밝기변화에 대한 모든 가능한 조합; (b) 국부적 밝기변화에 독립적인 전달특성함수(예: 비선형 그레디언트, 비선형 라프라시안); (c) 엔트로피 필터의 전달특성함수 (d) 제안한 필터의 전달특성함수

III. Loacal Thresholds Selection Using Fuzzy Inference System and Their Learning Using Neural Network

In this section, a fuzzy reasoning technique for establishing a local threshold is described. we present a fuzzy inference system and two fuzzy measures in order to use for selecting a threshold which is independent on being processed images.

In general, there have been attempted mode methods, P-tile methods and variable thresholding methods to establish a threshold for features extraction.[7-8] The simplest of all thresholding techniques is to partition the gradient histogram by using a single threshold. However, there are various histogram types according to images and the perception of features by the human visual system is an extremely complex process that is strongly influenced by prior knowledge. So, it is very difficult to select an optimal threshold by mode methods because of a number of histogram types. And in P-tile methods and variable thresholding methods, some prior informations about being processed images are needed for an efficient threshold. Besides, a global threshold method is ineffective to find the features in an image because there exist sketch features over a broad range of intensity distributions in an image and human visual system is more sensitive to features in dark region rather than a bright region. Haralick et al proposed a variable threshold in pixel (i,j) as follows:

$$\theta(i,j) = \frac{\sum_{i=-n}^{n} A(i,j)}{n \times n} (1 + \frac{p}{100}) , \quad \cdots\cdots\cdots\cdots (8)$$

where n×n denotes a window size and p is a probability. The variable threshold using equation (8) reflects local characteristics considerably well but it needs a prior image information because

probability value p should be set differently according to processed images. Kundu etal classified the intensity range of an input image as Devris-Rose region, Weber region and Saturation region. They proposed local thresholds considered not only local intensities but also intensity variations as follows:

$$E(i,j) = 1 \ \ if \ \frac{\Delta B}{\sqrt{B}} \geq K\sqrt{\alpha_2 B_t} \ \ \cdots\cdots\cdots\cdots\cdots (9)$$

$$when \ \alpha_1 B_t \leq B \leq \alpha_2 B_t \ \ or$$

$$if \ \frac{\Delta B}{B} \geq K$$

$$when \ \alpha_2 B_t \leq B \leq \alpha_3 B_t$$

$$if \ \frac{\Delta B}{B^2} \geq \frac{K}{\alpha_3 B_t}$$

$$when \ B \geq \alpha_3 B_t$$

$$E(i,j) = 0 \ otherwise$$

,where

$$B = \sum_{i=-n}^{n} \sum_{j=-n}^{n} \frac{I(i,j)}{n \times n} \ \ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (10)$$

$$\Delta B = |I(i,j) - B|$$

$$0 < \alpha_1, \alpha_2, \alpha_3 < 1$$

$$B_t = I(i,j)_{max} - I(i,j)_{min}$$

$$K = \frac{1}{100} \beta (\frac{\Delta B}{B})_{max}$$

and β is 2 approximately. The above method is very efficient for extracting feature in images but it has 4 parameters which should be set differently according to images.

as reviewed in the above, there is also an ambiguity in the process of selecting a threshold deciding whether a pixel in an image is a feature or not. Hence, in this section we introduce a fuzzy inference system to evaluate local thresholds for extracting image features. The overall process for a color sketch feature map is show in Figure 1.
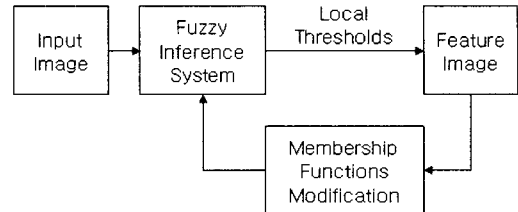

Figure 3. the overall process for color sketch feature map.
그림 3. 칼라 스케치 특징점 맵을 위한 처리과정

To accomplish our goal, the DBAH and DF(Degree of Fuzziness) are used as fuzzy measures for a local threshold decision to extract features in an image. The DF which is the DBAHs' mean in all pixels of a window has some relation with the degree of featureness in a local region. The DF is defined as follows.

$$DF(i,j) = \frac{1}{9} \sum_{l=-1}^{1} \sum_{m=-1}^{1} DBAH(i+l, j+m) \ \cdots\cdots\cdots (11)$$

$$- DBAH(i,j)$$

,where l and m denote the number of pixel rows and pixel columns in a window. However, the values computed by using Eq. (7) and Eq. (11) for local thresholds are very ambiguous and have imprecise boundary, so we represent them as qualitative and linguistic descriptions and define them as fuzzy set with membership functions. We classified DBAH and DF into three fuzzy classes represented by the three fuzzy set values low, medium and high. The fuzzy partitions of input and output spaces which represent the probability of being features and the level of thresholds are shown in Figure 4.
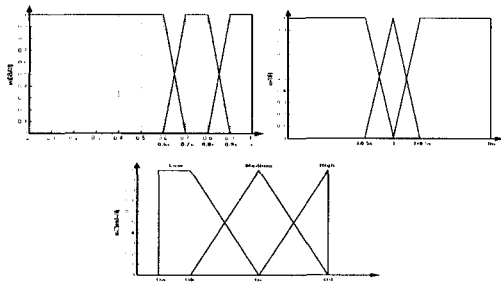
Figure 4. Fuzzy values of fuzzy variables DBAH, DF, and Threshold
그림 4. 퍼지변수 DBAH와 DF의 퍼지값과 임계치

In general, a global threshold for feature extraction is found by a heuristic method. In our case, we chose a value corresponding to upper 15% in the feature strength histogram obtaining from applying DBAH to an input image and made a tuning its membership function by a trials and errors method as shown in Figure 4. In Figure, Oa, Ob, Oc and Od should be set differently according to an in image. We normalized a mean value resulting from applying DBAH to an input image by its standard deviation, and assigned them to values of a mean of DBAHs′, a mean of DBAHs′+1.5, a mean of DBAHs′+2, a mean of DBAHs′+2.5 divided by a standard deviation of DBAHs′, respectively. To achieve our goal for inferencing local thresholds, we established the fuzzy rules for a local threshold evaluation as follows.

Table 1. Fuzzy Rules for Local Thresholds Reasoning.
표 1. 국부 임계치 추론을 위한 퍼지 규칙

DBAH DF	Low	Medium	High
Low	High	High	Medium
Medium	High	Medium	Low
High	Medium	Low	Low

Finally, we make a defuzzification process by using the center of gravity method and establish a feature image. The membership functions are iteratively modified by the method of trial and error until an desirable output image is generated. The finally tuned membership functions are used as the learning data for the artificial neural network which is capable of selecting local thresholds without human intervention.

Now, in order to make a neural network learn the membership functions of fuzzy inference system we propose the artificial neural network shown in Figure 5. The number of input nodes and hidden nodes are equal to the number of fuzzy measures and their membership functions of the fuzzy inference system.
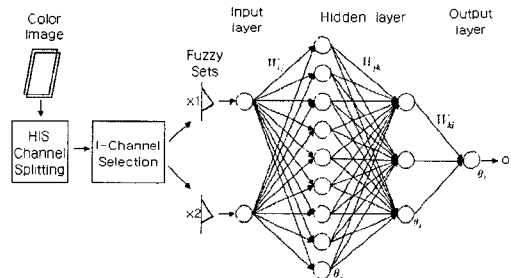

Figure 5. The Neural Network Architecture for Automatic Local Thresholds Decision.
그림 5. 국부임계치 결정을 위한 신경회로망 구조

In this paper, we aim to select local thresholds without human intervention for feature extraction in color images. Hence, we use tuned membership functions generated by the process shown in Figure 3 as inputs of the artificial neural network. The procedure of the proposed learning algorithm is shown as follows:

Step 1 : Generate fuzzy membership functions from the learning images
Step 2 : Initialize connection weights and bias of the artificial neural network
Step 3 : Update connection weights applying learning data to the input of the artificial neural network.

Step 4 : Go to Step 3 until convergence condition is satisfied

The connection weights are determined recursively by the equations 12, 13 and 14, and the appropriate weight changes are made in order to make the value of the equation 16 which is our measure of the error minimize.[9]

$$\delta W_{kl} = -(o-d)f'(\sum_{l=1}^{n}\sum_{k \neq l} W_{kl}z_k - \theta_l) \quad \cdots\cdots\cdots\cdots\cdots (12)$$

$$\delta W_{jk} = -(o-d)f'(\sum_{l=1}^{n}\sum_{k \neq l} W_{kl}z_k - \theta_l) \quad \cdots\cdots\cdots\cdots\cdots (13)$$
$$\times f'(\sum_{k=1}^{n}\sum_{j \neq k} W_{jk}y_j - \theta_k)$$

$$\delta W_{ij} = -(o-d)f'(\sum_{l=1}^{n}\sum_{k \neq l} W_{kl}z_k - \theta_l) \quad \cdots\cdots\cdots\cdots\cdots (14)$$
$$\times f'(\sum_{k=1}^{n}\sum_{j \neq k} W_{jk}y_j - \theta_k)$$
$$\times f'(\sum_{i=1}^{n}\sum_{i \neq j} W_{ij}x_i - \theta_j)$$

where xi, yj, zk, and o are output values for each input unit, hidden unit and output unit respectively and d is the desired output value of the neural network. $f'()$ is the derivative of the activation function in equation 15.

$$f(x) = \frac{1}{1 + e^{-x}} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots (15)$$

$$E = \sum_{l=1}^{n}(o_l - d_l) \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots (16)$$

IV. Performance Results

Figure 6 shows the effectiveness of the fuzzy inference system using DBAH and DF as fuzzy variables in order to extract features in digital images. Figure 6(a) and (b) show the 256 × 256× 8 bits Girl and Lena intensity images. Figure 6(c) and (d) which are the feature images obtained

when applying the above fuzzy inference system to Figure 5(a) and (b), respectively. When our fuzzy membership functions for each local threshold decision are tuned and the magnitude of the DBAH in each pixel is above the inferenced local threshold, we select the pixel as a feature and configure a feature image. One can see from these figures that our method creates feature maps which look detailer than other conventional filter such as nonlinear gradient, nonlinear laplacian, logical laplacian and entropy filter et al. Hence, We used the membership functions which result in generating figure 6(c) and 6(d) as learning data for the propose artificial neural network.

(a)   (b)

(c)   (d)

Figure 6. original images; (a)-(b) and their feature images; (c)-(d) used to generate input and output membership functions for learning the neural network.
그림 6. (a)-(b) 원영상; (c)-(d) 신경회로망 학습용 입출력 멤버쉽 함수의 생성을 위한 특징점 영상

We used figure 7(a), 7(b), 7(c) and 7(d) as input images to evaluate our proposed method. Figure 7(a), 7(b), 7(c) and 7(d) show that the artificial neural network has a good performance in extracting sketch features.
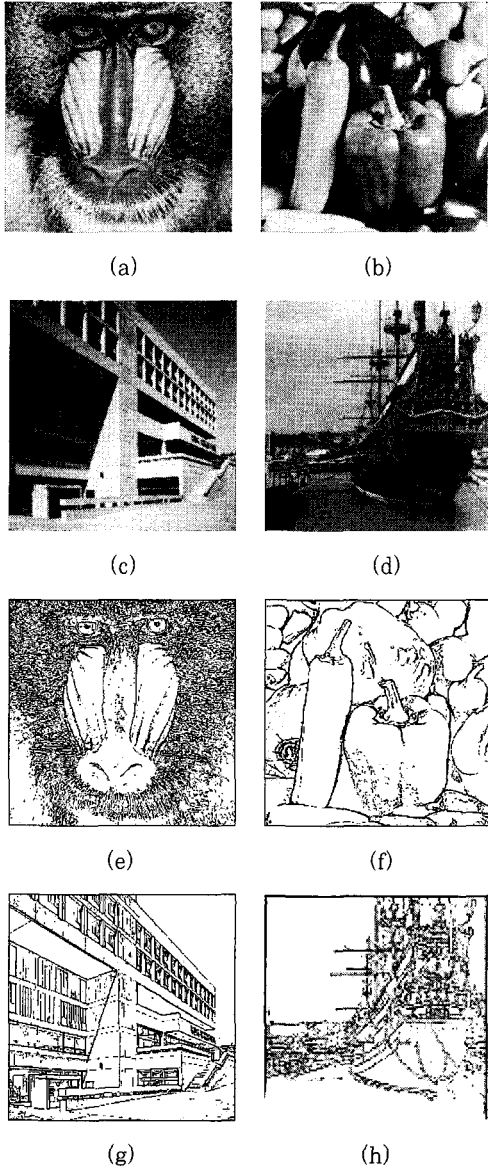
(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

Figure 7. Experimental input images; (a)-(d) and their feature images; (e)-(h) using the proposed method.

그림 7. (a)-(d) 실험을 위한 입력영상; (e)-(h) 제안한 방법을 사용한 특징점 영상

V. Conclusion

We showed that the artificial neural network which is learned by the membership functions can be used for selecting local thresholds. Each local threshold for making a decision of whether a pixel is on a feature may be obtained by making the neural network learn the membership functions which is tuned to learning data. We showed that the fuzzy neural network has a good performance in extracting sketch features without human intervention.

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저 자 소 개

조성목

Sung-Mok Cho
1988. 2. Kyungbook Nat'l Univ.
        Dept. of Electronics (B.S.)
1990. 2. Kyungbook Nat'l Univ.
        Dept. of Electronics (M.S.)
1995년 Kyungbook Nat'l Univ.
        Dept. of Electronics (Ph.D..)
1992. 3. - 2006. 2.
            Tongmyong College
            Full time Lecturer
            -Associate Processor
2006. 3. - Tongmyong Univ.
        Dept. of Information Security
        Assistant Professor
<Area of interest> Image Processing, Fuzzy
                Theory, Neural Network

조옥래

1980. 2. Kyungbook Nat'l Univ.
        Dept. of Statistics (B.S.)
1983. 2. Kyungbook Nat'l Univ.
        Dept. of Statistics (M.S.)
2006년 Kyungbook Nat'l Univ.
        Dept. of Statistics (Ph.D..)
1992. 3. - 2006. 2.
        Tongmyong College
        F.T. Lecturer - Processor
2006. 3. - Tongmyong Univ.
        Dept. of Computer Eng.
        Associate Professor
<Area of interest> Baysian Theory,
                Mobile Computing