



## Unmanned Aerial Vehicle (UAV)-powered Concrete Crack Detection based on Digital Image Processing

H. Kim<sup>1</sup>, S.H. Sim<sup>2</sup>, S. Cho<sup>3</sup>

- 1 Graduate Research Assistant, Smart Infrastructure and Systems Laboratory, Dept. of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology, Ulsan, Republic of Korea.  
E-mail: guswns3@unist.ac.kr
- 2 Assistant Professor, Smart Infrastructure and Systems Laboratory, Dept. of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology, Ulsan, Republic of Korea.  
E-mail: ssim@unist.ac.kr
- 3 Research Assistant Professor, Smart Infrastructure and Systems Laboratory, Dept. of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology, Ulsan, Republic of Korea.  
E-mail: soojin@unist.ac.kr

### ABSTRACT

Civil infrastructure can suffer from concrete cracks due to the creep, shrinkage, diverse natural loading, aging, and corrosion of reinforcement. Concrete cracks are one of the important features when analyzing the current condition of concrete structures. The shape, length, and width information on concrete cracks are possible to conduct an initial maintenance for the structure safety. Generally, concrete cracks in structures are inspected by the inspector who evaluates the structural health by observing and measuring visual damages on the surface of concrete structures. However, the visual inspection is time consuming and costly, it is dangerous for specialists, and improper environments can cause evaluation errors. Recently, digital image processing (DIP) has been introduced as an alternative automatic crack assessment to the visual inspection. However, image processing has some issues to conduct the crack identification of large-scale infrastructure in terms of the time, cost, and safety. Recent advancements in UAV technologies have enabled low-cost, high-performance UAVs that can be adopted in diverse technologies. In this paper, a prototype of the UAV-based image processing is proposed to identify concrete cracks. From the field experiment, the calculated crack width is similar with the measured crack width by crack gauges.

**KEYWORDS:** *Unmanned Aerial Vehicle, Single Board Computer, Digital Image Processing, Concrete Crack, Concrete Structure*

### 1. INTRODUCTION

Civil infrastructure (e.g., bridge, building, dam, and nuclear power plant) is exposed to loadings, such as earthquake, typhoon, ocean wave, and live and dead load. These inevitable loadings may cause the structural deterioration and damage, which can cause catastrophic collapses associated with significant socio-economic losses. Thus, a wide variety of maintenance strategies for the structural safety have been developed. Because most civil infrastructure is constructed by concrete that induces cracks due to the creep, shrinkage, and corrosion of reinforcements, crack assessment has been widely studied for the structural safety.

Crack information (e.g., number of cracks and crack width and length) represents the current structural health, which can be used for the proper maintenance to improve the structural safety. Cracks are generally inspected by the inspector who evaluates the structural health by observing and measuring visual damages on the surface of concrete structures. Although the visual inspection is a basic way to detect concrete cracks, this method is time consuming and costly, dangerous for specialists, and improper environments can cause evaluation errors.

Digital image processing (DIP) has been introduced as an alternative automatic crack assessment to the visual inspection. Tanaka and Uematsu 1998 performed the crack detection of concrete bridges using morphological techniques. Fujita and Hamamoto 2011 proposed the robust automatic crack assessment algorithm for noisy concrete surface images. Abdel-Qader 2006 proposed the principal component principles (PCA) based method to detect concrete cracks on concrete bridge decks. Kaseko, 1994 proposed the neural network classifier algorithm for inspecting cracks on the video of asphalt-concrete pavement surfaces. Saar and Talvik, 2010 proposed the novel approach method for the automatic crack detection on the pavement. The image processing

is possible to solve some of the disadvantages of the visual inspection, while these techniques have three significant issues for monitoring large-scale infrastructure: 1) the trouble to monitor all the elements of large-scale infrastructure, 2) the safety problem to inspectors who is taking crack images, 3) the revision of crack images according to the camera angle.

Recent advances in UAV technologies are considered as a prominent tool to scale the monitoring with lower labor and cost. In particular, the UAV associated with sensing capability and computer-vision can be an innovative approach for large-scale infrastructure monitoring. However, recent UAV-based crack detection has a significant issue that cannot identify all the crack widths due to the lack of measurement systems. To calculate crack widths, the UAV-based system is essentially needed to take crack images and associated distance information. In addition, the UAV-based image processing should be developed to control intrinsic vibrations and dynamic movements of UAVs for taking high-quality images.

In this study, an automated crack assessment method for large-scale infrastructure is proposed by adopting the UAV technology with the image processing. The proposed UAV is equipped with Raspberry Pi, camera, and ultrasonic displacement sensor, which can measure the crack image and distance information while UAV is flying. The used image processing strategies are subtraction with median filter (Biggs and M. Andrews 1997), Sauvola's binarization method (Hanisch 1997), image revision using eccentricity and connection of pixels, and crack decomposition and width calculation algorithm.

## 2. UAV-BASED IMAGE PROCESSING

### 2.1 UAV-based system

To develop a prototype for the proposed crack identification, the UAV and essential sensing capability are considered as shown in Fig. 2.1. The AR.Drone 2.0 of Parrot is adopted, as this UAV is a popular quadcopter in terms of the low-cost and high-performance. The adopted UAV is equipped with three significant items: 1) Raspberry Pi, 2) camera, 3) ultrasonic displacement sensor. The Raspberry Pi is connected with the camera and ultrasonic displacement sensor, which can take crack images and associated distance information from the camera to the crack. The measured crack information is transported to the computer using the remote control of the Raspberry Pi. A Raspberry Pi model B+ of the single board computer whose CPU is 700 MHz low power ARM1176JZFS applications processor, and memory is 512MB SDRAM. A Raspberry Pi camera model LS 20150 whose focal length is 2.8 mm, which contains 2592 pixels  $\times$  1944 pixels with the dimension of 3673.6  $\mu\text{m} \times$  2738.4  $\mu\text{m}$ . Thus, 1 mm of the image length has about 708 pixels. A HC-SR04 of the ultrasonic displacement sensor is employed to measure the displacement whose resolution is 0.3 cm.

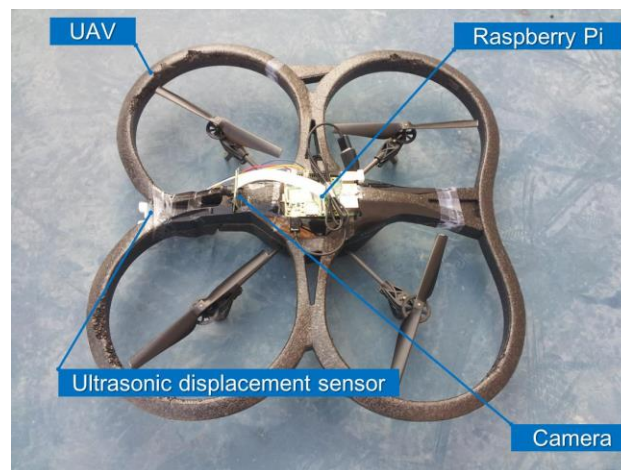


Figure 2.1 UAV-based systems for crack identification

### 2.2 Image processing for crack identification

The image processing strategy that is tailored to the UAV-based system has been developed to conduct the crack identification. The proposed image processing strategies are as follows, 1) subtraction with median filter, 2) binarization using Sauvola's method, 3) image revision using eccentricity and connection of pixels, and 4) crack

decomposition and width calculation algorithm as shown in Fig. 2.2.

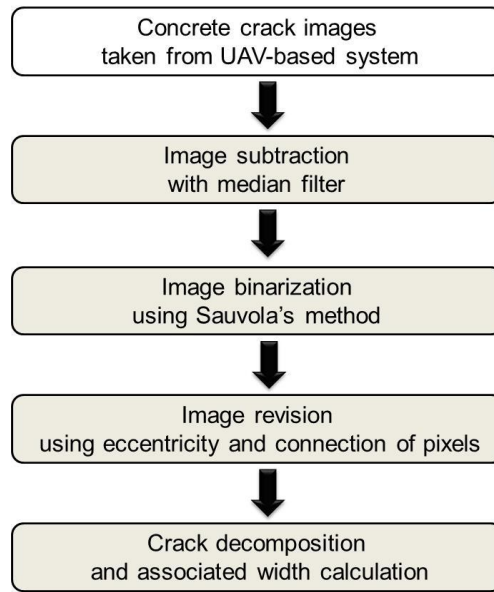


Figure 2.2 Flow diagram of image processing strategy

The median filter is the most widely used as a nonlinear filtering technique in the image processing, which is frequently adopted for both removing noises and enhancing crack shapes. The capability of the median filter is closely related to both shape and size of the filter window. The square shape of the filter window is selected in this study, which is frequently used. The filter window size is selected as the 50 pixels  $\times$  50 pixels.

The Sauvola's binarization method is an important process, which is to change a gray-scale image into a black and white image. The high-performance of the image binarization heavily depends on the selection of the threshold, a various methods have been proposed to determine the optimal threshold, such as Niblack's method (Niblack 1985), Otsu's method (Otsu 1979), and Wolf's method (Wolf 2003). The general purpose of the binarization is to identify text from the image, the text and crack detection have a similar purpose to identify specific objects in the captured image. Thus, the existing binarization methods are capable of the crack assessment algorithm. Especially, the Sauvola's method performs well, which method is adopted for the binarization of crack images in the proposed image processing.

After the binarization, the image revision algorithm is adopted for removing noises except concrete cracks, such as hole, dust, and mark. The noises have a specific shape that can be distinguished from concrete cracks, such as the smaller value of the eccentricity and connection of pixels. The proposed image revision algorithm removes the segment in terms of the eccentricity and connection of pixels.

The crack segments of the binary image are divided as skeleton (Lam 1992) and edge (Canny 1986), and then the crack width calculation algorithm is conducted using each skeleton pixel and the corresponding edge pixels. This algorithm contains four steps: 1) identify directions of each skeleton pixel, 2) find two nearest edge pixels from the selected skeleton pixel, 3) calculate the distance between the two nearest edge pixels, 4) convert the calculated crack width in pixels into the real crack width using the following camera pin-hole model as show in Eq. 2.1.

$$W_r = D_p W_p = \frac{D_w}{10P_c L_f} W_p \quad (2.1)$$

where  $W_r$  is the real crack width,  $D_p$  is the resolution of the imaging system,  $W_p$  is the crack width in pixels.  $P_c$  is the ppcm (pixel per centimeter) of the used camera,  $D_w$  is the working distance in mm, and  $L_f$  is the focal length of the camera in mm, respectively.

### 3. EXPERIMENTAL VERIFICATION

To evaluate the proposed UAV-based image processing, validation tests are conducted on the concrete wall with diverse shape and size of concrete cracks as shown in Fig. 3.1. The inspected area is about 1.5 m high on the ground.



Figure 3.1 UAV-based systems for crack identification

The captured image is processed through the proposed image processing techniques (i.e., image subtraction with median filter, Sauvola's binarization method, image revision using eccentricity and connection of pixels, and crack decomposition and width calculation algorithm) for calculating crack widths. The actual crack widths are measured using a crack gauge, which locations are displayed as the red circles as shown in Fig. 3.2. The actual crack widths are used as references for comparing with the calculated crack widths. The gray-scale image, subtraction using median filter, and result of binarization and image revision are represented as shown in Fig. 3.2.



Figure 3.2 Gray-scale image, subtraction using median filter, and result of binarization and image revision

The distinguished crack width, length, and direction are most similar with the crack information of the original image. In addition, the noises are effectively removed after the proposed image processing. The calculated crack widths are compared with the measured crack widths using a crack gauge as shown in Table 3.1. From the field experiment, the calculated crack widths are similar with the measured crack widths by using a crack gauge.

Table 3.1 Experimental results

Location	Calculated crack width	Measured crack width
1	0.36	0.35
2	0.25	0.25

## 4. CONCLUSION

In this study, automatic crack identification for large-scale infrastructure is proposed by adopting the UAV with image processing. The proposed UAV is equipped with Raspberry Pi, camera, and ultrasonic displacement sensor, which can measure the crack image and associated distance information while UAV is flying. The used image processing strategies are subtraction with median filter, Sauvola's binarization method, image revision using eccentricity and connection of pixels, and crack decomposition and width calculation algorithm. To evaluate the proposed UAV-based image processing, validation tests are conducted on the concrete wall with diverse shape and size of concrete cracks. The inspected area is about 1.5 m high on the ground. The actual crack information is used as references for comparing with the calculated crack width. From the field experiment, the calculated crack widths are similar with the measured crack widths by a crack gauge.

## ACKNOWLEDGEMENT

This research was supported by a grant(15SCIP-B065985-03) from Smart Civil Infrastructure Research Program funded by Ministry of Land, Infrastructure and Transport(MOLIT) of Korean government.

## REFERENCES

1. Abdel-Qader, I., Pashaie-Rad, S., Abudayyeh, O., and Yehia, S. (2006). PCA-based Algorithm for Unsupervised Bridge Crack Detection. *Advances in Engineering Software*. **37:12**, 771-778.
2. Biggs, D. S. C., and Andrews, M. (1997). Acceleration of Iterative Image Restoration Algorithms. *Applied Optics*. **36:8**, 1766-1775.
3. Canny, J. (1986). A Computational Approach to Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. **8:6**, 679-698.
4. Fujita, Y., and Hamamoto, Y. (2011). A Robust Automatic Crack Detection Method from Noisy Concrete Surfaces. *Machine Vision and Applications*. **22:2**, 245-254.
5. Hanisch, R. J., White, R. L., and Gilliland, R. L. (1997). Deconvolution of Hubble Space Telescope Images and Spectra. *Deconvolution of Images and Spectra (2nd ed.)*. 310-356.
6. Kaseko, M. S., Lo, Z. P., and Ritchie, S. G. (1994). Comparison of Traditional and Neural Classifiers for Pavement-Crack detection. *Journal of Transportation Engineering*. **120:4**, 552-569.
7. Lam, L., Lee, S. W., and Suen, C. Y. (1992). Thinning Methodologies-A Comprehensive Survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. **14:9**, 869-885.
8. Niblack, W. (1985). An Introduction to Digital Image Processing. *Strandberg Publishing Company*.
9. Otsu, N. (1979). A Threshold Selection Method from Gray-level Histograms. *IEEE Transactions on Systems*. **9:1**, 62-66.
10. Saar, T., and Talvik, O. (2010). Automatic Asphalt Pavement Crack Detection and Classification using Neural Networks. *In Proceedings of the 12th Biennial Baltic Electronics Conference (BEC10)*.
11. Tanaka, N., and Uematsu, K. (1998). A Crack Detection Method in Road Surface Images Using Morphology. *MVA* 98. 17-19.
12. Wolf, C., and Jolion, J. M. (2003). Extraction and Recognition of Artificial Text in Multimedia Documents. *Pattern Analysis and Applications*. **6:4**, 309-326.