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STUDY OF FILMING CONDITION FOR DEEP LEARNING BASED CRACK DETECTION METHOD

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Abstract

Recently, the study of extending the service life of bridges has gained attention. In Japan, there are about 730,000 bridges with a length of 2 m or longer, and many of these were built during a period of high economic growth, and have now reached the end of their service life. Therefore, their rebuilding and the extension of their service life must be considered. However, some local public organizations have problems that insufficient manpower relative to the number of bridges to manage, as well as insufficient funding for maintenance. Thus, these organizations are unable to perform routine close visual inspections. Specific problems include “notably less staff and consulting technicians relative to the number of bridges to be managed” and “high inspection cost preventing from funding for repair.” As issues with the continuing close visual inspection of bridges are surfacing, the remote imaging system is expected to become a new inspection method that replaces close visual inspection. The practical potential of bridge inspections using images captured with a super-high-resolution camera was examined. A super-high-resolution camera enables us to take a wide area picture of a target bridge from a long distance. An image processing method could improve the efficiency of image-based inspection method. For example, a deep learning-based image processing method could extract a damaged area on a surface of a bridge automatically with high accuracy faster than human inspection. In general, the accuracy of an image processing method is affected by the quality of an input image. Filming conditions are one of the factors that determine the quality of a photo image. It is important to evaluate the effect of filming conditions to improve the reliability of an image processing method. In this paper, we evaluate the effect of the filming conditions for an image processing method by comparing the results of a deep learning-based crack detection method.

Keywords: bridge inspection, crack detection, image processing, filming conditions, deep learning

1 Introduction

Recently, the study of extending the service life of bridges has gained attention. In Japan, there are about 730,000 bridges with a length of 2 m or longer, and many of these were built during a period of high economic growth, and have now reached the end of their service life. Therefore, their rebuilding and the extension of their service life must be considered. An owner of a bridge is required to monitoring a bridge with close visual inspection per 5 years according to the national criteria in 2014 in Japan.

However, some bridges owned by a local government have not completed the inspection due to a lack of an engineer of bridge inspection or budget. Such bridges are not expected to manage with aggressive preventive maintenance in the future.
One of the reasons for this problem is the expensive cost of close visual inspection for a bridge. Some bridges are hard to access for engineers to inspect. Such bridges need scaffolding or an expensive special car to perform a close visual inspection. It increases the cost of the inspection. In some case, bridge inspection needs traffic control and it makes economic loss. So more reduce economical cost and simplified process of inspection method is required for a future bridge maintenance inspection and already many novel inspection methods are proposed [1], [2], [3]. We focus on the remote imaging system which is expected to become a new inspection method that replaces close visual inspection [4]. In this system, an engineer inspects the bridge by photo image of the target bridge. So engineer no needs to closing the target bridge to inspect. This system can solve many problems of current close visual inspection.
The practical potential of bridge inspections using images captured with a super-high-resolution camera was examined [4]. A super-high-resolution camera enables us to take a wide area picture of a target bridge from a long distance. An image processing method could improve the efficiency of the image-based inspection method. For example, a deep learning-based image processing method could extract a damaged area on a bridge surface automatically with high accuracy and faster than human inspection. In general, the accuracy of the image processing method is affected by the quality of the input image. Filming conditions are one of the factors that determine the quality of the photo image. Setting appropriate filming conditions is one way to make the quality of the photo high. But the weather changes very often and all bridges are not located on a plane field. It is difficult to control filming conditions in real bridge inspection. So, it is important to evaluate the effect of filming conditions to improve the reliability of the image processing method. Unfortunately, there is no discussion about the effect of filming conditions for accuracy of image processing method using real crack on a concrete building.
In this paper, our purpose is not discovering appropriate filming conditions but measuring the degree of effect of filming conditions to image processing methods. We focus on two factors of filming conditions: the distance of the camera and the lighting. We evaluate these factors using a photo image of a real crack on the surface of a concrete building. We compare the results of the deep learning-based crack detection method to evaluate the effect.

2 Related works

There are many kinds of method for detecting crack on a concrete surface by image processing. Fujita et al. [5] proposes a crack detection method considering the effect of noise such as irregular shading and blemishes. They focus on the robustness of crack detection. They did not evaluate the effect of noise. A supervised machine learning method for crack detection is mainstream recently. Bu et al. [6] proposed Support Vector Machine based crack detection method. They applied three feature extract methods from the input image; Zenki moment, carbon filter, and wavelet transformation. Convolutional Neural Networks is one of the popular deep learning methods for image processing. Many researchers use it for the crack detection task. Cha et al. [7] prepared 40000 images for the training model of crack detection. This method can surround crack on a concrete surface image with a bounding box and has around 98 % precision for detection.

3 Evaluation

We evaluate the effect of the filming conditions by shifting the distance of a camera and change the light of a field. We compare the precision and recall of crack detection rate for the evaluation.

3.1 Image processing based crack detection method

We adapt the semantic segmentation method as an image processing based crack detection method. We use DeepCrack [8] model for crack detection. This model can output crack area with a pixel unit (Fig. 1). This model trained with a paired input image: raw image and annotation image (Fig. 2). We used 13,700 concrete bridge surface images as training data. All image has same size 256 × 256 pixel. 137 images are extracted from the photo image of real concrete bridge surface. Such photo images had taken by a super-high-resolution camera which has a resolution of about 100 million pixels count. The other images are created by augmentation with the deep learning method [9]. We have trained 137 augmentation models with the above 137 images to generate concrete surface images. We created augmentation images by 137 annotation patterns (Fig. 3).

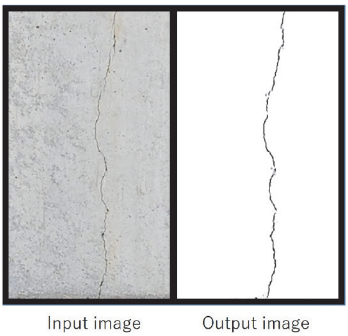

Figure 1 Example of crack detection by DeepCrack

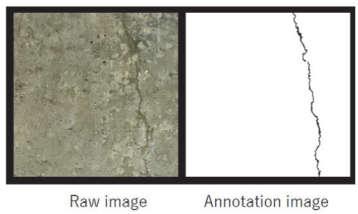

Figure 2 Example of training data set

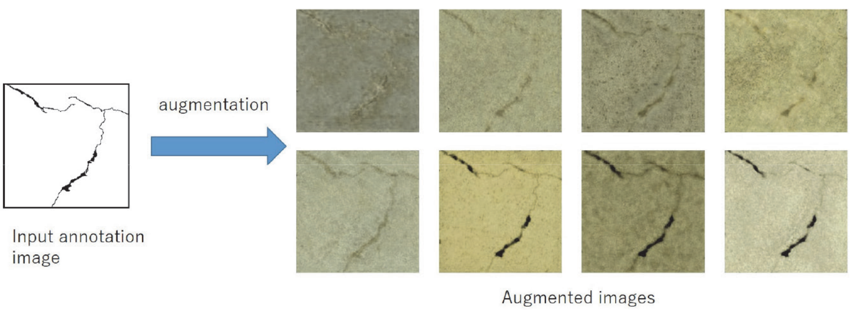

Figure 3 Example of image augmentation

3.2 Test dataset

We set four different cracks on a concrete building as a target crack of test data. We used a super-high-resolution camera which has a resolution of about 100 million pixels count to take a picture. We set six filming points to evaluate the effect of filming distance (Fig. 4). We put two floodlights (intensity is 5500 lumen) near the target crack (distance is 50 cm). To evaluate the effect of light, we set a four-light condition: both lights are turned off, the right one is running, the left one is running, both lights are running (Fig. 5).

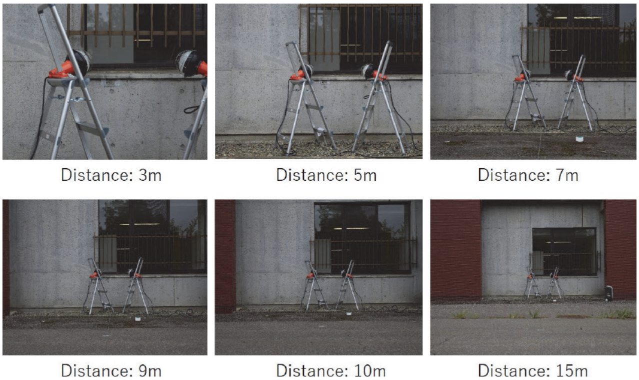

Figure 4 Example of each shooting distance images

Figure 5 Example of light conditions

In this paper, we focus on the effect of filming conditions. But, the target crack area is too small than the original photo image size. It would make decrease the precision of crack detection and make it difficult to evaluate the effect of filming conditions. All test images are cropped image of a crack area of each test data (Fig. 6).

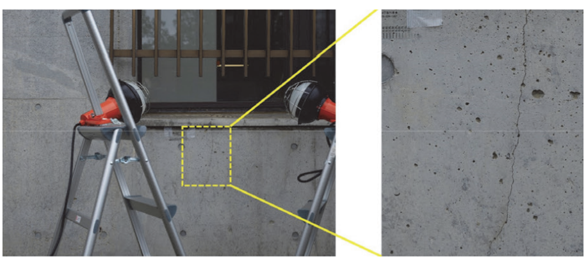

Figure 6 Example of test image cropped target crack area

The crack annotation data of test data made by tracing crack area on the cropped images at each shooting distance. Note that different shooting distance annotation data are not the same (Fig. 7). The annotator could trace small crack on image taken by close shooting distance. On the other hand, the annotator could distinguish only a big crack on an image taken by far shooting distance. The crack annotation data made by one annotator.

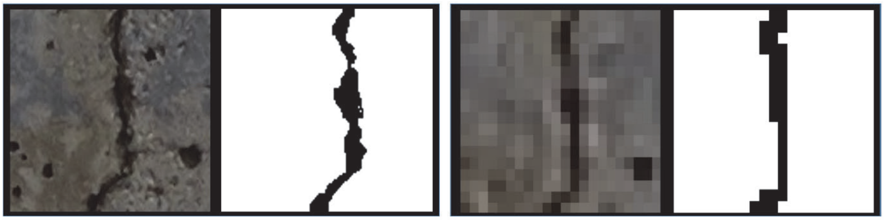

Figure 7 Comparison of enlarged raw crack images and annotated images

3.3 Results of crack detection

We evaluate the effect of shooting distance and light field by comparing the precision and recall. These values are results of image processing for detect cracks on the concrete surface of each condition. We show the average results of crack detection of four different crack images. The precision and recall of crack detection were calculated by the rate of concordance of the results of detection by the image processing method and annotator annotated crack in pixel unit.

Fig. 8 show the precision values of different shooting distance and light of field. When focusing on the change in shooting distance, the worst precision value is 0.280 and the best precision value is 0.423. The difference is 0.143. Note that the worst precision value is not the result of the farthest shooting distance and the best precision value is not the result of the nearest shooting distance. These results show that setting the best shooting distance with low overdetection is difficult. When focusing on the change in light of field, we compare the case of both lights off and the other case. When comparing the precision values, it decreases 0.036 in the worst case and increases 0.023 in the best case. The best light condition of each shooting distance is different.

Fig. 9 show the recall precision values of different shooting distance and light of field. When focusing on the change in shooting distance, the worst precision value is 0.542 and the best precision value is 0.859. The difference is 0.317. The recall value of far-shooting distance becomes higher than one of close-shooting distance. It is because of a difference in resolution of test image data. In the case of shooting distance is far, an annotator could not distinguish a small crack on the image. Because a big crack which is easy to detect by crack detection remains in far shooting distance data, the recall value becomes high when shooting distance is far (Fig. 10). Note that this result does not ensure any far shooting distance make high recall value always. When the surface of the target concrete has a narrow crack only, the recall value may become low. When focusing on the change in light of field, comparing the recall value as with comparing of precision value. When comparing the precision values, it decreases 0.084 in the worst case and increases 0.022 in the best case. As same as the precision values, the best light condition of each shooting distance is different. We should evaluate the mean error in future.

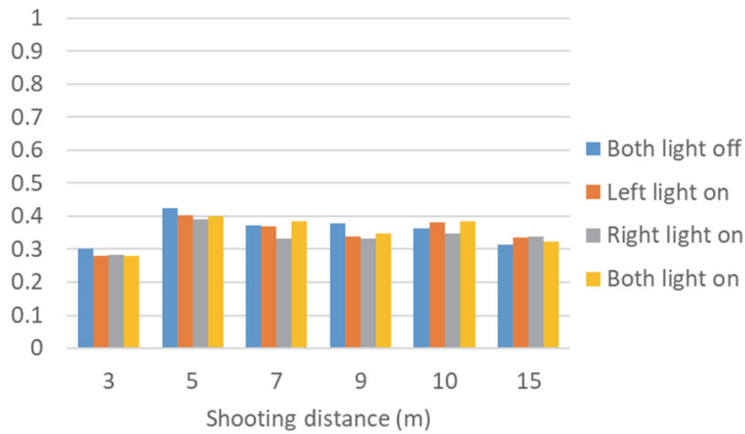

Figure 8 Results of precision

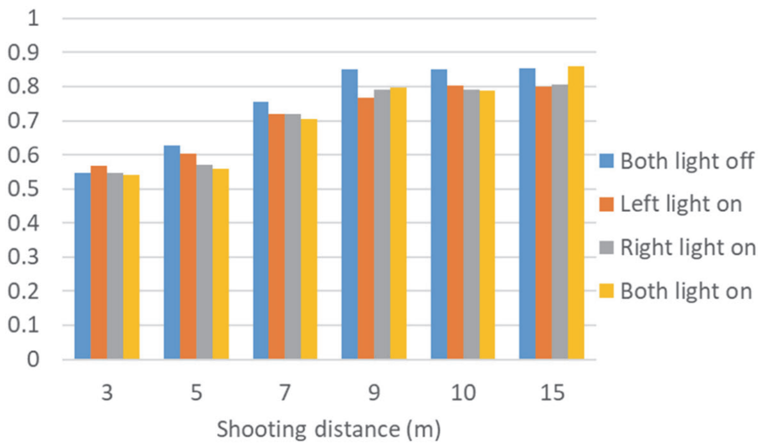

Figure 9 Results of recall

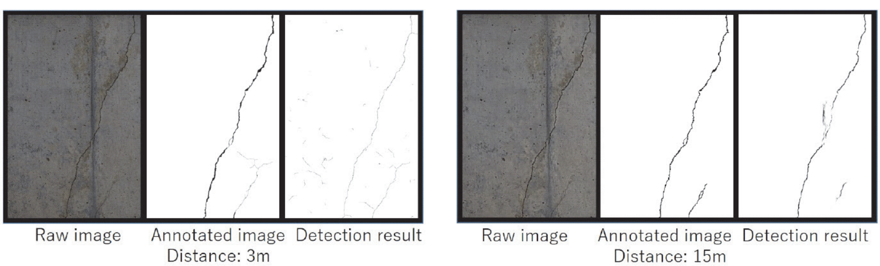

Figure 10 Comparison of different shooting distance

4 Conclusion

A bridge inspection needs much cost. So an efficient bridge inspection method is necessary for future japan. One of the alternative methods of the current close visual inspection is the image-based bridge inspections using images captured with a super-high-resolution camera. An image processing method could make efficient an image-based inspection but be affected by filming conditions of the input image.
We have evaluated the effect of shooting distance and light of field for deep learning-based crack detection by comparing precision and recall of crack detection results. The results of the evaluation show the concrete effect of filming conditions.
The results of this evaluation are not robust because of the small test dataset. In future work, we make a big test dataset by decreasing filming conditions and target crack on a concrete surface. We will make clear that a robust effect of filming conditions and the reason for filming conditions changes the results of crack detection.

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