Development of Crack Detection and Crack Length Calculation Method using Image Processing

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***Abstract*—To evaluate the integrity of a building, many experts and engineers have evaluated the damage classification of a building based on superficial visual information through field surveys. On-site surveys are hazardous and require several years of experience and expertise. In this study, a system for detecting the presence or absence of cracks and calculating their lengths was developed using image processing technology. The accuracy of the system was examined using crack image data obtained from shear force experiments. For crack detection, a crack detection method was developed using canny edge, threshold, and HSV color detection. The detection of the presence of cracks was proposed to be coupled with image segmentation to improve detection accuracy. A method for calculating the crack length using image processing was also developed. In this study, we proposed a method to calculate cracks as straight lengths, and obtained results with 98.1% accuracy. However, for curved cracks, it was necessary to rotate or segment the image.**

Keywords—Image processing; crack detection; length calculation; color detection; canny; threshold; OpenCV

I. Introduction

Once a building is constructed, it will last several decades before the next renovation or reconstruction [1]. Therefore, the "lock-in effect" is very large, which makes it difficult to address. Additionally, natural disasters and deterioration have reduced the functionality of many buildings [2]. To evaluate the integrity of a building, many experts and engineers have evaluated the damage classification of a building based on superficial visual information through field surveys [3, 4]. However, assessing damage classification from the superficial visual information of reinforced concrete (RC) requires many years of experience and expertise. Other field investigations involving hazards are difficult to conduct [5, 6]. In Japan, the Ministry of Land, Infrastructure, and Transport created an "Inspection Support Technology Performance Catalog" to provide inspection support technologies [7, 8]. However, the support is inadequate in terms of ensuring hazards.

In recent years, image processing technology has been used to determine building damage, which eliminates the need to conduct dangerous on-site surveys. Image processing techniques are evolving daily [9,10,11], and in the field of architecture, many studies have been conducted on crack detection using image classification techniques, such as tunnel crack detection [12,13], bridge and road crack detection [14,15,16], and fatigue degradation detection of material deterioration [17,18]. Many of these studies used existing trained models to detect the presence or absence of cracks [19, 20]. Crack detection has been studied for several years, and various detection methods have been proposed. However, the various local environmental factors make it difficult to respond efficiently. In addition, there is insufficient specific information regarding the expertise of engineers and experts. Therefore, methods for detecting cracks and evaluating damage classification have not been sufficiently investigated.

In this study, an experimental study was conducted on the shear strength of a reinforced concrete column with a wing wall on one side. [21]. The crack image data obtained in the experimental process were subjected to Canny edge detection [22], threshold detection [23], and HSV color detection [24] to investigate crack detection and crack length calculation methods. The accuracy of the model was verified by comparing it with visual crack detection. Finally, we aim to develop a system that can predict the future direction in which cracks will propagate and reach a failure mechanism. In this paper, we developed a method for detecting the presence or absence of cracks and a system for evaluating the degree of damage using image processing technology based on image data. In particular, an efficient crack-detection method using image segmentation is considered.

II. Literature Review

Research on crack detection using image processing techniques can be divided into civil engineering and architecture [25]. Civil engineering is primarily concerned with crack detection in tunnels, bridges, and roads. On the other hand, in the architectural, research has been conducted on crack detection caused by earthquake damage and deterioration.

First, we discuss previous research in the architectural field. Lu et al. [5] developed a method for determining the presence or absence of damage by Canny edge detection using image data of building exteriors. Wang et al. [26], Fan et al. [27] improved an existing crack detection model and conducted a case study on a data set to improve the model's performance. The shape of the cracks was confirmed by counting the pick cells in the crack image. Zhang et al. [28] proposed a crack detection model by adding an ensemble algorithm to existing crack detection models. Cracks could be detected in any type of image. Yamaguchi et al. [29, 30] proposed a crack detection method for concrete surfaces using image processing techniques. A method for efficiently detecting cracked areas in images using mask processing methods was identified.

Next, we discuss previous studies in the field of civil engineering will be presented. Liu et al. [31] used existing trained convolutional neural networks (CNN) models to classify cracks in buildings and roads. Cracks were detected differently depending on the number of pixels in the input image. Li et al. [32] attempted to use FoSA's learning genetic algorithms to detect cracks in roads. A case study was conducted using five image data sets. It was found to be difficult to detect depending on the brightness of the images. Wang et al. [33] used threshold detection in image processing technology to detect the degree of road damage at different brightness levels in the image. Kulambayev et al. [34] developed a method to detect the degree of road damage in real time using a deep learning model. Maeda et al [35] and Abbas et al. [36] installed cameras in cars and used CNN models to detect road cracks and abnormal conditions. Yadav et al [37] used three crack detection algorithms to detect crack presence/absence classification and crack patterns. 2-3% improved detection performance compared to existing crack detection systems.

Crack detection research is active in both architectural and civil engineering. However, most previous studies have focused on model improvement with new images and crack detection using trained models. Therefore, pretreatment methods for crack detection and crack length calculations have not yet been adequately studied. In this study, we developed a preprocessing method for crack images using image processing technology and clarified the method for calculating the crack length.

III. Methodology

In this study, image data of the cracks were collected through shear strength experiments. Subsequently, a crack presence/absence detection method and crack damage evaluation was conducted (see Fig. 1). Three full-scale 1/3-scale specimens were fabricated for shear strength experiments. This experiment was conducted to investigate the ultimate shear strength and failure mechanism of the columns with single-sided walls.

Crack image data were recorded on video with a 4 K camera installed in front of the experimental subject, as shown in Fig. 1. The video recording was performed continuously from the beginning to the end of the experiment. The video recording was set to 30 FPS at 3840 × 2160 pixels high quality and saved in *.MP4 files. The same settings were used to capture the videos of the three experimental subjects. The captured video data were converted into image data for crack detection using the following procedure (see Fig. 2). In addition, it was difficult to obtain the expected results in this study because each region in the image had a different brightness depending on the shooting situation. Therefore, we considered a method in which the input image was divided into 7 × 5 images, image processing was performed in more detail, and the images were merged into the original image.

1) The cracked video was edited only for the necessary parts. 3 hours (size:30.2 GB) video edited to 27 minutes (size:1.96 GB).

2) The edited video was saved as a still image by using OpenCV.

3) The still image was selected and cut out only where cracks occurred.

4) The cropped images were divided into 7 × 5 images.

5) Segmented images were used to detect the presence of cracks using image-processing technology.

6) The processed images were then combined and returned to the original image.

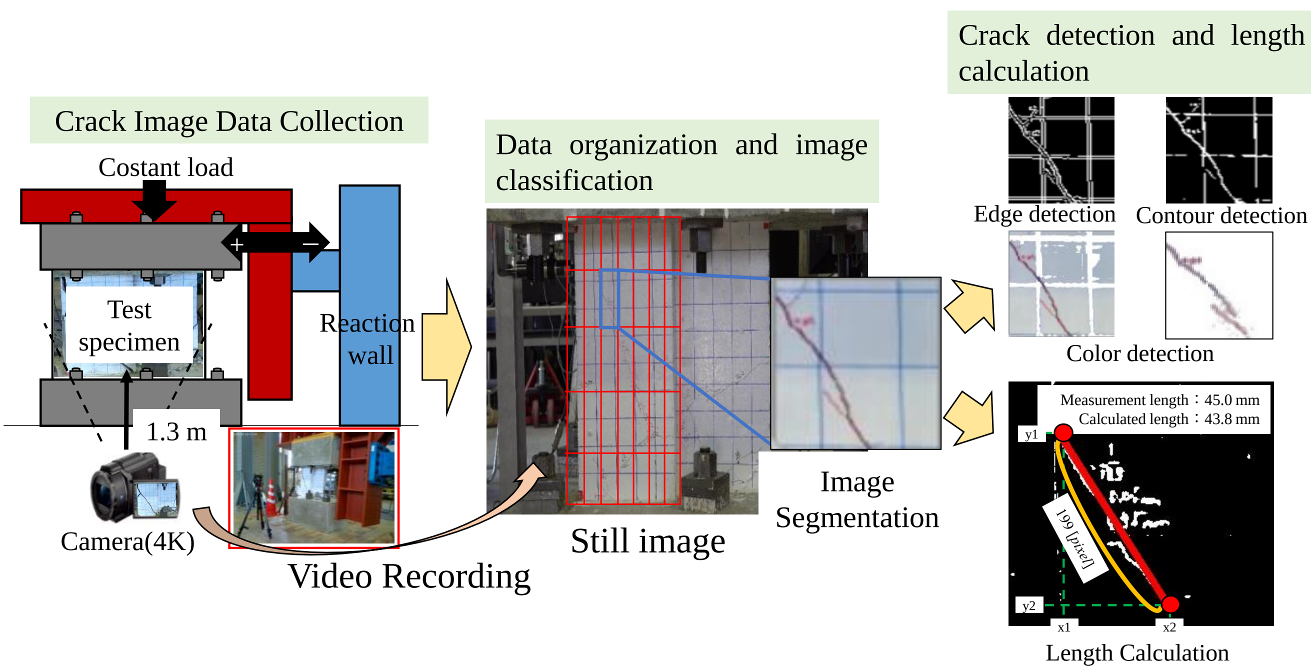


Fig. 1. An overview of this study.

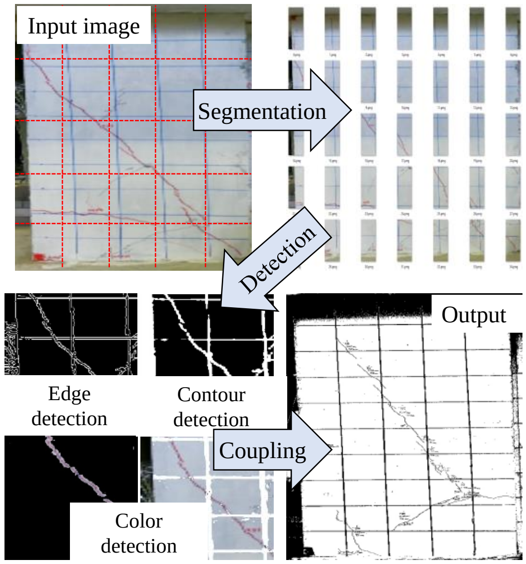


Fig. 2. Preprocessing for crack detection.

For crack detection, data organization and image processing were performed according to the above procedure.

IV. Experiment and Discussion

Crack detection was performed by organizing videos obtained from shear strength experiments and using image processing techniques to detect the presence of cracks. In this study, three image processing techniques were used to detect the presence of cracks. The three image processing techniques are Canny edge detection, Threshold detection, and HSV color detection. Each method for detecting the presence of cracks is described using the input images in Fig. 3. We also describe a method for calculating the length of cracks using image processing techniques.

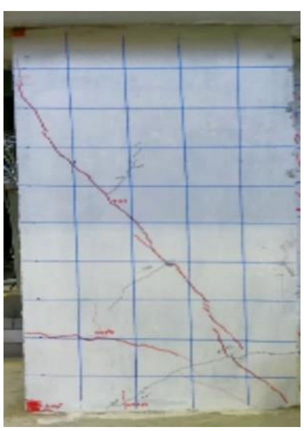
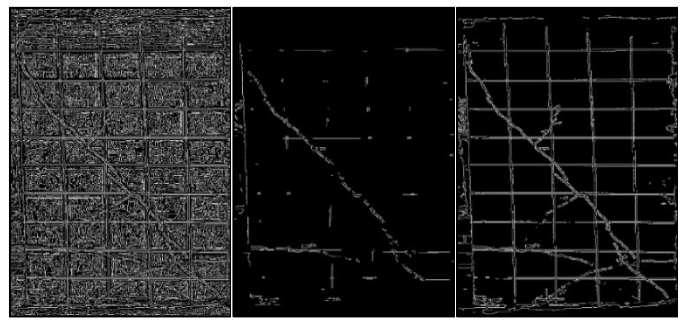


Fig. 3. Input image for crack detection.

A. *Canny Edge Detection*

Canny edge detection is a method for detecting vertical and horizontal edges that indicate points where the pixel values change abruptly in one direction [38]. The accuracy of edge detection depends on the value of the parameter. Therefore, it was necessary to adjust the values of the appropriate parameters. In this study, we employed OpenCV Track Bar to determine the appropriate parameter values. The Track Bar also allows for real-time fine-tuning of parameter values. Fig. 4 shows the results of crack presence detection by adjusting the parameter values. The smaller the value of the parameter, the more noise is generated and the more difficult it is to detect cracks (see Fig. 4(a)). However, the larger the value of the parameter, the less noise there is, but some cracks are removed along with the noise (see Fig. 4(b)). The results with appropriate parameter values indicated that the cracks were easily detected (see Fig. 4(c)).

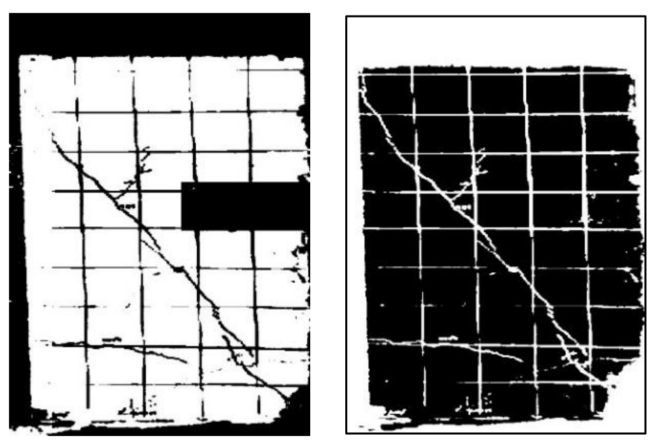


(a) Minimal parameters (b) Maximal parameters (c) Optimal parameters

Fig. 4. Edge detection using the Canny method

B. *Threshold Detection*

Threshold detection converts an image pixel value to white if it is greater than a parameter value and to black otherwise, and binarizes the image [39]. In this study, we used the THRESH_BINARY model, which adjusts parameter values directly, as in Canny edge detection, and the OTSU model, which adjusts them automatically [40, 41]. Both models were compared to examine their accuracy in detecting the presence of cracks. The THRESH_BINARY model uses a Track Bar to adjust the parameter values. Fig. 5 shows the results of the comparison of the models. Both models were able to detect cracks. However, the OTUS model automatically adjusts the values of the parameters; therefore, detection is not possible places. The OTUS model has a significant effect on the resolution of the input image.

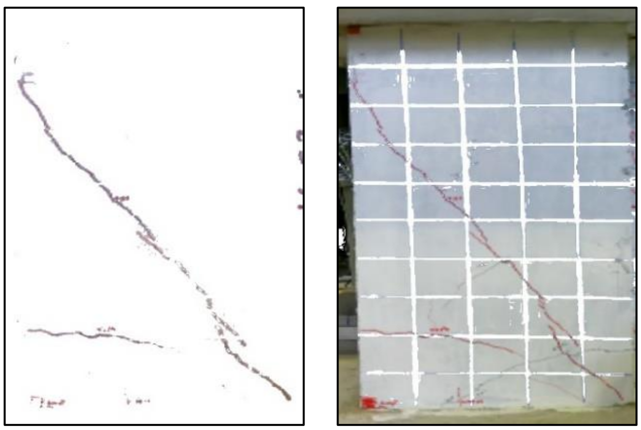


(a) OTUS (b) THRESH_BINARY

Fig. 5. Contour detection using the threshold method.

C. HSV Color Detection

In the shear force experiments conducted in this study, cracks were visually identified and marked during the experiment. Color markings were marked black for positive forces and red for negative forces. The authors considered a method to detect cracks by directly detecting color. In this study, we attempted to detect red and blue colors using the HSV color space model. Fig. 6 shows the results of the red and blue detection. In red detection, the method detects the areas marked in red and changes all other areas to white. In blue detection, the method detects blue and changes the color of the area to white. Both detection methods were able to detect cracks using color detection. However, some areas appear to have failed to be detected in certain regions. Color detection was found to be less accurate, depending on the resolution of the input image.



(a) Color detection (red) (b) Color detection (blue)

Fig. 6. Color detection results by HSV model.

D. Crack Length Detection

Crack lengths were calculated using OpenCV and Numpy. In this study, the crack lengths were calculated linearly. The crack length is determined by Eq. (1) to Eq. (4). Eq. (1) determines the number of pixels on the diagonal of an input image. In Eq. (2), the number of pixels is used to determine the resolution. Eq. (3) converts pixels to centimeters and calculates the length of one pixel. In Eq. (4), the length is calculated by counting the total number of pixels in the cracks to be calculated. The crack length was calculated by determining the values of the parameters based on the input image size. The value of parameter is the established reference point for the input image at the shooting distance (see Fig. 7).

$$dots = \sqrt{(w^2 \times l^2)} \quad (1)$$

$$dpi = dots \div inch \quad (2)$$

$$px = (25.4\, mm \div dpi) \times cv \quad (3)$$

$$L_t = px_t \times px \quad (4)$$

where $dots$ is the number of diagonal pixels of the input image [dots], w is the number of horizontal pixels of the input image [dots], l is the number of vertical pixels of the input image [dots], dpi is the resolution of the input image [dots/inch], $inch$ is the length of the diagonal of the input image [inch], px is the length per pixel of the input image [mm/pixel] (1 inch = 25.4 mm), cv is the correction factor for the input image size [mm], L_t is the total length between stickers [mm], and px_t is the total number of colored pixels [pixels].

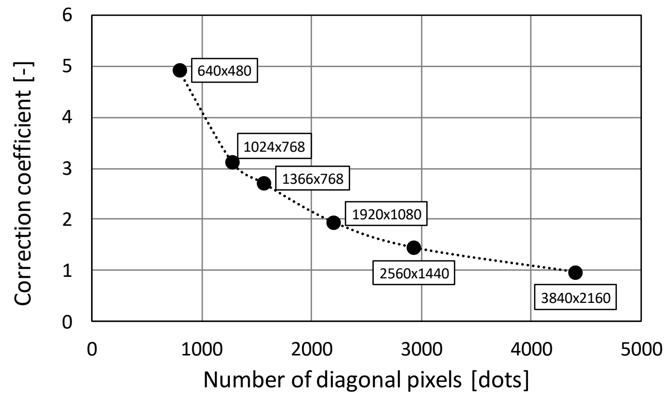


Fig. 7. Correction factor in image size.

In particular, Eq. (3) requires an accurate length per pixel. This length per pixel has a significant impact on the calculation accuracy. The accuracy of the length per pixel was determined using the blue border of the input image as the reference line. The blue line was 50 mm in length and width, which confirms the per-pixel validity. The following procedure was used to calculate the crack length (see Fig. 8).

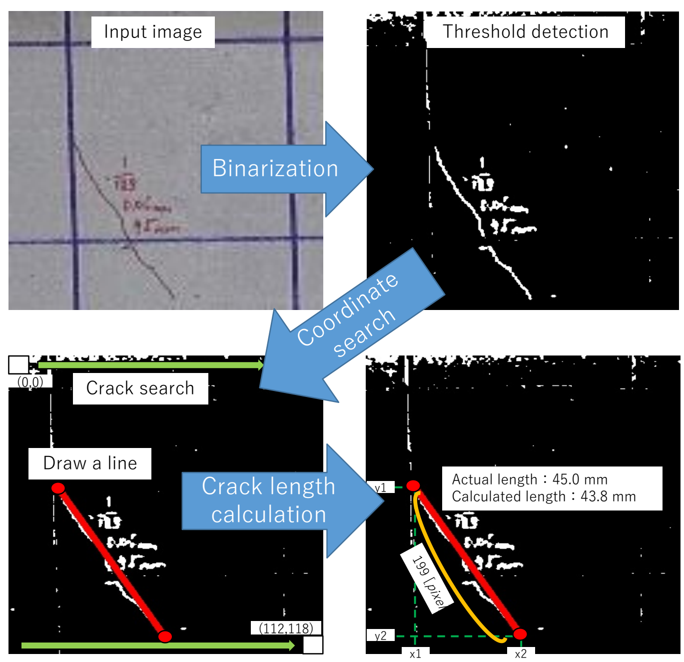


Fig. 8. Crack length calculation method.

1) The input image is converted into black and white binarizations.

2) Images converted to black and white were classified as the background and cracks, respectively.

3) The size of the input image was determined.

4) *Based* on its size, cracks are searched from the first to the last coordinates.

5) *Select* a location to calculate the length of the crack and draw a straight red line on the image.

6) *The* red pixels are counted linearly.

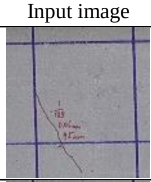
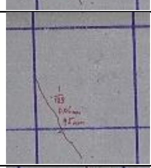
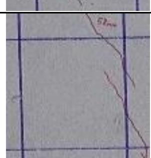
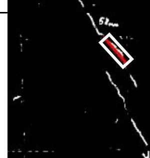
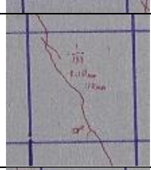
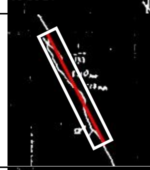
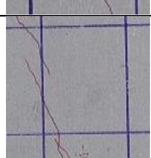
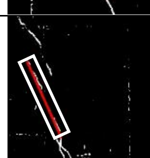
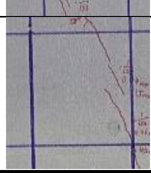
7) *The* crack length was calculated using Eq. (4).

E. Crack Length Calculation

Using the crack length calculation method described above, the lengths were calculated for the six cracks, as shown in Fig. 9. Table I lists the calculated lengths for each crack image. Images 1-6 were intended for cracks that were as continuous as possible. Cracks were examined through visual inspection during the shear force tests, and crack lengths were measured linearly using a tape measure. The measured length was compared to the calculated length to determine the accuracy of the calculation.

The results of the crack-length comparison yielded a 98.1% correct response rate. The closer the percentage of correct answers is to 100%, the more likely it is that the length is similar to the measured value. Crack lengths were calculated for crack images 3, 4, and 5, and were somewhat similar to the measured lengths for which crack lengths were compared. However, for images 1 and 2, the errors were 2.7% and 4.6%, respectively, which are much larger than the measurement results. It is thought that the point of the crack length measured at the time of measurement and the point of calculation were slightly different. It is also believed that the calculation error is affected by the accuracy of the binarization image processing. Other images of each crack had different image sizes depending on the area from which the crack was extracted. Therefore, the lengths corresponding to the pixels were different, which may have caused an error in the length calculation. In this study, the crack length was obtained linearly. If curved cracks are targeted, it is necessary to change the angle of the input image or to split the image.

TABLE I. COMPARISON OF ACTUAL CRACK LENGTHS AND CALCULATED RESULTS

No	Input image	Crack detection image	Image Size [pixel]	Measurements value [mm]	Calculated Value [mm]	Error rate [%]
1			112×118	45.0	43.8	2.7
2			112×118	28.0	26.7	4.6
3			107×107	15.0	15.1	0.7
4			107×108	40.0	40.2	0.5
5			134×111	56.0	56.6	1.1
6			113×105	30.0	29.5	1.7

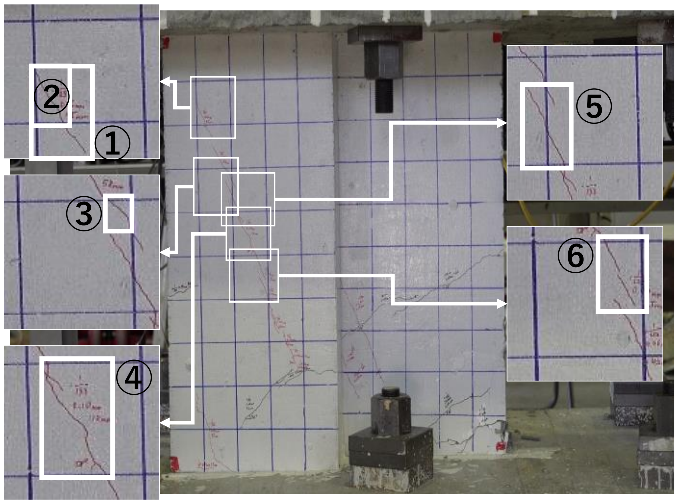


Fig. 9. Results for length of cracks.

V. CONCLUSION

In this study, crack image data were collected using a 4K camera during shear force experiments. Image data were used to develop a method for detecting the presence of cracks and calculating their lengths. Cracks were detected using edge, contour, and color detection. A method for calculating the crack length using image processing was also developed. The results obtained were as follows:

1) The visibility of the edge detection results differed depending on the adjustment of parameters.

2) The OpenCV Track Bar allows for easy parameter adjustment and proper crack detection.

3) The results obtained for contour detection varied significantly depending on the brightness of the image. As with edge detection, the accuracy of detection depends on the parameter values.

4) Color detection requires a different method for each color. In this paper, we propose a method that combines image segmentation.

5) The crack length calculation method is significantly affected by the length per pixel of the input image. Therefore, a reference line must be established and verified.

6) In this study, we proposed a method to calculate cracks as straight lengths, and obtained results with 98.1% accuracy. However, for curved cracks, it was necessary to rotate or segment the image.

7) For crack photography, adjusting the brightness using light according to the local environment is linked to detection accuracy.

8) A comprehensive study of crack detection methods tailored to these conditions is required to address a variety of environments.

FUTURE RESEARCH WORKS

In the future, the machine learning of crack patterns will be used to build a model that can predict crack growth by classifying whether pattern deviations are within an acceptable range.

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