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ASSESSMENT OF BRIDGE ENGINEERS ON OUTPUT DISPLAY SIZE IN AUTOMATIC DETECTION OF FREE LIME USING DEEP LEARNING

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Abstract

Conventional close visual inspection of bridges has high cost and lack of skilled engineers. New technologies, such as AI, UAV, and robots, can be provided to help the inspection process and substitute previous inspection methods to save labor effort and reduce costs. We develop damage detection system for bridge inspection by adopting image recognition technology based on deep learning. It detects damage from bridge images and provides the accurate outline. Such technology can reduce inspection work by detecting the damage instead of inspectors, and they can focus on important tasks such as damage determination. However, it takes a lot of time to collect and annotate for training images. Although linear damage such as cracks requires a fine outline for each pixel, planar damage such as free lime is presumed to be allowable even at low precise boundaries. If low precise boundaries are allowed, training data is obtained in less time. To determine damage with the same accuracy as close visual inspection, the limits of allowable low precision display need to be determined. This study examined the limis of low precise boundaries for free lime. The bridge engineers compared with the detection output of gradually reduced precision boundaries and investigated the limits of the low precision they allow.

Keywords: bridge inspection, free lime, automatic detection, AI, deep learning

1 Introduction

About 720, 000 bridges have been constructed in Japan, and most of them were constructed in the high economic growth period and are getting old. In 2030, about 55 % of bridges will be more than 50 years old [1]. In order to reduce the life cycle cost by the maintenance of bridges, the national government established the guideline that municipalities conduct the close visual inspection once in 5 years from 2014. However, it is difficult to conduct continuous close visual inspection for municipalities that are insufficient in financial and human resources. Therefore, the damage detection using the deep learning is expected as an alternative technique of the close visual inspection [1].

The automatic detection system of bridge damage was developed using image recognition by deep learning. This automatic detection system organizes information necessary for diagnosis such as damage area, crack width, and length in advance. As a result, the work of bridge engineers is reduced, and they can focus on diagnosis. However, it takes a lot of time to collect and annotate images for training. Because every pixel in the image requires to be annotated. Especially, the crack needs to be measured its width and length in the fineness

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in pixel unit [2]. Therefore, in many studies, crack is detected in pixels [3-6]. Free lime is one of the damages that occurs with cracks. Free lime indicates inner degradation of concrete [7]. However, according to the procedure of national government in Japan, there is no measurement value for the area of damage classification of free lime (Table. 1). Thus, even if the detection outline of free lime is low precise per pixel, it is considered that engineers can determine the damage.

Table 1 Damage classification of free lime and leakage

Classification	Damage condition
a	No damage.
b	-
c	There is leakage from crack and little rust or free lime.
d	There is free lime from the crack and little rust.
e	There is significant leakage and free lime from the cracks. The water leakage contained a large amount of mud and rust.

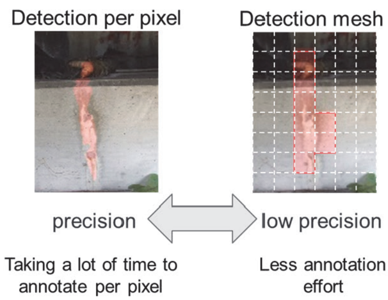

Figure 1 Differences in display in pixel or mesh units (for free lime)

As shown in Fig. 1, in detection per pixel, an accurate outline is provided, but it takes a lot of time to annotate each pixel for training data. On the other hand, boundaries with low precision can reduce annotation work. However, as the detection of free lime, the precision such as pixel unit or mesh unit and the saving of datasets work have not been sufficiently studied. Therefore, the assessment of low precision detection output by bridge engineers was investigated. The output of the mesh display reproduces the low precision boundaries. First, the bridge image was divided into specific mesh sizes, and then the mesh containing free lime was defined as a detection area (Fig. 1). Then, each image detected by pixel unit and mesh unit of free lime was shown to the bridge engineers, and the assessment was examined.

2 Purpose

Previous studies have detected free lime in bounding box, polygons, and segmentation [8-12]. The bounding box can prepare the datasets more easily than the segmentation, but the outline is unclear. On the other hand, segmentation is an accurate outline, but it takes a lot of time to annotate and prepare the datasets.
We have developed an automatic damage detection system [13] for bridge engineers to diagnose appropriately. It is considered the boundaries of the detected objects need to be provided suitably for bridge engineers. However, it has not been examined how precise boundaries are necessary for bridge engineers to detect free lime. If the engineer does not require a high precision outline, the detection of per-mesh is allowed instead of per-pixel such as

segmentation. The cost of datasets work is reduced by annotating with polygons rather than per pixel.
This study investigates the precision of detection boundaries required by bridge engineers to improve the efficiency of annotation work of datasets for training. The proportion of free lime in the detection area is calculated, and the accuracy of boundary detection, which allows the engineers to diagnose the damage, is assessed.

3 Building an automatic detection model of free lime

The automatic detection model of free lime was built that can change the precision of the output display by detecting pixel and mesh units.

3.1 Datasets

The datasets of the detection model collected 112 free lime images from bridge inspection records in K prefecture. The collected 112 images were annotated with free lime in pixel units, 92 images were used as training data, and 20 images were used as test data. 92 training data were image edited such as inversion, enlargement, reduction, rotation, and movement, and the number of training data was increased to 920.

3.2 Building a free lime detection model

The image recognition technology used for the automatic detection of free lime is DeepCrack [14] which is one of semantic segmentation. Semantic segmentation is a technique that enables to identify objects in an image. This method performs feature extraction based on convolutional neural network (CNN) and estimates the area in pixel units. Using the pre-trained model, the image area is automatically estimated as “free lime area” and “non-free lime area”. The detection threshold for free lime was set to detect a pixel with a probability of free lime more than 1 %. The detection result of the test data is shown in Fig. 2.

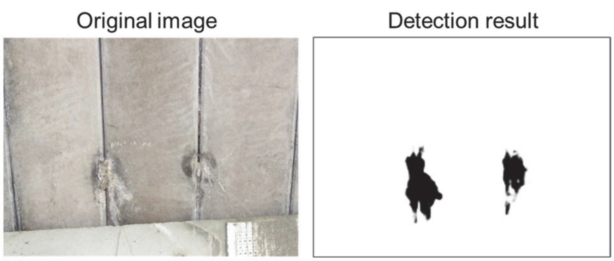

Figure 2 Detection result of free lime by deep learning

4 Examine the precision of boundaries of detection results

Output images of low precision detection of free lime boundaries were generated. The bridge engineers compared these images to assess which detection result was the lower limit of allowable precision when they determined the damage from the images.

4.1 Method

Using the free lime model constructed in Chapter 3, the detection output of free lime was displayed in pixel and mesh. In the mesh unit detection, the whole image is divided by a specific mesh size, and if the mesh includes pixels determined as free lime, the mesh is detected as the free lime region mesh. The detection mesh size was varied from 10 pixel mesh to 100 pixel mesh for every 10 pixels, and the mesh containing free lime was painted red (Fig. 3). The 10 free lime images were edited in the same way. The size each of the 10 images were about 920 × 715 pixels.

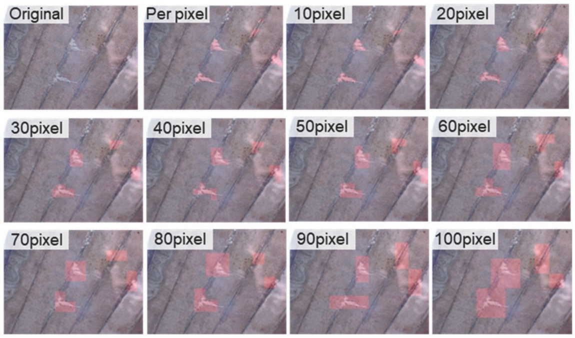

Figure 3 Image displayed the detection result by varying the mesh size

Even if the mesh size is the same, the proportion of the free lime region included in the detection mesh region is different depending on the image. The proportion of free lime in the mesh is expected to affect the engineer's allowance. In addition, when the resolution of the image is changed, the size of the detection display mesh needs to be changed. Therefore, as an index that can be compared even if the image size or output mesh size changes, "Free lime proportion", which free lime occupies in the detection mesh, was calculated according to Equation (1). The free lime proportion of all 10 free lime images is shown in Fig. 4.

$$\text{Free lime proportion in the detection mesh} = \frac{\text{Number of pixels of free lime}}{\text{Nuber of pixels in the detection mesh}} \quad (1)$$

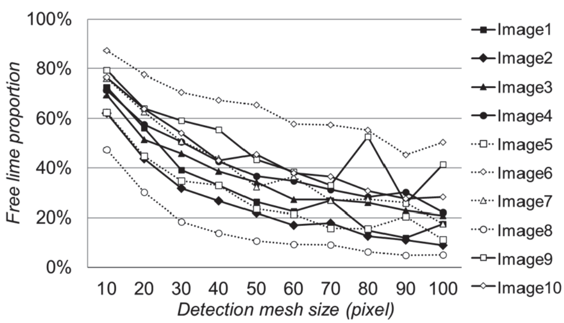

Figure 4 Free lime proportion at the detection mesh size

Even with the same detection mesh size, free lime proportion varied depending on the image. Images taken from a close distance have a high proportion of free lime even if the mesh size was large, and images taken from a distance have a low proportion of free lime even if the mesh size was small. A common feature of all images is that the larger the mesh size, the lower the proportion. The 25 bridge engineers were shown images 1 ~ 10 of various detection mesh sizes to and assessed the images with the lowest precision to determine damage.

4.2 Results of the survey

Fig. 5 shows the survey result of the detection mesh size allowed by engineers. As a cause of the variation of the allowable mesh size by the image, it is considered the difference of the free lime proportion and images taken in the different environment.
Then, the relation between the free lime proportion and the allowable proportion of engineers for each detected mesh size was examined. Fig. 6 shows the allowable proportion of engineers to the free lime proportion.

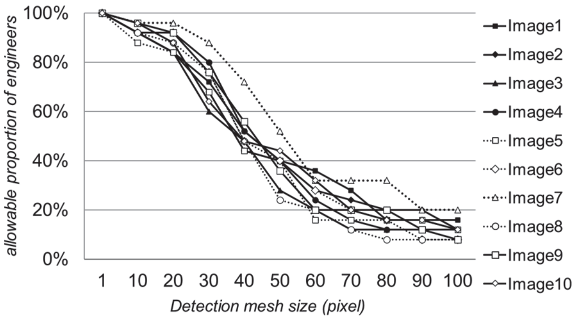

Figure 5 Allowable proportion of engineers for each detected mesh size

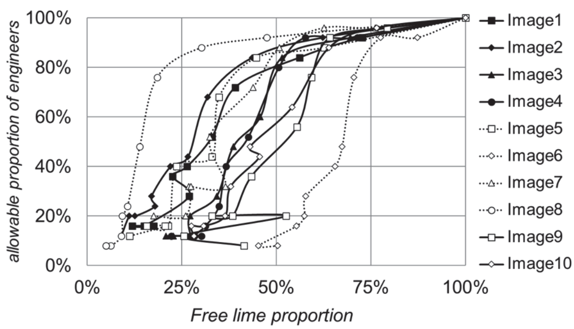

Figure 6 Allowable proportion of engineers to free lime proportion

Images with a lower proportion of free lime were highly variable. For example, in image 8, 25 % free lime proportion was allowable by more than 80 % of engineers, whereas in image 6, even 70 % free lime proportion was allowable by less than 80 % of engineers. In common, when the proportion of free lime was over 75 %, about 90 % of engineers tended to allow.

5 Conclusions and future work

In this study, free lime was detected using deep learning and the limits of low precision detection boundaries that bridge engineers could diagnose was examined. The output results were displayed with different detection mesh sizes and the correlation between the proportion of free lime and the bridge engineer's assessment was investigated.
As a result of the survey to the bridge engineers, when the free lime proportion of the detection result was 75 % or more, about 90 % of the engineers were able to determine the damage classification. This suggests that more than 75 % of the free lime proportion is sufficient for the output display of the detection result. In other words, the most accurate contour detection per pixel is not required for free lime. Instead of annotating every pixel in the training

datasets, it seems sufficient to annotate polygons. Annotations with a 75 % free lime proportion save time and cost on training datasets. As datasets are prepared more efficiently, the number of data sets can be increased, and the accuracy of the detection model improved. However, the analysis in this study included only a limited number of survey results and free lime images. In future, in order to improve the accuracy of the survey result, it is necessary to increase the sample number and to conduct further surveys using images adjusted for the conditions of the shooting environment.

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