A BASIC STUDY ON AUTOMATIC DETECTION OF THE VOIDS ON SHOTCRETE USING DEEP LEARNING

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Abstract

In Japan, about 70 % of the land is covered with forests, and many urban areas tend to be located along the sea. Therefore, road networks connecting urban areas often pass through mountainous areas. Road networks in mountainous areas include cut slopes, and many shotcretes have been adopted as slope protection works at that time. Many shotcretes were constructed during the period of high economic growth, and they are aging all at once. In the maintenance of shotcrete, it is important to grasp the deformation and take appropriate measures. Deformations of interest on the shotcrete include cracks, peeling, and floating. Of these deformations, it is difficult to visually confirm the void, and it has been confirmed by a hammering test. However, due to the shortage of inspection engineers and the financial difficulties of the national and local governments, there is a limit to the continuous diagnosis of the void by hammering tests. In this study, we developed a deep learning model using infrared images acquired from an infrared camera mounted on a UAV, taking advantage of the difference in heat capacity between the void part and the not void part. In this study, we adopted CNN (Convolutional Neural Network), which is one of the deep learning methods and is used in image recognition, and learned the model by featuring the temperature distribution around the void part. In addition, as a result of verifying the deep learning model by core sampling, it was confirmed that damage can be detected with high accuracy.

Keywords: shotcrete, deep learning, infrared image

1 Introduction

1.1 Background of this study

In Japan, mountains and hills account for about 70 % of the total land area. In addition, cities tend to be located in coastal areas, and many roads, including major roads connecting urban areas, run through steep mountains and hills, resulting in the formation of many slopes in a wide area. Even if a slope is stable immediately after it is cut, it can collapse due to heavy rainfall, water inflow, or earthquakes. To prevent the surface of the slope from collapsing and weathering, slope protection structures are installed. Of the slope protection methods, shotcretes were widely used around 1970 because they were easy to apply and could be applied to uneven slopes. At present, more than 40 years have passed since the construction of these shotcretes, and they are all aging at the same time, with disasters occurring due to peeling, spalling, and collapsing of the sprayed surfaces. In the maintenance and management of shotcrete, it is important to identify any deformations and take appropriate measures. However, voids are difficult to confirm visually and are estimated by hammering tests

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among these deformations. Also, there is a limit to the continuous diagnosis of voids only by percussion inspection under the circumstances of the shortage of inspection engineers in Japan and the financial difficulties of the national and local governments [1, 2]. To properly maintain and manage shotcretes with a limited budget and manpower, a more efficient inspection method needs to be developed.

1.2 Objectives of this study

In this study, as a framework to support efficient inspections of the shotcrete, an automatic detection system for voids on the shotcrete (Fig. 1) is constructed by using deep learning.

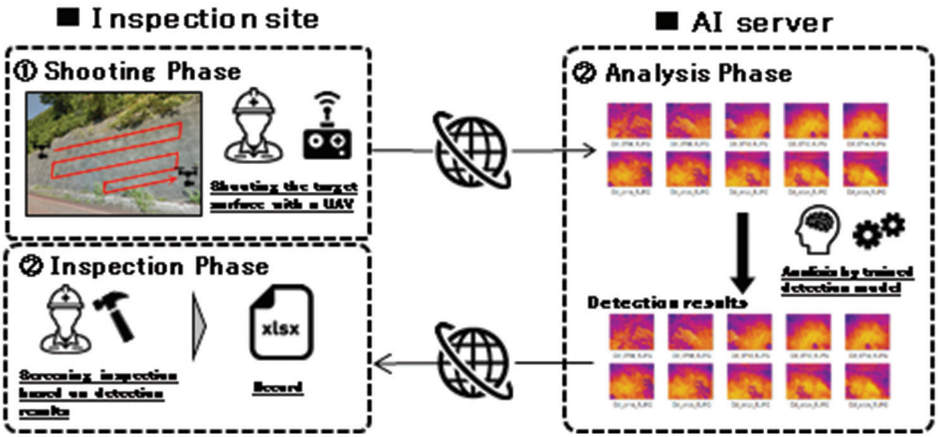


Figure 1 Automatic detection system for a cavity on the shotcrete

In recent years, there have been many studies on the automatic detection of damage using deep learning methods [3, 4], but there have been no studies on the automatic detection of voids on shotcrete. On shotcrete, the surface temperature characteristics of the voids and the no voids are different, resulting in differences in visual characteristics on the infrared image. In this study, automatic detection of voids on the shotcrete is attempted by combining the temperature distribution visualized on an infrared image and a CNN (Convolutional Neural Network) that can automatically extract visual features and classify them.

2 Obtaining training data

This study used UAVs equipped with infrared cameras to acquire data on shotcrete at four locations scattered throughout Ishikawa Prefecture. In this study, 24 images taken during the noon hour, when the temperature difference in the infrared image is most pronounced, were used as the training data. To create the model, it is necessary to know the position of the voids in the infrared image, but it is difficult to visually check the void. In this study, the voids were identified by hammering tests by a concrete diagnostician, and the voids were identified in the infrared image by attaching an aluminum plate to the boundary of the voiding part (Fig. 2).

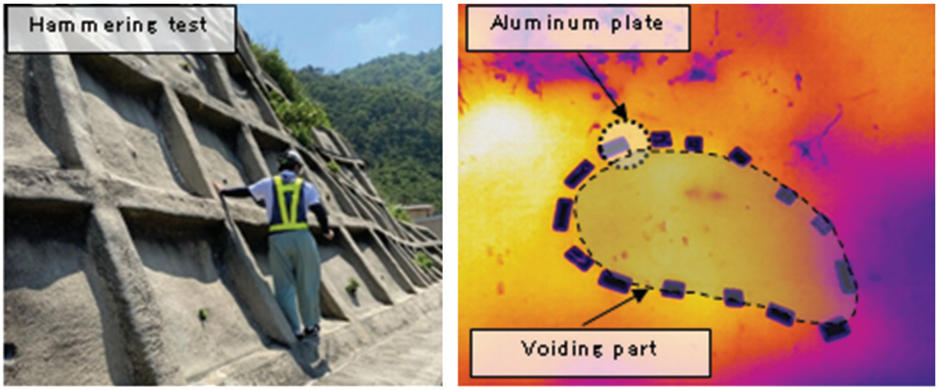


Figure 2 Hammering test and identification of voids

3 Creating a model for automatic detection of voids

3.1 Automatic detection model for voids (model-1)

In this study, a model (model-1) was constructed to automatically detect voids by classifying the input infrared images into 128x128px area units (Fig. 3.). In this study, 37 images with voids and 122 images without voids were obtained as training data. In this study, the images of the class with the smallest number of images among the two classes were rotated clockwise by 90° and 180°, and the number of images in the class containing the void with the smallest number of images was increased to 111, thereby reducing the bias in the number of images in the two classes. In this study, all data were divided into training, validation, and test data, and models were trained using 65 training images with voids and 73 images without voids. When building a CNN model, the number of convolutional and pooling layers and the appropriate parameters need to be determined through trial and error. In this study, the basic structure of the CNN model, VGG16 [5], was used to modify the shape of the input layer, the fully connected layer, and the output layer. For learning CNN, binary cross-entropy error was used as the loss function, and Stochastic Gradient Descent (SGD) was used as the optimization algorithm to minimize it. The learning rate, momentum, weight decay, and batch size were set to 0.01, 0.9, 10^{-6}, and 8, respectively, and 100-epoch iterative training was conducted as the parameters for optimization.

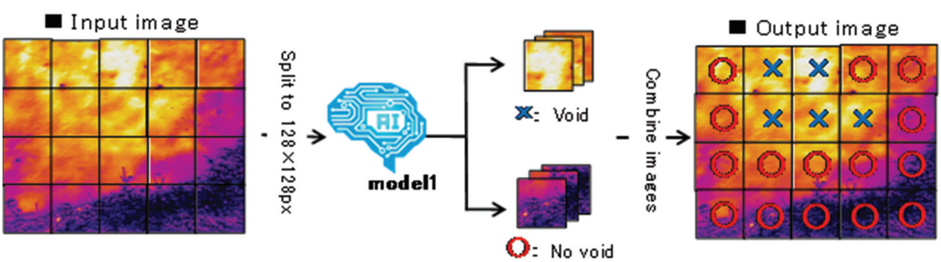


Figure 3 Summary of model-1

3.2 Automatic detection model for voids (model-2)

In this study, as shown in Fig. 4., model-2 was created with a feature extraction area of 192 x 192 px, including eight areas bordering the evaluation target area (64 x 64 px). This enables judgment based on the temperature distribution in the surrounding area centered on the area of judgment as a feature. For training model-2, 689 void images and 805 images without void were used, and the same deep learning model, hyperparameters, and optimization methods as for training model-1 were used.

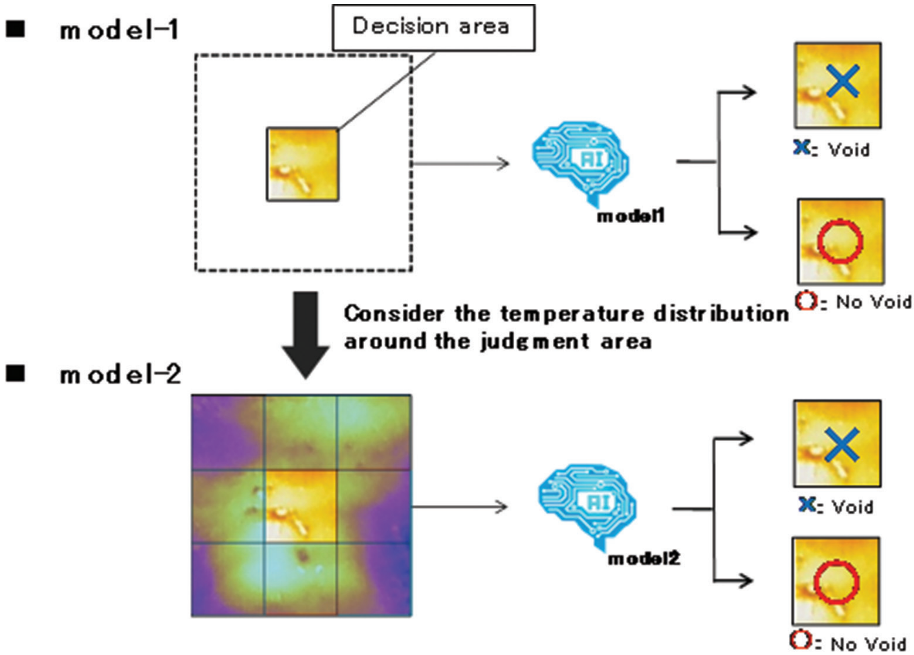


Figure 4 Summary of model-2

4 Evaluation of automatic detection model for voids

4.1 Evaluation by Hold-out method

The hold-out method divides all data into three subsets: train data, validation data, and test data, and uses the test data to evaluate the model. Comparing model-1 and model-2, the Accuracy of model-2 is 0.9279, which means that the classification can be done with very high accuracy. In contrast, the accuracy of model-1 was 0.7676, indicating that its classification performance was slightly inferior to that of model-2. In the evaluation by the holdout method, all the data are divided and used randomly. Therefore, it is possible that the training data and the test data contain many similar images. For automatic detection models, it is important to have a generalization performance that can classify with high accuracy on infrared images that are not used for training, but it is considered difficult to verify the generalization performance by the holdout method. Therefore, in this study, two infrared images not used in the training are used for detection to verify the generalization performance.

4.2 Evaluation of generalization performance

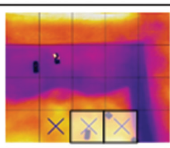
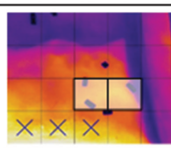
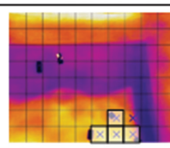
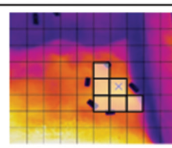
In this study, infrared images, which are not used in the training data, are used to test the generalization performance of the created model. In this study, two evaluation indices are used: Precision, a quantitative index for over-detection, and Recall, an index for missed detection in the model. Precision and Recall are expressed in the following Eq. (1). and Eq. (2). The variables in the equations are defined by the confusion matrix shown in Table 1.

Table 1 Confusion matrix

Void		Ture class	
		No void	
Predicted class	Void	TP (True Positive)	FP (False Positive)
	No void	FN (False Negative)	TN (True Negative)

Table 2 shows the analysis results and evaluation values for model-1 and model-2. Based on the detection results of model-1, it is considered that model-1 detects the areas in the infrared image that have high temperatures and are close to white or yellow in the image. However, when a region with high temperature is included even though it is not voids part for some reason, it is considered difficult to determine the voiding part only by the high and low temperature. In contrast, model-2, which can take into consideration the features of the surrounding areas in the decision area, can detect the floating area appropriately.

Table 2 The analysis results and evaluation values for model-1 and model-2.

	model-1		model-2	
	Image 1	Image2	Image1	Image2
Detection results				
Evaluation value	Precision : 0.80 Recall : 1.00	Precision : 1.00 Recall : 0.17	Precision : 0.80 Recall : 1.00	Precision : 1.00 Recall : 0.17

☐ Void ✕ Area identified by the model as voids

5 Validation of the model by core sampling experiment

5.1 Results of a core sampling experiment

In this study, model-2 is used to analyze the thermal images. A core sampling experiment is conducted based on the analysis results to validate the model and confirm the conditions of the behind shotcrete. The core sampling results showed a total of four types of conditions at the core sampling locations: void, mortar embrittlement, mortar bilayer, and no void, as shown in Fig. 5. In this study, the damage of shotcrete is defined as the condition excluding no void. At this time, no void was assumed for the bilayer and mortar spraying embrittlement.

Figure 5 Conditions identified in core sampling

5.2 Evaluation of detection performance of void in model-2

Based on the results obtained from the core sampling experiment, in addition to precision and recall, the evaluation is performed using NPV (Negative Predictive Value), which is the proportion of negative areas that were actually negative, and F-measure, which is the harmonic mean of recall and precision. The F-measure is shown in Eq. (3). below. In this study, the NPV is the percentage of areas that the detection model determines are not voids that do actually not void and is shown by the following Eq. (4). A confusion matrix based on the results of the core sampling experiment is shown in Table 3. Table 4 shows the performance evaluation indices calculated from the confusion matrix. Table 4 shows that model-2 has a recall of 1.00 for the detection of void, indicating that the model does not miss anything. However, since the precision is approximately 0.58, it is considered that the voids tend to be over-detected. This is due to the fact that embrittlement and are bilayer determined to be a void.

Table 3 Confusion matrix for detection of voids

Void		Ture class	
		No void	
Predicted class	Void	TP (15)	FP (11)
	No void	FN (0)	TN (4)

Table 4 The detection performance of voids results of model-2

Evaluation value	Voids detection performance results of model 2
Recall	1.00
Precision	0.58
NPV	1.00
F-measure	0.73

5.3 Evaluation of detection performance of damage in model-2

In this study, the detection model for voids was created by learning the voiding area estimated by hammering inspection. However, it is difficult to accurately estimate only voids by hammering tests, and there is concern that damage other than voids may be included in the training data. Therefore, it is suggested that the model developed in this study is capable of detecting embrittlement and bilayer of shotcrete in addition to voids. In this section, model-2's damage detection performance is quantitatively evaluated based on the confusion matrix shown in Table 5. Table 6 shows the evaluated values of damage detection performance on shotcrete calculated by a confusion matrix. The recall and NPV values are 1.00 and no misses were detected, and precision is 0.92, suggesting that it is possible to detect damage with very high accuracy.

Table 5 Confusion matrix for detection of damages

		Ture class	
		Damage	**No damage**
Predicted class	Damage	TP (24)	FP (2)
	No damage	FN (0)	TN (4)

Table 6 The detection performance of damages results of model-2

Evaluation value	Damage detection performance results of model 2
Recall	1.00
Precision	0.92
NPV	1.00
F-measure	0.96

6 Conclusion

In this study, an automatic detection models of voids were created by combining infrared images and deep learning. Model that takes into account the temperature distribution around the judgement area was able to detect voids more accurately. A total of four types of conditions were identified from the core sampling experiment: void, mortar embrittlement, a bilayer of mortar, and no void. The training data used in this study were estimated by hammering tests and may in fact include damage other than void. In this study, the three identified deformities were defined as damage, and the model was evaluated. The results suggest that it is possible to detect damage with very high accuracy, with a recall and NPV of 1.00, no misses, a precision of 0.92, and only 2 over-detected locations out of 30 core-sampled locations. In future work, the model will be refined through continuous core sampling to accumulate data linking temperature distribution and back surface conditions and to improve the classification of damage and detection performance.

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