A Study on the Recognition of Concrete Cracks using Fuzzy Single Layer Perceptron

Hyun-Jung Park, *Member, KIMICS*

Abstract— In this paper, we proposed the recognition method that automatically extracts cracks from a surface image acquired by a digital camera and recognizes the directions (horizontal, vertical, -45 degree, and 45 degree) of cracks using the fuzzy single layer perceptron. We compensate an effect of light on a concrete surface image by applying the closing operation, which is one of the morphological techniques, extract the edges of cracks by Sobel masking, and binarize the image by applying the iterated binarization technique. Two times of noise reduction are applied to the binary image for effective noise elimination. After the specific regions of cracks are automatically extracted from the preprocessed image by applying Glassfire labeling algorithm to the extracted crack image, the cracks of the specific region are enlarged or reduced to 30x30 pixels and then used as input patterns to the fuzzy single layer perceptron. The experiments using concrete crack images showed that the cracks in the concrete crack images were effectively extracted and the fuzzy single layer perceptron was effective in the recognition of the extracted cracks directions.

Index Terms— Concrete Surface Crack, Glassfire Labeling Algorithm, Fuzzy Single Layer Perceptron,

I. INTRODUCTION

Because the cracks in concrete structures have bad effects on the tolerance, the durability, the waterproof and the appearance of the structures, they bring about some worse problems in the structures. Therefore the causes of cracks must be accurately examined and the durability and the safety of the structures must be evaluated[1,2].

In this paper, we proposed the recognition method, which automatically extracts cracks from a surface image acquired by a digital camera and it also recognizes the directions of the cracks using the fuzzy single layer Perceptron. We compensate an effect of light on a concrete surface image by applying the closing operation, which is one of morphological techniques, extract edges of cracks by Sobel masking, and binarize the image by applying the iterated binarization technique[3]. Two separate times of noise reduction are applied to the binarized image for effective noise elimination. After minute noises are eliminated by using the average of adjacent pixels corresponding to a 3x3 mask, more noises are eliminated by analyzing the regular ratio of length and width with Glassfire labeling algorithm[4]. The specific region of cracks is extracted from the noise-eliminated binarized image.

Manuscript received February 20, 2008; revised May 11, 2008. Hyun-Jung Park with the Dept. of Architectural Engineering, Silla University, Busan, 617-736, Korea (Tel: +82-51-999-5724, Email: phj@silla.ac.kr)

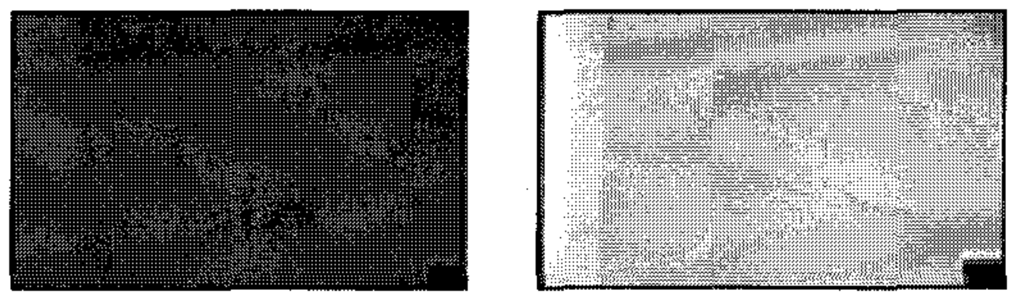
II. CRACK DETECTION

At first, cracks are extracted from a concrete surface image using some image processing techniques, and then, the directions of cracks are automatically recognized by applying the fuzzy single layer perceptron.

The brightness of the background varies according to the direction and the amount of light in an environment when photographing concrete surfaces. Sobel masking, which is sensitive to a value of brightness, cannot extract edges in the dark regions due to the effect of light. Therefore, for compensating effectively an effect of light, we applied the closing operation being one of the morphological techniques. The closing operation performs the dilation operation after the erosion operation. The dilation operation and the erosion operation are as follows:

$$(f \bullet g)(x) = \max\{y : g(z-x) + y << f(z)\} \quad (1)$$
$$(f \oplus g)(x) = \min\{y : -g(-(z-x)) + y >> f(z)\} \quad (2)$$

In Fig. 1, (a) is the original image and (b) is the closing image, which is generated by applying the closing operation to (a) and this shows appreciable cracks.



(a) Original image (b) Closing image

Fig. 1 Original image and closing image of a crack image

Sobel masking is applied to the closing image for improving the performance of edge extraction based on features such as the great difference between the brightness of cracks and the brightness of the surface of a concrete structure. The edge extraction finds the change of brightness by the differential operator

The iterated binarization selects the first estimated threshold value, it iterates an update of threshold value until the value doesn't change, and this is followed by it selecting the final threshold value.

For eliminating noises without the influence of the cracks and the background, noise reduction operation is applied twice. Firstly, after the 3x3 mask is applied to the binarized image, if 1's pixels are more than 0's ones among the adjacent 9 ones, the center pixel is set to 1. Otherwise, the center pixel is set to 0 as shown in Fig. 2. This process eliminates minute noises.

0	0	0
0	0	1
0	1	0

1	1	1
1	1	1
1	0	0

Fig. 2 3x3 Mask for noise reduction

Secondly, the Glassfire labeling technique is applied for eliminating additional noises. Glassfire labeling is the labeling method examining the adjacent pixels of the current pixel one by one recursively until all the adjacent pixels are labeled [5]. In the labeled image, the area of each labeled region is calculated by using the first pixel and last pixel of the region. In this paper, through the experiment, the criterion of the area is set to 1.7. Therefore, if the ratio of the length and width is less than 1.7, they are determined as noises and are eliminated.

III. CRACK RECOGNITION USING FUZZY SINGLE LAYER PERCEPTRON

In the conventional single layer perceptron, it is inappropriate to use when a decision boundary for classifying input pattern does not composed of hyperplane. Moreover, the conventional single layer perceptron, due to its use of unit function, was highly sensitive to change in the weights, difficult to implement and could not learn from past data[6].

Therefore, we construct, and train, a type of fuzzy neural net to model the linear function. Properties of this new type of fuzzy neural net include: (1) linear activation function; and (2) a modified delta rule for learning.

A fuzzy single layer percetron algorithm can be simplified and divided into four steps. For each input, repeat step 1, step 2, step 3, and step 4 until error is minimized.

Step 1: Initialize weight and bias term.

Define, $W_{ij}(1 \le i \le I)$ to be the weight from input j to output i at time t, and θ_i to be the bias term in the output node. Set $W_{ij}(0)$ to small random values, thus initializing all the weights and bias term.

Step 2: Rearrange A_i according to the ascending order of membership degree m_j and add an item m_0 at the beginning of this sequence.

$$0.0 = m_0 \le m_1 \le \cdots \le m_j \le m_J \le 1.0$$

Compute the consecutive difference between the items of the sequence.

$$P_k = m_j - m_{j-1}, \text{ where } k = 0, \cdots, n$$

Step 3: Calculate a node (O_j)'s actual output.

$$O_i = \sum_{k=0}^{J-1} P_k \times f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right)$$

where $f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right)$ is linear activation function, where $i = 1, \cdots, I$

The linear activation function expression is represented as follows:

$$f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) = 1.0, \ where\ f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) > 5.0$$

$$f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) = \rho \times \left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) + 0.5, where -5.0 \le \left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) \le 5.0, \ \rho \in [0.1, 0.4]$$

$$f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) = 0.0, \ where\ f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) < -5.0$$

The formulation of the activation linear function is follow.

$$f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) = \left(\frac{1}{range \times 2}\right) \times \left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) + 0.5$$

where the range means monotonic increasing internal except for interval except for the interval between 0.0 and 1.0 of value of the $f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right)$.

Step 4: Applying the modified delta rule. And we derive the incremental changes for weight and bias term.

$$\Delta W_{ij}(t+1) = \eta_i \times E_i \times \sum_{k=0}^{j} P_k \times f\left(\sum_{j=k}^{J-1} W_{ij} + \theta_i\right) + \alpha_i \times \Delta W_{ij}(t)$$

$$W_{ij}(t+1) = W_{ij}(t+1) + \Delta W_{ij}(t+1)$$

$$\Delta\theta_i(t+1) = \eta_i \times E_i \times f(\theta_{ij} + \alpha_i \times \Delta\theta_i(t))$$

$$\theta_{ij}(t+1) = \theta_{ij}(t) + \Delta\theta_{ij}(t+1)$$

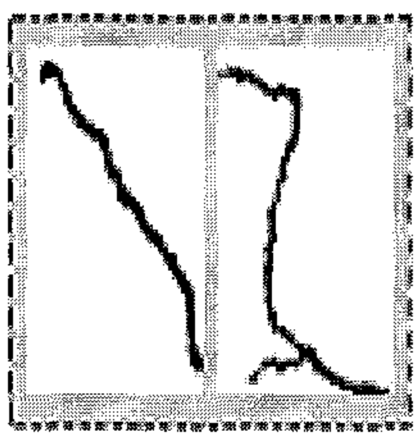
where η_i is learning rate and α_i is momentum.

Finally, we apply the training speed by using the dynamical learning rate and momentum based on the division of soma.

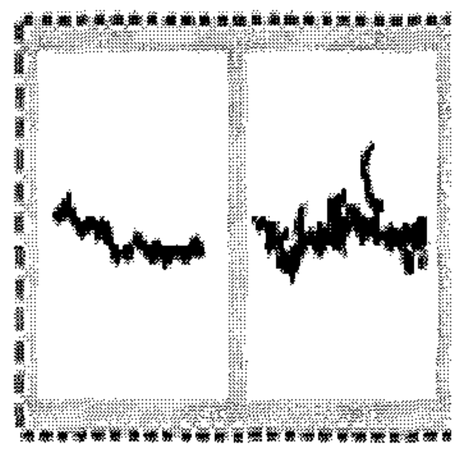
$$if(Inactivation_{totalsoma} - Activation_{totalsoma} > 0)$$
$$then\ \Delta\eta_i(t+1) = E^2\ \eta_i(t+1) = \eta_i(t) + \Delta\eta_i(t+1)$$
$$if(Inactivation_{totalsoma} - Activation_{totalsoma} > 0)$$
$$then\ \Delta\alpha_i(t+1) = E^2\ \alpha_i(t+1) = \alpha_i(t) + \Delta\alpha_i(t+1)$$

IV. EXPERIMENTAL RESULTS

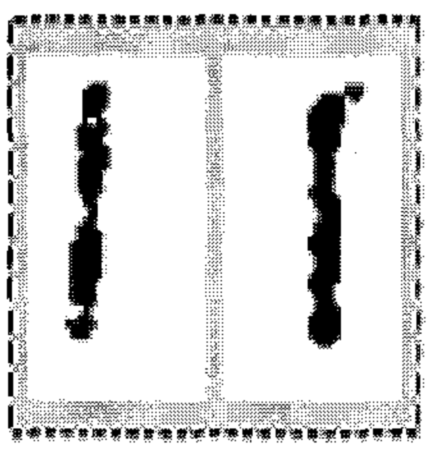
The crack images are acquired by Sony's Cyber-shot 5.0 digital cameras. Fig. 3 is the result of the recognized directions of extracted cracks.



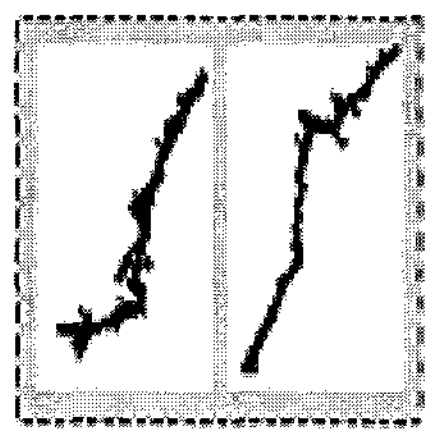
(a) diagonal (-45°)



(b) horizontal



(c) vertical



(d) diagonal (45°)

Fig. 3 Result of crack recognition

For analyzing the performance of the fuzzy single layer perceptron, the extracted 25 crack patterns are used as input patterns.

Table 1 Learning and recognition result of specific cracks

	fuzzy single layer perceptron
The number of Epoch	328
Recognition rate	23/25

Table 1 summarizes the performance measurement of the fuzzy single layer perceptron. In Table 1, the failure cases in crack recognitions are the ones which use enlarged or reduced images as input images, and the recognition of the non-directional cracks. In the table 1, the error criterion was set to 0.09. And we set up initial learning rate and initial momentum as 0.5 and 0.75, respectively. Also, we set up the range of weight [0,1].

V. CONCLUSIONS

In this paper, we proposed the recognition method to automatically extract the cracks of a concrete surface image acquired by the digital camera and to recognize the direction (horizontal, vertical, -45 degree, and 45 degree) of the specific cracks using the single layer perceptron. We compensate an effect of light on a concrete surface image by applying the closing operation, which is one of the morphological techniques, extract the edges of cracks by Sobel masking, and binarize the image by applying the iterated binarization technique. Noise reduction is applied twice to the binary image for effective noise elimination. After the specific regions of cracks are automatically extracted from the preprocessed image by applying Glassfire labeling algorithm to the extracted crack image, the cracks of the specific region are enlarged or reduced to 30x30 pixels and then used as input patterns to the single layer perceptron. Though, we considered only the case of single layer, the networks has the capability of high speed during the learning process and rapid processing on the crack patterns. The single layer percptron shows the possibility of the application to the crack image recognition in neural network by single layer structure.

In the future study, it will be examined the enhanced fuzzy algorithm that recognizes non-directional cracks by extracting parameters being able to be features according to the informations of cracks.

REFERENCES

[1] B. Y. Lee, Y. Y. Kim, J. K. Kim " Development of Image Processing for Concrete Surface Cracks by Employing Enhanced Binarization and Shape Analysis Technique," *Journal of the Korea Concrete Institute*, Vol. 17, No. 3 (2005) 361-368

[2] K. B. Kim, H. K. Yang, S. H. Ahn, "Recognition of Concrete Surface Cracks using ART2-based Radial Basis Function Neural Network," *Lecture Notes in Computer Science*, LNCS 3982, Springer, pp.279-286, 2006.

[3] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, Digital Image Processing, *Pearson Prentice Hall*, 2004.

[4] I. Pitas, Digital Image Processing Algorithms and Applications, *John Wiley & Sons INC*, 2000.

[5] K. B. Kim, H. J. Park, "Recognition of Concrete Surface Cracks Using Enhanced Max-Min Neural Networks," Journal of The Korea Society of Computer and Information, Vo.10, No.3, pp.77-82, 2007.

[6] C. S. Park, J. H. Cho, K. B. Kim, "An Enhanced Fuzzy Single Layer Perceptron With Linear Activation Function," The Journal of The Korea Institute of Maritime Information & Communication Scineces, Vol.11, No.3, , pp.1387-1393, 2007.

Hyun-Jung Park
Received her M.S. and the Ph.D. degrees in Department of Architectural Engineering from Pusan National University, Busan, Korea, in 1995 and 2001, respectively. From 2003 to present, she is an assistant professor, Department of Architectural Engineering, and Silla University in Korea. Her research interests include Neural Network, Image Processing, and Fuzzy Logic.