A novel automated crack identification method for concrete bridge structure using an unmanned aerial vehicle

To cite this article: Chung T Truong *et al* 2023 *IOP Conf. Ser.: Mater. Sci. Eng.* **1289** 012037

A novel automated crack identification method for concrete bridge structure using an unmanned aerial vehicle

Chung T Truong[1,*], My Q Dang[1], Tung P Pham[1], Phong V Do[2], Huy Q Tran[1]

[1] Faculty of Civil Engineering, Nha Trang University, Nha Trang 57100, Vietnam
[2] T27 Consultant Company, Nha Trang 57100, Vietnam

[*] Corresponding author's e-mail: chungtt@ntu.edu.vn

Abstract. This study explores an automated method for identifying cracks on a concrete bridge structure using an unmanned aerial vehicle (UAV) equipped with a high-resolution camera. First, images are captured from the bridge, then a novel automated algorithm are used to isolate the region of interest. The deep learning algorithm then detects cracks on the structure using a pre-trained Convolutional Neural Network (CNN) model. The proposed method was tested on Tran Phu bridge, and the results confirmed the effectiveness of the UAV-based inspections for identifying cracks on structures.

1. Introduction

Various factors such as external load, fatigue load and thermal expansion can cause decrease in performance of bridge structures over time. As cracks directly reflect the condition of the bridge structures, it is considered an important parameter for structural health monitoring [1-4]. Crack detection are often carried out by human inspection. However, this method has limitations in terms of time consumption, cost, and accessibility to certain areas.

In recent years, unmanned aerial vehicles (UAVs) equipped with high-resolution cameras for bridge inspection were gain much interest due to their safety and reliability [5-8]. These UAVs capture digital images of the bridge structure, which are then analyzed by crack identification methods such as histogram [9], thresholding [10], and edge detection [11-12]. However, these techniques have very limited effectiveness in real-world scenarios due to challenges such as lighting changes, shadows, stains, and rough surfaces. To overcome these limitations, recent research has focused on deep learning-based crack detection methods [13-15], which have demonstrated greater robustness and accuracy compared to conventional image processing techniques.

One significant challenge associated with using UAVs for crack identification is the abundance of irrelevant content in the collected images [16]. Often, only a small portion of the image contains the relevant region of interest for the crack identification algorithms. Without proper image processing prior to applying the crack identification algorithms, a significant number of false-positive and false-negative errors are likely to occur. Such errors would significantly reduce the reliability of the techniques.

In this study, a novel automated algorithm was developed to isolate region of interest from the images captured by the UAV. The proposed method was tested on Tran Phu bridge to confirm its effectiveness.

IOP Conf. Series: Materials Science and Engineering 1289 (2023) 012037 doi:10.1088/1757-899X/1289/1/012037

2. UAV-based crack identification method

The schematic of the proposed UAV-based crack identification method is as follows (Figure 1). First, images are acquired from the bridge by the UAV. Then an automated algorithm is used to isolate the region of interest (ROI) for the crack identification algorithms. The deep learning algorithm then applied to ROI to detect cracks using a pre-trained Convolutional Neural Network (CNN) model called SqueezeNet [17-18]. Finally, the locations of the cracks are mapped onto the 3D point cloud model of the structure.

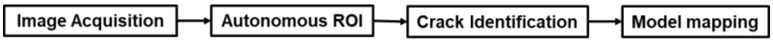

Figure 1. UAV-based crack identification method of bridge structure.

2.1. Image acquisition

The UAV used in this study is the Phantom 4 RTK manufactured by DJI (Figure 2), equipped with a 20-megapixel camera that captured images with a maximum size of 5472×3648. The flight control was operated manually to maintain a distance of approximately 6 meters from the concrete deck. However, due to the high winds during the field test, it was impossible to maintain a constant distance as well as keeping the horizontal orientation of the captured images. Planar markers with checkerboard pattern were attached on the bridge to correct the distorted image as well as estimating the relationship between image coordinates in the unit of pixels and world coordinates in the units of millimeter (scale factor).

Figure 2. Phantom 4 RTK for image acquisition.

2.2. Automated algorithm for isolation of the region of interest

In the case of the bridge, the region of interest is the area of the image containing the side of the concrete deck and the girder below the deck. Since the shape of ROI is consistent across the bridge, it is possible to develop an automated algorithm for isolation of the region of interest.

The flowchart of the algorithm is shown in Figure 3 with the illustration shown in Figure 4. First, the color image (Figure 4a) is converted to grayscale. Then thresholding technique is used for isolation of the concrete deck of the bridge (Figure 4b). Next, the line below the deck is detected using Hough transform technique. This detected line is then used to rotate the image to ensure the concrete deck is horizontal (Figure 4c). Finally, a rectangular window is used to select the ROI (Figure 4d) with the size of the window is estimated using the calculated scale factor.

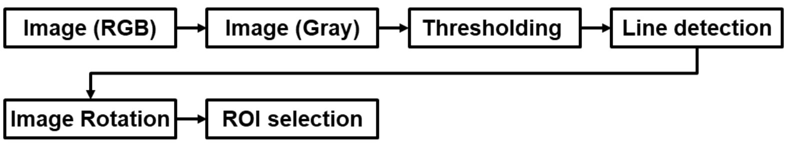

Figure 3. Automated algorithm for isolation of the region of interest.

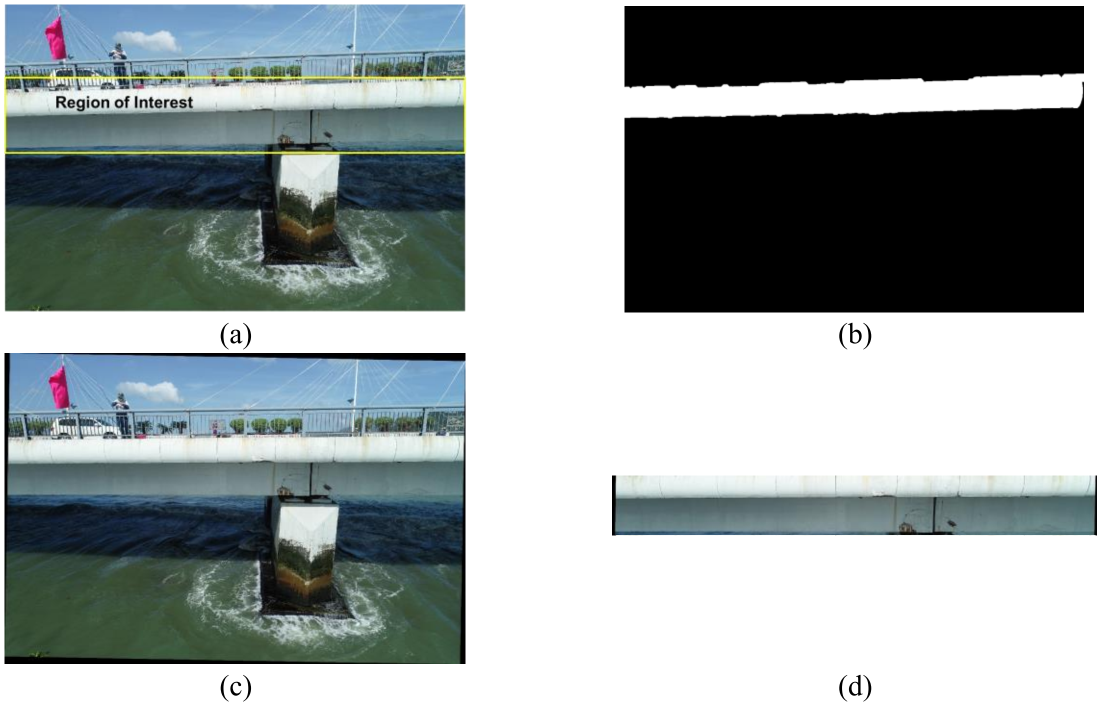

Figure 4. (a) Original image, (b) Thresholding technique to isolate the bridge deck, (c) Rotated image, (d) Isolated region of interest (ROI).

2.3. Crack identification using deep learning

The overview of the process for crack identification using deep learning is shown in Figure 5. First, an image database is used for training the Convolutional Neural Network (CNN) model. Once the training process is completed, the CNN model can effectively differentiate between crack and non-crack images. The sliding windows technique is then utilized to scan the real-world image for crack identification.

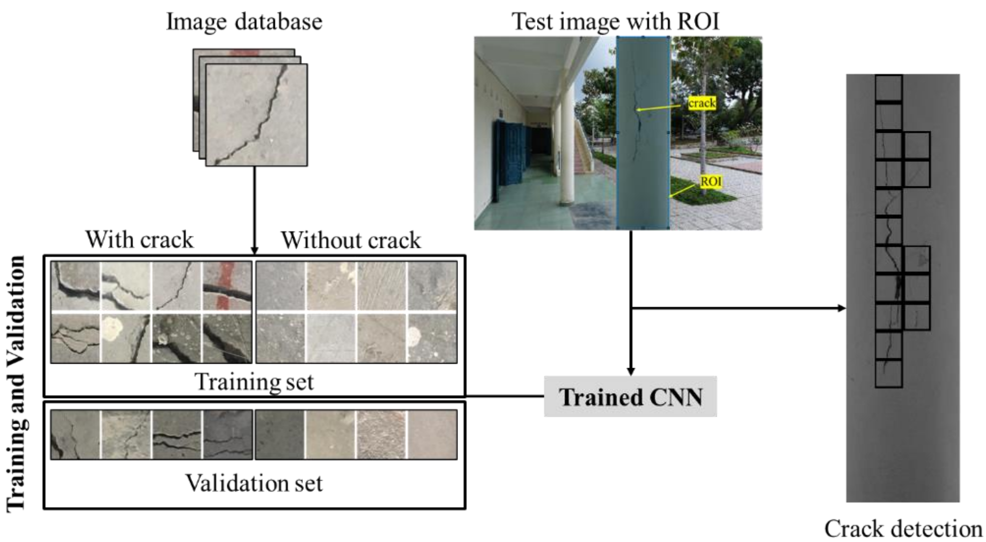

Figure 5. Overview of crack identification using deep learning.

2.3.1. Image database. In this paper, we used the image database provided by Özgenel and Sorguç [19]. It contains 40,000 images, separated into sets of positive (containing cracks) and negative (not containing cracks) images. Sample images from the database are shown in Figure 6. The image database was randomly divided into 70% of images for training, 15% for validation and 15% for testing.

Figure 6. Sample images of concrete structures with and without cracks.

2.3.2. Convolutional Neural Network model. To automatically detect cracks in concrete bridge structures, we utilized a pre-trained Convolutional Neural Network model called SqueezeNet. This model has 18 layers and takes in images of size 227×227, with the output being a binary classification of crack or non-crack. Figure 7 illustrates SqueezeNet's advantage over other pre-trained neural networks, which is the small size and fast.

We used MATLAB 2020b for running the CNN model using a computer with following specifications: Intel Xeon W-2223 CPU @ 3.6 GHZ 8 cores, 16 GB RAM, GPU NVIDIA Quadro P2200. The training parameters are provided in Table 1. The model achieved a 99.6% accuracy in distinguishing between images with crack and without cracks.

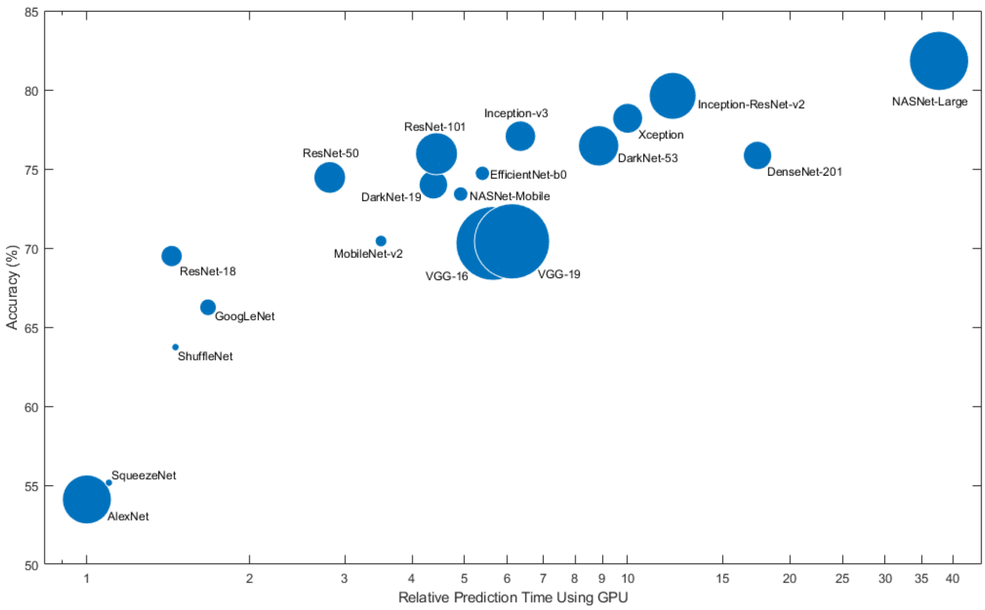

Figure 7. Comparison of pre-trained Convolutional Neural Networks [20].

Table 1. Parameters for training of SqueezeNet.

Epoch	Batch size	Weight decay	Learning rate	Learning rate decay	Momentum
100	64	0.0002	0.01	0.1	0.9

3. Field test result

A field test was conducted on Tran Phu bridge (Figure 8) to verify the effectiveness of the proposed UAV-based crack identification method. Located in Nha Trang City, the bridge spans the Cai River. It is 458 meters long and 22 meters wide, featuring four traffic lanes. The bridge construction began in September 1999 and was completed in September 2002. Since the bridge has been in service for a long period, it is now scheduled for inspection in anticipation of forthcoming maintenance work.

The targets of the field test were the inaccessible areas such as the side of the bridge deck, the girder below the bridge deck, and the piers. The crack identification result of one section of the bridge is shown in Figure 9, where the cracks at the bridge bearing and other locations were successfully identified. It is noticed that the gap between each section of the bridge deck is also marked as crack; however, these false positives can be easily removed in post-processing.

Figure 8. Field test on Tran Phu bridge (March 2023).

Figure 9. Crack identification in one section of the bridge.

4. Conclusions

In this paper, we proposed a UAV-based method for identifying cracks of concrete bridge structure. A novel automated algorithm was developed to isolate region of interest from the images captured by the UAV. The proposed method was successfully tested on Tran Phu bridge and yielded satisfactory results. Although the program may occasionally misidentify some expansion joints as cracks during automatic analysis, such misidentifications can be readily addressed through post-processing.

Acknowledgment

This research was supported by Nha Trang University via grant number TR2022-13-08 and grant number SV2022-13-01. The authors acknowledge the contributions of the research team at the SA-NDE-T Lab, Faculty of Civil Engineering, Nha Trang University.

References

[1] Fujita Y, Mitani Y, and Hamamoto Y 2006 A Method for Crack Detection on a Concrete Structure *18th International Conference on Pattern Recognition* **3** 901-904
[2] Yamaguchi T, Nakamura S, Saegusa R, and Hashimoto S 2008 Image-Based Crack Detection for Real Concrete Surfaces *IEEJ Transactions on Electrical and Electronic Engineering* **3**(1) 128-135
[3] Cheng H D, Chen J R, Glazier C, and Hu Y G 1999 Novel approach to pavement cracking detection based on fuzzy set theory *J. Comput. Civ. Eng* **13**(4) 270-280
[4] Fujita Y and Hamamoto Y 2011 A robust automatic crack detection method from noisy concrete surfaces *Mach. Vis. Appl.* **22**(2) 245-254
[5] Kim I H, Jeon H, Baek S C, Hong W H, and Jung H J 2018 Application of crack identification techniques for an aging concrete bridge inspection using an unmanned aerial vehicle *Sensors* **18**(6) 1881
[6] Kim H, Lee J, Ahn E, Cho S, Shin M, and Sim S H 2017 Concrete crack identification using a UAV incorporating hybrid image processing *Sensors* **17**(9) 2052
[7] Eschmann C, Kuo C M, Kuo C H, and Boller C 2013 High-resolution multisensor infrastructure inspection with unmanned aircraft systems *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* **40** 125-129
[8] Pereira F C and Pereira C E 2015 Embedded image processing systems for automatic recognition of cracks using UAVs *Ifac-PapersOnline* **48**(10) 16-21
[9] Kirschke K R and Velinsky S A 1992 Histogram-based approach for automated pavement-crack sensing *J. Transp. Eng.* **118**(5) 700-710
[10] Oliveira H and Correia P L 2009 Automatic road crack segmentation using entropy and image dynamic thresholding *17th European Signal Processing Conference* 622-626
[11] Santhi B, Krishnamurthy G, Siddharth S, and Ramakrishnan P K 2012 Automatic detection of cracks in pavements using edge detection operator *J. Theor. Appl. Inf. Technol*. **36**(2) 199-205
[12] Abdel-Qader I, Abudayyeh O, and Kelly M E 2003 Analysis of edge-detection techniques for crack identification in bridges *J. Comput. Civ. Eng* **17**(4) 255-263
[13] Protopapadakis E, Makantasis K, Kopsiaftis G, Doulamis N, and Amditis A 2016 Crack Identification Via User Feedback, Convolutional Neural Networks and Laser Scanners for Tunnel Infrastructures *VISIGRAPP* 725-734
[14] Cha Y J, Choi W, and Büyüköztürk O 2017 Deep learning-based crack damage detection using convolutional neural networks *Comput.-Aided Civ. Infrastruct* **32**(5) 361-378
[15] LeCun Y, Bengio Y, and Hinton G 2015 Deep learning *Nature* **521**(7553) 436-444
[16] Yeum C M, Choi J, and Dyke S J 2019 Automated region-of-interest localization and classification for vision-based visual assessment of civil infrastructure *Struct. Health. Monit.* **18**(3) 675-689
[17] Zhang L, Yang F, Zhang Y D, and Zhu Y J 2016 Road crack detection using deep convolutional

neural network *ICIP* 3708-3712

[18] Iandola F N, Han S, Moskewicz M W, Ashraf K, Dally W J, and Keutzer K 2016 SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size *arXiv* preprint arXiv:1602.07360

[19] Özgenel Ç and Sorguç A G 2018 Performance comparison of pretrained convolutional neural networks on crack detection in buildings *Isarc. proceedings of the international symposium on automation and robotics in construction* **35**

[20] https://www.mathworks.com/help/deeplearning/ug/pretrained-convolutional-neural-networks.html , access April 13, 2023