

Vision-based Crack Identification on the Concrete Slab Surface Using Fuzzy Reasoning Rules and Self-Organizing

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ABSTRACT

Identifying cracks on the surface of concrete slab structure is important for structure stability maintenance. In order to avoid subjective visual inspection, it is necessary to develop an automated identification and measuring system by vision based method. Although there have been some intelligent computerized inspection methods, they are sensitive to noise due to the brightness contrast and objects such as forms and joints of certain size often falsely classified as cracks. In this paper, we propose a new fuzzy logic based image processing method that extracts cracks from concrete slab structure including small cracks that were often neglected as noise. We extract candidate crack areas by applying fuzzy method with three color channel values of concrete slab structure. Then further refinement processes are performed with Self Organizing Map algorithm and density based noise removal process to obtain basic crack characteristic attributes for further analysis. Experimental result verifies that the proposed method is sufficiently identified cracks with various sizes with high accuracy (97.3%) among 1319 ground truth cracks from 30 images.

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1. INTRODUCTION

Cracks in concrete slabs have harmful influence on the tolerance, durability, waterproofing, and appearance of the structure thus they should be measured correctly in time. There have been numerous studies using sensor technique [1] or from the structure health monitoring (SHM) point of view by vibration-based methodologies for various structures in [2]-[6] and several reviews may summarize techniques and their characteristics in [7],[8].

While most SHM methods based on vibration analysis try to extract global modal features as signatures of structural integrity, Nondestructive Evaluation (NDE) methods, especially when two or higher dimensional imaging methods are employed, are able to provide a direct characterization of local structural damage [9]. Thus, we are interested in such an approach for identifying cracks in concrete slab structure with intelligent image processing.

In practice, engineers largely rely on visual inspection which is qualitative and subjective in nature that depends on the inspector's expertise [10]. Thus, it is much needed methodology to automate identifying and analyzing crack characteristics such as width, length and direction with image processing techniques [11].

Unfortunately, there is no firm mathematical model for the crack figures. And the concrete structure is exposed to the external environment right after the construction, consequently a perfect crack extraction

method is yet to be developed. Various image processing techniques such as Wavelet transform, Fourier transform [12], advanced filtering [13], adaptive thresholding [14], percolation [15], C-V model [16], fractal dimension analysis [17], and incorporating statistical inference [18] for various goals.

One of the practical difficulties in developing automatic crack identification tool with image processing technique is removing noise effectively and accurately. Especially for concrete slab structure, it is much harder than that of vertical materials like walls in that frequently, forms and joints are falsely identified as cracks [19]. Even the tracks of water leaking could be misidentified as cracks since often times, the brightness contrast is not enough to discriminate such objects automatically.

Thus, previously we applied intelligent binarization procedures and image restoration treatment to reduce such false positives as shown in [11],[20],[21]. However, in practice, it is found that such methods have difficulties when there is no clear distinction in brightness between the crack and the surface and sensitive to the outdoor lights.

Thus, in this paper, we propose a method to overcome or at least mitigate such weaknesses. The highlights of our new method are extracting candidate crack areas with fuzzy reasoning which has been applied to many engineering areas successfully [22] by giving R, G, B channel values of concrete surface independently and removing noise from those candidates by Self Organizing Map (SOM) [23]. With such treatment, minute noises (less than 1cm long) that were not removed before are successfully discriminated by the density distinction between the normal surface and the crack.

2. IDENTIFYING CRACKS FROM CONCRETE SLAB SURFACE IMAGE

The overall diagram of the proposed crack extraction method is as shown in Figure 1.

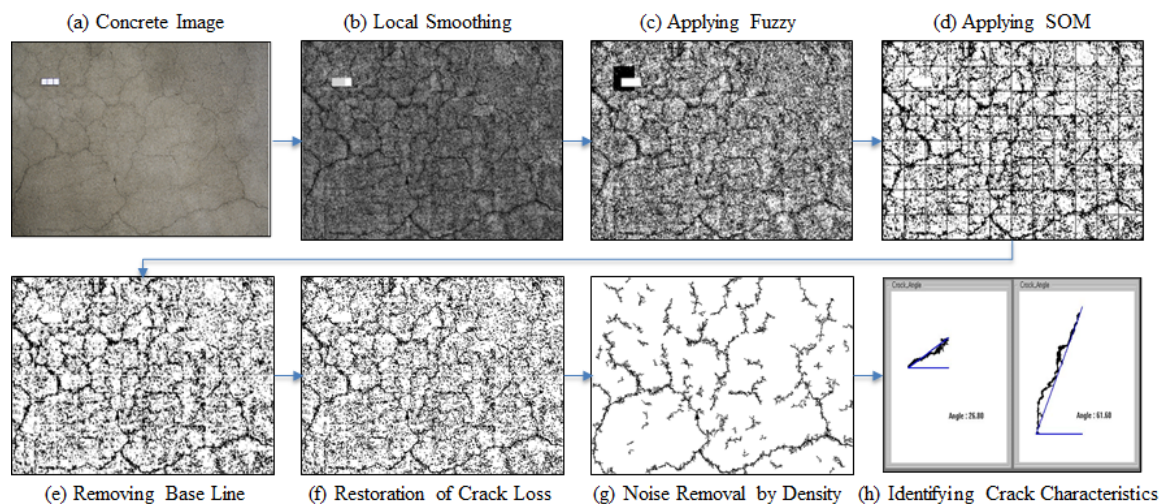


Figure 1. Algorithm outline

2.1. Local Smoothing

In order to enhance the brightness contrast, we use local smoothing technique which divides the image into multiple blocks and apply smoothing function S_k defined as formula (1) to each block.

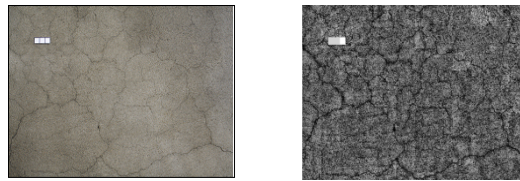
$$S_k^i = T^i(X_k) \sum_{j=0}^k P_X^i(X_j) = \sum_{j=0}^k \frac{n_j^i}{n^i} \quad (1)$$

$$0 \leq X_k \leq 1, \quad T^i(X_{L-1}) = \sum_{j=0}^{L-1} P_X^i(X_j) = 1$$

$$f_{HE}^i = S_k^i(L-1)$$

where n^i denotes the number of pixels in the i^{th} block and n_k^i denotes the brightness value of k^{th} brightest pixel in the i^{th} block and $T_i(X_k)$ is the cumulated sum of histogram $P_X^i(X_j)$ for each of L blocks. The result of this process is to obtain enhanced normalized brightness value among L blocks as defined in formula (1).

Minute cracks are similar to noises in brightness. In order to distinguish them, we divide the original image to small objects and apply local smoothing method as following and the result is as shown in Figure 2 (b).



(a) Original image (b) After local smoothing

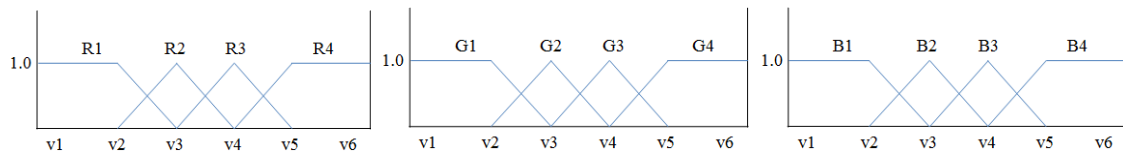
Figure 2. Local smoothing effect

2.2. Extracting Candidate Crack Areas with Fuzzy method

The original concrete image may have low contrast such that the cracks and adjacent noise area have similar brightness range. Using this characteristic, we divide locally smoothed image into many small random objects and compute average gray value. Then for the area having below average gray value, we apply fuzzy method to R, G, B channel information with corresponding membership functions defined as Figure 3. Membership function range for Figure 1 is defined as Table 1. The notation like R (G, B) in Table 1 denotes the average color channel value in object area in R, G, B channel in respectively. For example, in Table 3, variable V3 is determined as;

- average(R channel value) × (3/4) in R channel
- average(G channel value) × (3/4) in G channel
- average(B channel value) × (3/4) in B channel
- within [0, 255]

and that variable notation v3 is on the x-axis of Figure 3 (a)-(c) in respectively. By applying membership function as shown in Figure 3, we have fuzzy symbol R1-R4, G1-G4, B1-B4 with respect to the brightness value of the pixel.



(a) R membership function (b) G membership function (c) B membership function

Figure 3. Membership functions of R, G, B Channel - first part

Table 1. Membership function range for Figure 3

v1	0
v2	R(G, B) / 2
v3	R(G, B) * (3 / 4)
v4	R(G, B) * (5 / 4)
v5	R(G, B) * (6 / 4)
v6	255
R(G, B) = average R(G, B) in object area	

Then we can extract candidate crack areas by the following fuzzy reasoning rules. Again, this set of rules is symmetric with respect to the color channel R, G, and B thus we denote range variable R1, G1, and B1 with respect to the color channel as R1(G1, B1) for notational convenience.

IF X is R1(G1, B1) and Y is R1(G1, B1) then W is C1	IF X is R3(G3, B3) and Y is R1(G1, B1) then W is C2
IF X is R1(G1, B1) and Y is R2(G2, B2) then W is C1	IF X is R3(G3, B3) and Y is R2(G2, B2) then W is C3
IF X is R1(G1, B1) and Y is R3(G3, B3) then W is C2	IF X is R3(G3, B3) and Y is R3(G3, B3) then W is C3
IF X is R1(G1, B1) and Y is R4(G4, B4) then W is C3	IF X is R3(G3, B3) and Y is R4(G4, B4) then W is C4
IF X is R2(G2, B2) and Y is R1(G1, B1) then W is C1	IF X is R4(G4, B4) and Y is R1(G1, B1) then W is C2
IF X is R2(G2, B2) and Y is R2(G2, B2) then W is C2	IF X is R4(G4, B4) and Y is R2(G2, B2) then W is C3
IF X is R2(G2, B2) and Y is R3(G3, B3) then W is C2	IF X is R4(G4, B4) and Y is R3(G3, B3) then W is C4
IF X is R2(G2, B2) and Y is R4(G4, B4) then W is C3	IF X is R4(G4, B4) and Y is R4(G4, B4) then W is C4

Fuzzy reasoning rule (1)

With above fuzzy reasoning rules, we have the qualitative range variable C1 to C4. Then, the second fuzzy membership function defined as Figure 4 is used to obtain the final membership degree. For example, each G channel value is given to the membership function defined in Figure 3 to compute the membership degree. Then the reasoning rule (1) is applied with Max-Min method. Then the second membership function defined as Figure 4 is applied to determine the membership degree and it is defuzzified by center of gravity method as formula (2).

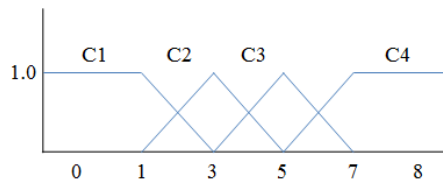


Figure 4. Membership function - second part

$$W = \frac{\sum u(X)X}{\sum u(X)} \tag{2}$$

Then the decision rule for candidate area of crack is defined as Table 2.

$0 < W < 2$	
$2 < W < 4$	Candidate Cracks
$4 < W < 6$	
$6 < W < 8$	Noise Area

2.3. Further Refinement by Self Organizing Map Algorithm

RGB color information may not be sufficiently strong to distinguish cracks from noises. Thus we apply self-organizing map algorithm on the image after applying fuzzy method shown as Figure 5.

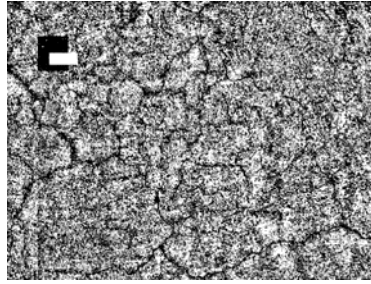


Figure 5. Image after applying fuzzy method

SOM is an unsupervised neural network learning algorithm that mimics the characteristics of human cerebral cortex and has been successfully applied to many engineering applications [23]. The performance of SOM learning is known as being influenced by the type of learning radius shown as Figure 6 and we adopt the rectangle type in this paper.

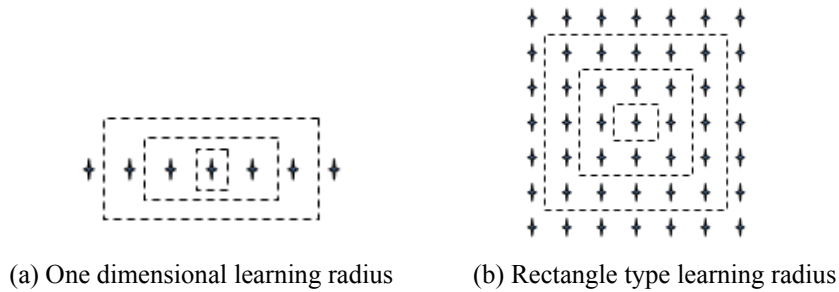


Figure 6. Learning types of SOM

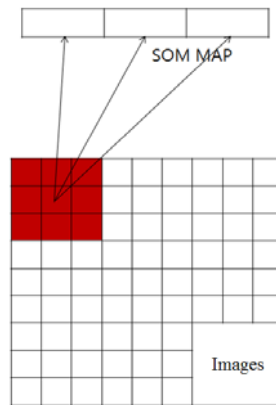


Figure 7. Applying SOM algorithm

From the locally smoothed image, we apply average gray value of 3×3 mask shown as Figure 7 to SOM learning and the output is computed by formula (3) with connection strengths controlled by formula (4).

$$D(j) = \sum_i (W_{ji} - X_i)^2 \tag{3}$$

$$W_{ji}^{k+1} = W_{ji}^k + \alpha(x_i - W_{ji}^k) \tag{4}$$

where D denotes the similarity, X denotes the pattern, W is the connection strength and α is the learning rate.

The same patterns of 3×3 mask and average gray values are used to recognize any minute candidate cracks from the image after fuzzy method shown as Figure 8. The baselines in Figure 8 are removed afterwards.

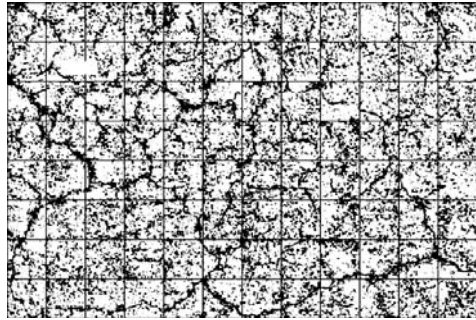
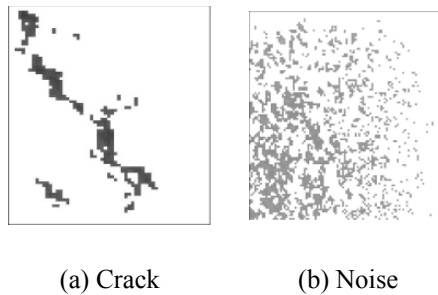


Figure 8. After applying SOM

2.4. Noise Removal by Density Information

Cracks have lower density and lower brightness, higher length/width rate than that of random noise as shown in Figure 9. Thus, we use formula (5) after applying Grassfire algorithm [21].



(a) Crack

(b) Noise

Figure 9. Density differences

$$f = \frac{A_{ob}}{A_x \times A_u} \quad (5)$$

where A_x , A_u denotes the width and height of rectangle circumscribed with objects extracted by Grassfire algorithm in respectively and A_{ob} denotes the number of pixels in extracted object.

Then we apply the final decision rule shown as Table 3 and the result is like as shown in Figure 10. The experimental threshold 0.3 was obtained from prior observation of 10 random images not used in this experiment that the characteristic coefficient f of formula (5) has certain tendency. Since cracks have higher length/width rate, that tendency with respect to the object labelling Grassfire algorithm can easily be formulated.

Table 3. Final crack decision rule

$f \geq 0.3$	Noise
$f < 0.3$	Crack

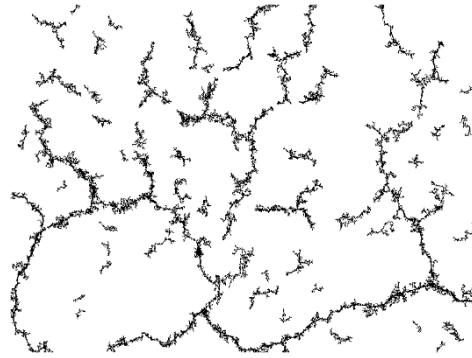


Figure 10. Final crack extraction

For the analysis, we compute the length, width, and the angle of the identified crack with respect to the method used in [24].

3. EXPERIMENT AND ANALYSIS

The proposed method was implemented with Microsoft Visual studio 2008 and experiments were performed on IBM-compatible PC with Intel i5 3.0 GHz CPU and 4GB RAM. Thirty Digital images of concrete surface taken with a Canon 350D digital camera of 800×600 size were used in the experiments.

In our previous attempt [21], the gray value was used in crack extraction as is. Thus, the method was sensitive to the influence of the outdoor light or may face with environment like low brightness contrast between concrete surface and crack candidates. However, the proposed method uses R, G, B values as color information and applies fuzzy method and SOM in noise removal.

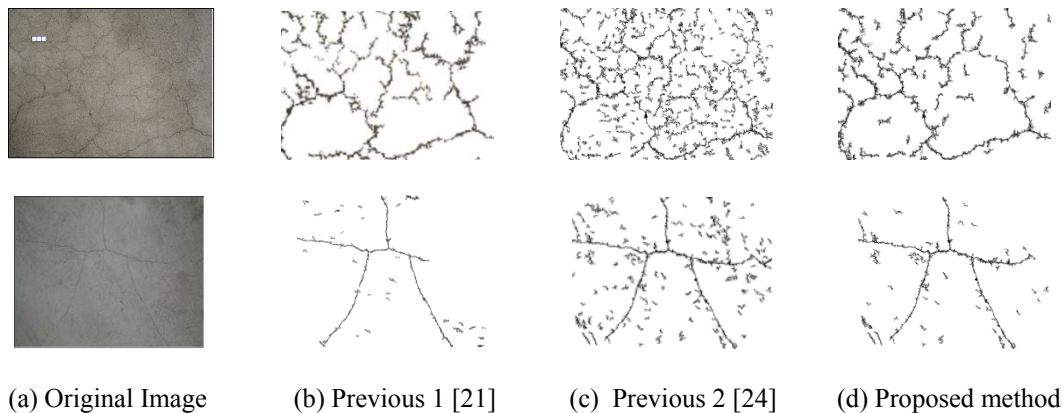


Figure 11. Comparison of the proposed method and previous methods

There is another related approach with slightly different purposes. In [25], it tries to recognize five crack patterns – horizontal, vertical, left diagonal, right diagonal, and undirectional – with back propagation neural network in conjunction with image processing techniques. During the process, it is supposed to extract the cracks but as shown in Figure 11 (d), that method is especially weak for “undirectional” cracks in that the system is prone to recognize false positive noises as cracks due to low intensity contrast.

We believe that such improvement gives us more accurate crack identification result shown as Figure 12 as a comparative example in that the proposed method is more accurate and discriminative in extracting minute cracks. However, if the concrete surface has relatively long (>1cm) furrows or filths, the proposed method fails to extract cracks correctly as shown in Figure 12.

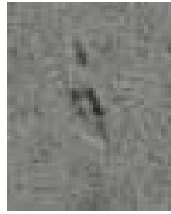


Figure 12. False identification example

Figure 13 demonstrates the labelled crack result in order to analyze some characteristics of cracks. Such characteristics - width, length, direction - are summarized in Table 4.

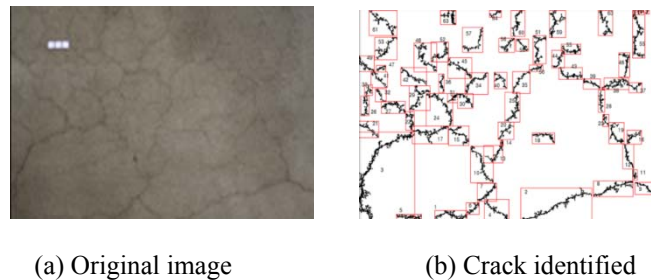


Figure 13. Crack identification example

Table 4. Crack characteristics for Figure 17

Crack#	Length(cm)	Width(cm)	Angle(°)	Crack#	Length(cm)	Width(cm)	Angle(°)
1	11.127	0.276	24.23	14	4.533	0.409	48.01
2	14.654	0.743	56.25	15	1.919	0.231	40.49
3	3.723	0.323	12.97	16	3.954	0.212	49.57
4	6.211	0.319	20.21	17	2.910	0.301	50.74
5	4.214	0.218	22.88	18	4.507	0.499	39.23
6	6.035	0.349	56.08	19	1.618	0.248	31.94
7	3.727	0.228	64.54	20	2.163	0.229	23.82
8	3.651	0.361	53.13	21	4.319	0.369	63.54
9	3.286	0.249	46.54	22	3.158	0.368	25.55
10	3.722	0.408	37.20	23	3.009	0.320	40.42
11	5.952	0.410	49.25	24	4.449	0.425	57.26
12	4.654	0.336	61.86	25	2.998	0.521	40.90
13	3.873	0.409	25.03	26	1.989	0.229	28.41

For all 30 images used in this experiment, we identified 97.3% of cracks as summarized in Table 5 where the ground truth cracks are verified by field engineer.

Table 5. Crack identification statistics

Images	# of Cracks	Identified	Accuracy
30	1319	1283	97.3%

From literature review, this result is better than using other various image processing techniques [15] which reported the error identification rate of 3.56-8.95% from different image set using 5 different image processing techniques.

4. CONCLUSION

In this paper, we propose a new method to extract and analyze cracks on concrete slab structure by intelligent image processing techniques. While previous methods use gray value of the image directly, we use

R, G, B channel values as color information and apply fuzzy reasoning and SOM algorithm in extracting candidate cracks and removing noises. With those careful treatments, we can successfully extract minute cracks which were often ignored in previous studies. Then some characteristics of cracks such as length, width, and direction could be easily analyzed.

While the aim of this research was confined to extract cracks accurately and computes some basic characteristics of cracks, we expect that more intelligent and useful tools that can analyze the progression of cracks and directions of cracking for more intelligent maintenance of concrete structure in future research.

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