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RISK ASSESSMENT ON DEFECTED CONCRETE STRUCTURE BY USING HAMMERING SOUND TEST

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1. INTRODUCTION

Recently, amounts of infrastructures are approaching their designed life, thus the number of defected concrete structures is increasing rapidly. In order to apply the proper maintenances, inspections are conducted regularly on concrete structures. The regular inspection is based on visual inspection, and non-destructive inspections for more detailed information on the interior condition. Among non-destructive inspections, hammering sound test is one of the most popular methods because of its feasibility and low-cost advantages. In addition, a rotary hammering test that improve the efficiency of the conventional hammering sound test was also widely used. However, hammering sound tests are highly depend on the inspector's experiences of deterioration detection and sound data analysis which include the information on the defect inside concrete is not enough. Therefore, in this study, the objective is to develop an accurate and efficient evaluation method of the concrete structure soundness based on hammering sound test data using the convolutional neural network (CNN).

2. ASSESSMENT MODEL

2.1 Experimental Data and Data Processing

Experimental data from rotary hammering test conducted on mortar cuboid with artificial defect was used as the learning data to feed the classification model. Details of the experiment is explained as shown in Fig.1, based on 10×10×40 cm mortar cuboid specimen, artificial defect using styrofoam was used to simulate defect inside concrete structure. There were four different sizes of artificial defects, 2×3×5 cm, 2×5×10 cm, 2×5×15 cm, 2×7×20 cm. Images of spectrograms from acoustic data, as shown in Fig.2, was used as the learning data. In a spectrogram, there are three key features of acoustic data. The first feature is the maximum amplitude, it tends to be obviously greater of a deteriorated structure than of a soundness one. The second feature is the time duration which deteriorated structures are also greater than normal ones. Last key feature is the distinct pattern of frequency characteristic which is gained from applying Fourier transform. By using the spectrogram, all these three features can be used as the references to for classification.

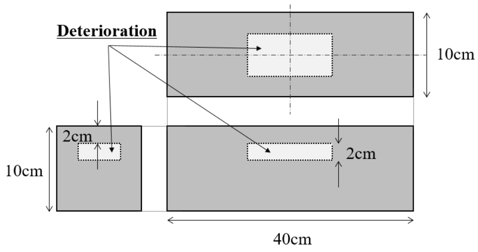

Fig.1 Motar Cuboid

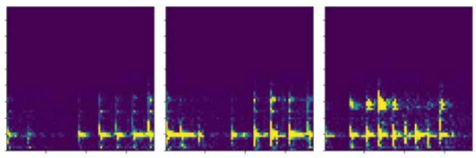
Fig.2 Spectrogram

2.2 CNN Classification Model

The CNN model is shown as the flow chart Fig.3. Input data contains spectrogram generated from the previous procedure, and classification of each spectrogram data as labels. Base on the input labels and the output from classification model, bias and weights are updated by the optimizer. As the learning proceeds, loss function decreases, while the accuracy of prediction increases respectively, as shown in Fig.4, and both tends to be stable. Finally, data that was not used in the learning process was supplied to the classifier model to predict its defect class. In this study, 80% of the data prepared were used as learning data, and 20% of the data were used as validation data. The classifier was tested by validation data to detect the defect level of experimental data, and the final accuracy of validation became 91.3%.

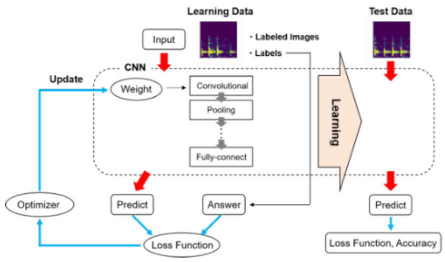

Fig.3 CNN Classification Model

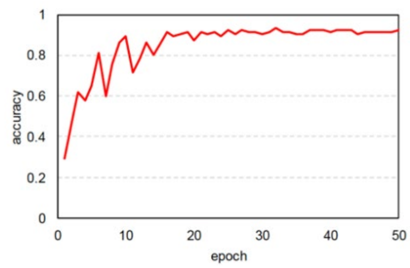

Fig.4 Prediction Accuracy

Keywords: Risk Assessment, Hammering sound test, Convolutional neural network
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3. VALIDATION

3.1 Validation on Inspection Data

The CNN model was validated with actual inspection data. The inspection data used in the validation were the results by rotary hammering inspections of 4 bridges A~D. For each bridge, rotary hammering test was conducted on two intact areas, and two defected areas while the interior conditions were not clarified. Therefore, it is not feasible to classify the defects' sizes. Thus, in this validation, instead of the defects' sizes, the labels were considered as the level of defects, where level 1 is equivalent to normal, and level 2~5 are equivalent to the defect size of 2×3×5 cm,2×5×10 cm,2×5×15 cm,2×7×20 cm respectively. Inspection data was converted into spectrogram and inputted them into the CNN model for soundness prediction. The results of the predictions are shown as Table.1. The defected levels of normal areas are correctly predicted as level 1 in 5 inspection points out of a total number of 8. At the same time, for the defected areas, except for one inspection point, the predictions of defected levels of others are all resulted in at least level 2.

Table.1 Predicted Deteriorated Level

	A	B	C	D
Normal 1	3.4	2.7	1.0	1.0
Normal 2	1.0	3.4	1.0	1.0
Defected 1	3.1	2.0	3.5	2.6
Defected 1	4.3	3.3	2.3	1.4

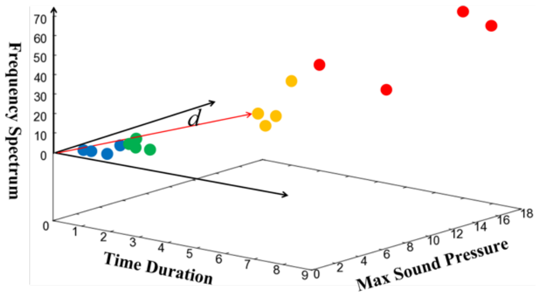

Fig.5 Present investigation method

3.2 Comparison with Present Method

Furthermore, the results were compared to consequences based on a previous study that used a three-dimensional diagram with amplitude ratio, time duration and frequency of hammering sound test data. As shown in Fig.5, the present method uses the distance from the origin point on the diagram to represent the defect level. The same data sets were also used in the evaluation by the CNN model. The comparison between the CNN model and 3-D diagram were shown in Table.2 and Table 3 seperated by the soundness of bridges. At first, regarding the healthy bridges, 5 of 8 of healthy spots are predicted correctly by the CNN classification model. However, there are three of them predicted as over defect level 2. Comparing to the 3-d diagram method, the distance from origin of those bridges are also higher than the others. It can be considered that those three spots could be closer to be defected. Next, regarding the deteriorated bridges, all 8 spots are predicted to be higher than defect level 1. According to the 3-D diagram, the distances of all spots are obviously larger than that of the normal bridges, which means the CNN model also successfully detected all deteriorated structures.

Table.2 Results Comparison - Normal

Location	CNN Model		3-D Diagram	
	Rank	Level	Rank	Distance
B2-N	1	3.4	1	2.8
A1-N	1	3.4	3	1.8
B1-N	3	2.7	2	2.4
D1-N	4	1.0	4	1.5
D2-N	4	1.0	5	1.5
C1-N	4	1.0	6	1.5
C2-N	4	1.0	7	1.4
A2-N	4	1.0	8	1.3

Table.3 Results Comparison - Deterioorated

Location	CNN Model		3-D Diagram	
	Rank	Level	Rank	Distance
A2-D	1	4.3	1	39.7
C1-D	2	3.5	6	18.9
B2-D	3	3.3	5	21.3
A1-D	4	3.1	3	25.5
D1-D	5	2.6	2	26.8
C2-D	6	2.3	4	22.4
B1-D	7	2.0	7	9.6
D2-D	8	1.4	8	8.1

4. CONCLUSIONS

In this study, the rotary hammering sound test risk assessment of concrete structure using convolutional neuron network was discussed. Firstly, rotary hammering test data was processed to spectrogram and inputted to a CNN model for training. Then the trained CNN model was validated using experimental data. At last, the CNN model was tested with inspection data of existing deteriorated bridges. The prediction accuracy of the CNN model based on spectrogram of acoustic signal from hammering sound test resulted in 91.3%, which proved that spectrogram could be an appropriate input data for assessment model. The prediction of defect level by the CNN model showed similar trends as the present investigation method, thus the CNN model using the rotary hammering test could be useful for actual bridge inspections.

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