ROBUST CRACK DETECTION IN CONCRETE STRUCTURE IMAGE USING MULTI-SCALE ENHANCEMENT AND VISUAL FEATURES

Xiangzeng Liu[1,2], Yunfeng Ai[1,3], Sebastian Scherer[1]

1. Carnegie Mellon University
2. Xi'an Microelectronics Technology Institute
3. University of Chinese Academy of Sciences

ABSTRACT

In order to improve the robustness of the crack detection in the complex background, a new crack detection framework based on multi-scale enhancement and visual features is developed. Firstly, to deal with the effect of low contrast, a multi-scale enhancement method using guided filter and gradient information is proposed to get the enhanced image. Then, the adaptive threshold algorithm is used to obtain the binary image. Finally, the combination of morphological processing and visual features are adopted to purify the cracks. The experimental results with different images of real concrete surfaces demonstrate the high robustness and validity of the developed technique.

Index Terms— Crack detection, guided filter, image enhancement, concrete structure

1. INTRODUCTION

With the rapid development of artificial intelligence technology, more and more robotic systems are applied in civil engineering to improve the work efficiency and reduce the risk of human safety. One of the typical applications is using Unmanned Aerial Vehicles (UAV) to inspect the safety of the buildings by capturing the surface images with the mounted cameras [1-4]. In particular, cracks on the concrete surface are an important early manifestation of the building degradation. Therefore, monitoring cracks during the life span of concrete structures has been an effective technique to evaluate the level of safety and make plans for reasonable maintenance in the future.

In recent years, automated crack detection by climbing robot or UAV is very popular due to high efficiency and low cost. In this case, variety of crack detection methods have been proposed: area-based detection, edge-based detection, and learning-based detection. The typical area-based algorithms include morphological techniques [5], segmentation method [1, 4], and percolation algorithm [7-8]. The first two methods failed in the complex texture and non-uniform illumination. The percolation algorithm has a good performance in low contrast and unclear images. However, the difficult is how to effectively choose the seeds for percolation and reduce the computational complexity. In edge-based detection, Abdel-Qader et al. [9] compared the effectiveness of crack detection on the bridge surface images by using several filters and concluded that the wavelet transform is the most reliable methods. Moreover, the combination of gradient calculation and morphological processing has been applied in the UAV crack systems [3, 4]. However, these algorithms only can be used in the images that have significant cracks and smooth background. In order to avoid manually tuning the threshold parameters, the learning algorithm has been applied in crack detection. The traditional neural network is used to classify the binary images processed by the feature extraction methods [10]. Furthermore, the deep convolutional neural network is trained to classify each image patch in the raw images, which get the better results than SVM and Boosting methods [11]. However, the learning-based methods need to build an image set that have variety of cracks in advance.

To improve the robustness of concrete crack detection in complex backgrounds with non-uniform illumination, low contrast and stain noise, this paper proposes a new crack detection framework based on multi-scale enhancement and visual features. The multi-scale enhancement algorithm using guided filter and gradient information is described in Section 2. The whole process of the crack detection algorithm with morphological processing and visual features is given in Section 3. Section 4 shows the validity of the proposed algorithm through experiments with images of a real concrete surface. Section 5 concludes the paper.

2. MULTI-SCALE EHANCEMENT BASED ON GUIDED FILTER

To deal with the effect of low contrast and noise in the crack detection, an image enhancement algorithm combining multi-scale guided filter with gradient information is developed, which can enhance the details selectively while suppress the noise to the maximum.

The guided filter is a smoothing operator which can smooth filtering, preserve the edge details and avoid the artifacts effectively [12]. Moreover, the guided filter naturally has a fast and non-approximate linear time algorithm, regardless of the kernel size and the intensity range. Therefore, it is usually applied in image enhancement and denoising [13]. The filtering process at a pixel i in image I can be formulated in a linear model as follows:

$$q_i = a_k I_i + b_k, \forall i \in \omega_k, \tag{1}$$

where q is the filtering out image, k is the index of a local square window ω. The filter coefficients a_k and b_k are computed as follows:

$$a_k = \frac{\sum_{i\in\omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \varepsilon}, \tag{2}$$

$$b_k = \bar{p}_k - a_k \mu_k, \tag{3}$$

where μ_k and σ_k are the mean and variance of image I in window ω_k, $|\omega_k|$ is the number of pixels within ω_k, p is the guided image, and $\bar{p}_k$ is the mean of p in window ω_k. ε is a regularization parameter controlling the degree of smoothness. The filtering out image can be presented by:

$$q_i = \bar{a}_i I + \bar{b}_i \tag{4}$$

where a_i and b_i are the average of a and b respectively on the window ω_i centered at i.

Usually a concrete surface image contains the cracks in different width and different clarity due to the non-uniform illumination and defocus of the camera. So we develop a multi-scale enhancement algorithm supervised by gradient information (MESG). The steps of the algorithm are shown in Fig. 1 which can be described as follows:

Step 1: Filter the input image I to four different scale base layers $IB_k, k = 0,1,2,3$ and three detail layers in different scales $ID_k, k = 0,1,2$ by the following equations.

$$IB_k = GF(r_k, \varepsilon_k) * I, \tag{5}$$

$$ID_k = IB_{k-1} - IB_k, \tag{6}$$

where $GF(r, \varepsilon)$ is the guided filter operator, and r is the radius of window ω. I and IB_0 is used as the guided image in the first filter and the following processing, respectively.

Step 2: Compute the gradients of $IB_k, k = 0,1,2$ by using Sobel filter respectively, and get $IG_k, k = 0,1,2$.

Step 3: Obtain the Detail enhanced image ID based on $ID_k, k = 0,1,2$ supervised by $IG_k, k = 0,1,2$ according to the equation (7).

$$ID(i, j) = \sum_{k=0}^{2} IG_k(i, j) \cdot ID_k(i, j) \tag{7}$$

where $ID(i, j)$ is the pixel value in (i, j).

Step 4: Get the base enhanced image IB using the plateaus histogram mapping [14] to IB_0.

Step 5: The output image EI can be computed by merging IB and ID with the equation (8).

$$EI = ID + \beta \cdot IB \tag{8}$$

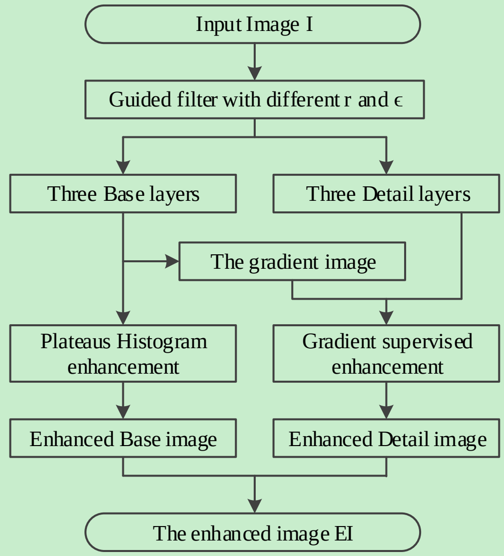

Fig. 1. The flowchart of multi-scale enhancement supervised by gradient information.

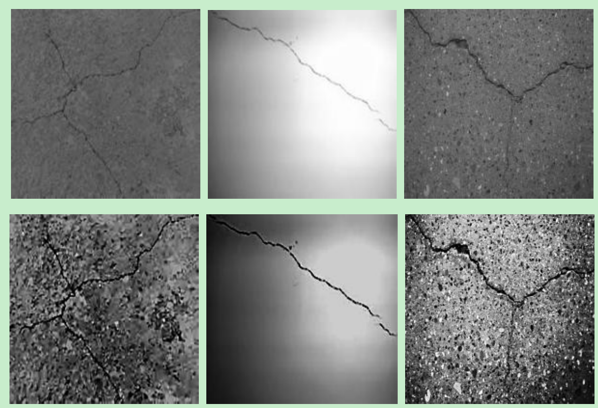

Fig. 2. The enhanced results of three images.

Fig. 2 shows the enhanced results of three images in different scenes, in which the original and enhanced images are shown in the top and bottom line respectively. In this experiment, four different sets of parameters ($r_0 = 1, \varepsilon_0 = 0.004, r_1 = 2, \varepsilon_1 = 0.025, r_2 = 4, \varepsilon_2 = 0.01, r_3 = 8, \varepsilon_3 = 0.04$ and β=0.8) are adopted. In the top line, cracks are similar to the background in the left image, non-uniform illuminations exist in the middle image, and cracks in different scales are contained in the right image. From the enhanced results of images, we can see the cracks in different cases are more significant than that in the original images while the backgrounds and noises are suppressed appropriately.

3. THE PROPOSED CRACK DETECTION ALGORITHM

A new crack detection framework using multi-scale enhancement and visual features is proposed in this section.

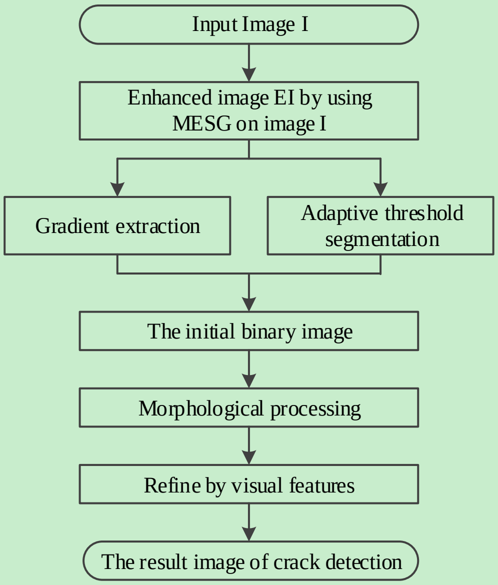

Fig. 3. Flowchart of the proposed crack detection framework.

In the framework, in order to improve the contrast of the input image, the multi-scale enhancement is operated by using the MESG developed in Section 2. To deal with the non-uniform illuminations in the image, the adaptive threshold segmentation is adopted [15]. Moreover, to refine the results the visual features are used, which include gradient and shape of the cracks, degree of area filling, the contrast between cracks and background. The flowchart of the framework is shown Fig. 3. The detailed procedure of the algorithm is described as follows:

Step 1: The enhanced image EI can be obtained from the image I by using the MSEG algorithm.

Step 2: Apply the Sobel operator and the adaptive threshold segmentation to image EI and get the gradient image GI and the binary image BI, respectively.

Step 3: Get the initial binary image $InBI$ from BI by the supervising of the gradient image GI, which based on the fact that the edge pixel of the crack has larger gradient value than background. The pixel value of the image $InBI$ at (i, j) can be computed as follows:

$$InBI(i,j) = BI(i,j) \cdot 1(GI(i,j) > \lambda \cdot mean(GI)), \tag{9}$$

where the $1(\cdot)$ is an indicator function.

Step 4: Use the closed operator and small area removal operator in the morphological processing to combine the fragmented cracks and delete the noises.

Step 5: The final results are given by refining the cracks according to the shape of cracks, degree of area filling, the contrast between cracks and background.

In step 5, the shape of cracks can be constrained by using circularity defined as follows:

$$F = \frac{4 \times C}{\pi \times L^2} \tag{10}$$

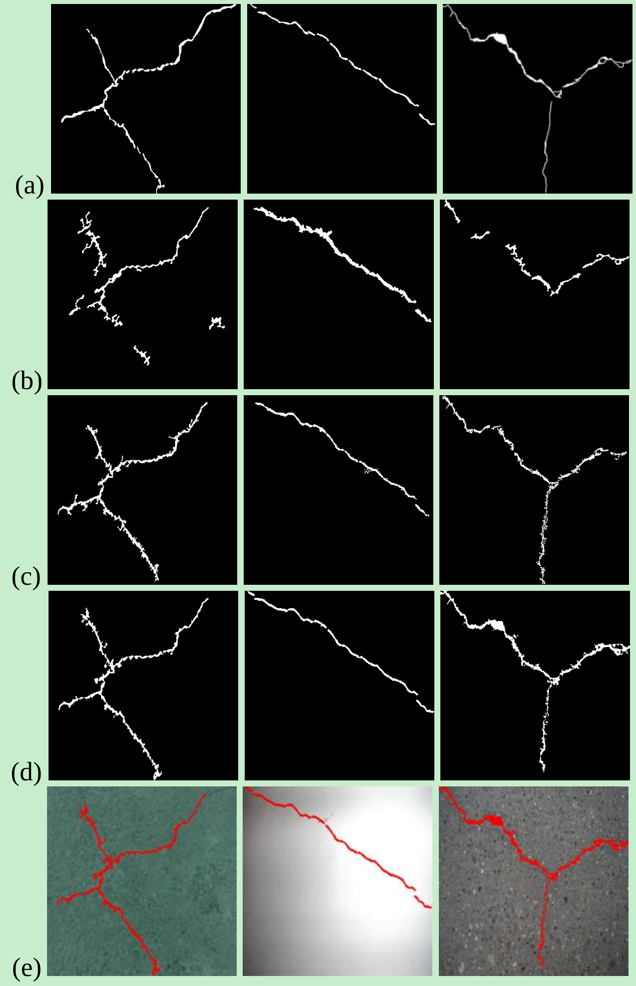

Fig. 4. The comparison of the proposed algorithm, OSMA, and PMM with images in three different scenes.

where C is the number of candidate crack pixels in a small region, and L is the maximum length of the region. If the region belongs to crack area, the value of F is close to 0 and degree of area filling is less than 0.5. Moreover, the degree of area filling can be defined as the proportion of the candidate crack area to the minimum external rectangle area. In order to delete the straight lines, it should be less than 0.75. The difference of the pixel value between cracks and background should be larger than 5 after the enhancement processing. Therefore, the crack can be refined by the above processing.

4. EXPERIMENTAL RESULTS

In this section, to evaluate the validity and efficiency of the proposed crack detection algorithm, we apply it to two different sets of images. The first set contains three concrete surface images captured in different scenes, which are used to evaluate the efficiency by comparing with the OTSU and morphology-based algorithm (OSMA) in [4] and the percolation model based method (PMM) in [8]. The learning-based method is not compared with the proposed algorithm because it mainly focuses on the existence of the cracks rather than the accuracy of crack pixels in an image.

In the first set, three images in different scenes are shown in top line of Fig. 2, each image has 480×480 pixels, the left image has the similar texture, the middle image contains non-uniform illuminations, and the right image has different scales and clarity. Fig. 4(a) shows the ground truth of the cracks in different images. The results of the crack detection by using OSMA, PMM, and the proposed algorithm are given in Fig. 4(b)-(d). The reconstructed images based on Fig. (d) are shown in Fig. (e). From the those figures, we can see the results obtained by OSMA lost many parts of cracks in left and right images which dues to the OTSU and Sobel operator are invalid in some complex background. The PMM has a better performance than OSMA, but it still lost few thick parts of cracks and is very consuming. The performance of our proposed algorithm is most close to the ground truth images.

In order to evaluate the detection results from a quantitative point of view, the receiver operating characteristics (ROC) analysis is performed, which was used in [8]. The change trend of the true positive rate (TPR) with the false positive rate (FPR) growing can accurately reflect the detection accuracy. The performance of an algorithm is better if it can get a larger TPR in a smaller FPR. Table 1 shows the quantitative analysis of results in Fig. 4(b)-(d). It demonstrates that the proposed algorithm has the highest TPR in the case that FPR less than 1.5% and low time consuming. Due to the limit of space, the ROC curves in the top right image of Fig. 2 by different methods are given in Fig. 5. From those curves, we can see the curve of the proposed algorithm is closer to the upper left than the other two methods, which means our method can get higher TPR when the FPR is smaller. So the proposed algorithm has a better performance than OSMA and PMM.

The second set contains 200 concrete surface images (4000×6000) captured in different scenes by Sony ILCE 7M-2K camera at NSH of CMU. The differences in crack scales, illuminations, and clarity are included in those images. For fast the processing, the images are resized to the size of 400×600. The ground truth images are obtained by PMM whose seeds are selected manually. Due to the OSMA failed in a lot of frames, just the results computed by PMM and the proposed algorithm are shown in Fig. 6. From the results, it can be seen that the TPR of our algorithm is higher than the PMM in most cases when the FPR less than 0.5%. In the few frames, the proposed algorithm are little lower than PMM because that the cracks are very thin and similar to the backgrounds. The average TPR of PMM and the proposed algorithm are 87.24% and 94.22% respectively which demonstrates our algorithm has a robust performance during the test. Furthermore, the average run time of the proposed algorithm is less than 1 second, which is 30 times faster than that of PMM.

Table 1. The quantitative analysis of results in Fig. 4(b)-(d).

Method	TPR(%)			FPR (%)			Time (s)		
OSMA	41.3	88.3	42.1	1.85	1.27	0.72	0.5	0.4	0.6
PMM	76.2	82.5	62.7	1.32	0.34	0.97	25	15	28
The proposed algorithm	76.3	89.7	83.8	1.08	0.35	1.20	0.6	0.5	0.8

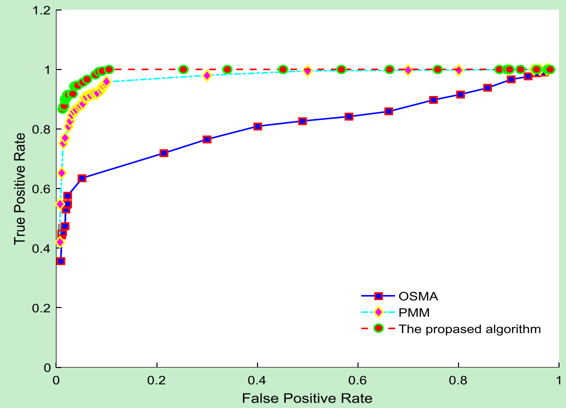

Fig. 5. The ROC curves in the top right image of Fig. 2.

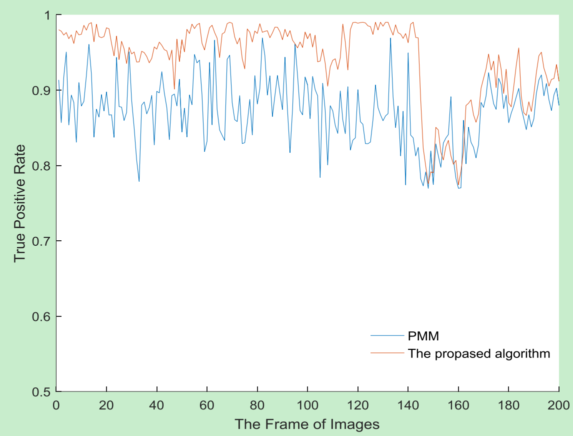

Fig. 6. TPR curves by PMM and the proposed algorithm on the second set of images.

5. CONCLUSIONS

In this paper, we proposed a robust crack detection frame based on multi-scale enhancement and visual features. The image enhancement algorithm combining multi-scale guided filter with gradient information can effectively enhance the cracks while suppress the noises. To deal with the non-uniform illuminations in the image, the adaptive threshold segmentation is adopted. Moreover, the visual features which include gradient and shape of the cracks, degree of area filling, the contrast between cracks and background are used to refine the results. Experimental results in two sets of images show the validity and efficiency of the proposed algorithm.

6. REFERENCES

[1] H. Kim, S.H. Sim, and S. Cho, “Unmanned aerial vehicle (UAV)-powered concrete crack detection based on digital image processing,” in International Conference on Advances in Experimental Structural Engineering, Aug. 2015.

[2] J.W. Kim, S.B. Kim, and J.C. Park, J.W. Nam, “Development of crack detection system with unmanned aerial vehicles and digital image processing,” in Advances in Structural Engineer and Mechanics, Aug. 2015.

[3] F.C. Pereira and C.E. Pereira, “Embedded image processing systems for automatic recognition of cracks using UAV,” in International Federation of Automatic Control, Aug. 2015, pp. 16-21.

[4] S. Dorafshan, M. Maguire, and X. Qi, “Automatic surface crack detection in concrete structures using OTSU thresholding and morphological operations,” UTC Report, Aug. 2016.

[5] N. Tanaka and K. Uematsu, “A crack detection method in road surface images using morphology,” IAPR Workshop on Machine Vision Applications, Nov. 1998, pp. 17-19.

[6] M. Miwa, T. Kobayashi, X. Zhang, and M. Sato, “Detecting cracks on the tunnel wall using watershed and graph analysis,” ITE Technical Report, vol. 29, no. 59, pp. 11-14, 2005.

[7] T. Yamaguchi and S. Hashimoto, “Fast crack detection method for large-size concrete surface images using percolation-based image processing,” Machine Vision and Applications, vol. 21, pp. 797-809, 2010.

[8] Z. Qu, L. Lin, Y. Guo, and N. Wang, “An improved algorithm for image crack detection based on percolation model,” IEEJ Transactions on Electrical and Electronic Engineering, vol. 10, pp. 214-221, 2015.

[9] I. Abdel-Qader, O. Abudayyeh, and M.E. Kelly, “Analysis of edge detection techniques for crack identification in bridges,” Journal of Computing in Civil Engineering, American Society of Civil Engineers, vol. 17, no. 3, pp. 255-263, 2003.

[10] P. Prasanna, K. J. Dana, N. Gucunski, and B. B. Basily, H.M. La,R.S. Lim, and H, Parvardeh, “Automated crack detection on concrete bridges,” IEEE Transactions on automation science and engineering, vol. 13, no. 2, pp. 591-599, 2016.

[11] L. Zhang, F. Yang, Y. D. Zhang, and Y. J. Zhu, “Road crack detection using deep convolutional neural network,” in the proceedings of IEEE International Conference on Image Processing, Sept. 2016, pp. 3708-3712.

[12] K. He, J. Sun, and X. Tang, “ Guided image filtering,” IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 35, no. 6, pp. 1397-1409, 2013.

[13] C.C. Pham and J.W. Jeon, “Efficient image sharpening and denoising using adaptive guided image filtering,” IET Image Process, vol. 9, no. 6, pp. 71-79, 2015.

[14] S.B. Yang, W.L. Cui, and D.F. Zhang, “Night vision image enhancement based on double-plateaus histogram,” Communications in Computer and Information Science, vol. 143, pp. 74-79, 2011.

[15] D. Bradley, G. Roth, “Adaptive thresholding using the integral image,” Journal of Graphics Tools, vol. 27, no. 2, pp. 13-21, 2007.