10th International Conference on Fracture Mechanics of Concrete and Concrete Structures
FraMCoS-X
G. Pijaudier-Cabot, P. Grassl and C. La Borderie (Eds)

IMPROVEMENT OF IMPACT-ECHO METHOD BY APPLYING IMAGE RECOGNITION OF SOUND SPECTROGRAM

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Key words: Impact-Echo Method, Spectrogram, Image Recognition, Machine Learning

Abstract: The authors are investigating a method for lifetime prediction of concrete structures by a comprehensive judgment of survey results and information on design and environment. In this paper, we tried to apply impact-echo acoustic spectrogram to image recognition by machine learning in order to have a better estimation of defects in concrete. impact-echo sound sampling was conducted on specimens containing variated voids in depth and diameter. Each sound spectrogram was transformed into 28 by 28 pixels grayscale picture. As a result of the study, it was confirmed that the estimation by machine learning showed competitive accuracy as estimation by a human expert. Also, it was shown that the depth and diameter of the void are predictable under certain conditions. Furthermore, the authors showed the possibility of this method in actual concrete structure.

1. INTRODUCTION

The authors are developing a comprehensive evaluation method of degradation state of concrete structures for the purpose of their deterioration evaluation, life prediction, maintenance support. For this purpose, we try to organize multiple diagnostic techniques, like "electro magnetic exploration for chloride intrusion[1)]", "Infrared examination for reinforcement corrosion[2)]" and "Impact-echo method for defects of concrete". We aim to estimate the initial state, the degradation speed, and the service life by integrating environmental information and design information, deterioration information of structures obtained from these diagnostic methods.

2 IMPACT-ECHO MONITORING

Degradation diagnosis of concrete structures by Impact-echo monitoring is widely used because it can detect defects in concrete in a simple way. However, it is necessary to have a certain degree of experience in judging properly the defects, and even the judgment of experienced person shall have considerable uncertainty. Furthermore, it becomes very difficult to find out when the depth of defects exceeds a certain extent. In this paper, as a part of the comprehensive deterioration evaluation of the concrete structure, a method of evaluating the impact sound itself of "impact-echo survey" was studied. That is, instead of using a vibration pickup which needs to be fixed to concrete, a method using recorded sound by a microphone is adopted. The recorded sound data are converted into spectrograms, and the images are recognized by supervised learning, whereby the state of the defect in concrete. We examined the applicability of this method by indoor experiments and field tests.

Research on quantitative evaluation method of impact-echo method has been conducted many researches since long-time. Kamata et al.[3] showed the equivalence of blow sound and surface vibration. Miyoshi et al.[4] extracted feature quantities of impact-echo sound by acoustic analysis. Matsuyama et al.[5] applied SIBIE procedure to visualize defects in concrete based on impact-echo method. All of these are studying the relationship between frequency spectrum and defects. Schubert et al.[6] presented signature analysis using impact-echo sound spectrogram. Meanwhile, in recent years, the possibility of machine learning attracts attention as computer performance has improved. As an application of machine learning to impact-echo survey, Zhang et al.[7] applied machine learning to wavelet conversion of impact vibration. Fujii et al.[8),9)], Kubota et al.[10] investigated aiming at detecting defects in concrete by a method of applying short-time Fourier transform of impact-echo sound to discriminators, and they developed a survey system. We tried to confirm the applicability of the spectrogram to impact-echo survey. We acquired impact sound data by an indoor test for the purpose of acquiring trial data for machine learning optimization.

3 INDOOR EXPERIMENTS

3.1 SPECIMEN

Two test specimens of 850mm square and 300mm thickness were cast with embedding round shaped polystyrene foam thickness of 10mm to simulate voids in the concrete. The diameter and depth of voids were decided around the border where it was possible or impossible to detect the voids by impact test by a human, with reference to previous studies [11),12)] as shown in Figure 1.

The arrangement of voids in test specimens is shown in Figure 2. Lines are drawn in 50mm pitch on the surface the specimens vertically and horizontally to manage the hit point. The specimen A has voids with the diameter of 250mm (hereinafter abbreviated as D250, the same applies to others), and the depths are 20mm, 35mm, 65mm or 80mm. The specimen B has voids with the depth of 50mm (hereinafter abbreviated as d50, the same applies to others), and the diameters are 80mm, 100mm, 150mm, 250mm or 340mm.

3.2 TEST METHOD

A small test hammer with a mass of 400g and a length of 600mm was used for hitting the specimen and the impact sound was recorded with a digital recorder ZOOM H6 near the hit point.

Impact sounds for training data of each void were obtained from the inner area of the void. The impact sounds for training data of no-void point were obtained from the area which is

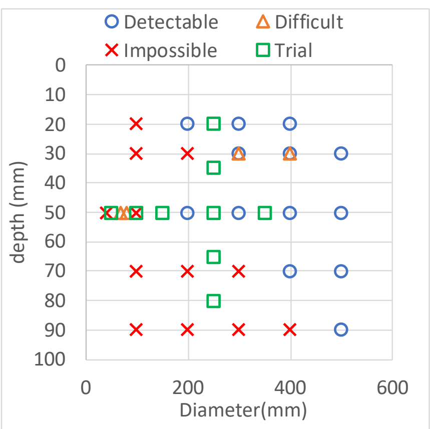


Figure 1: Setting of Void Parameters

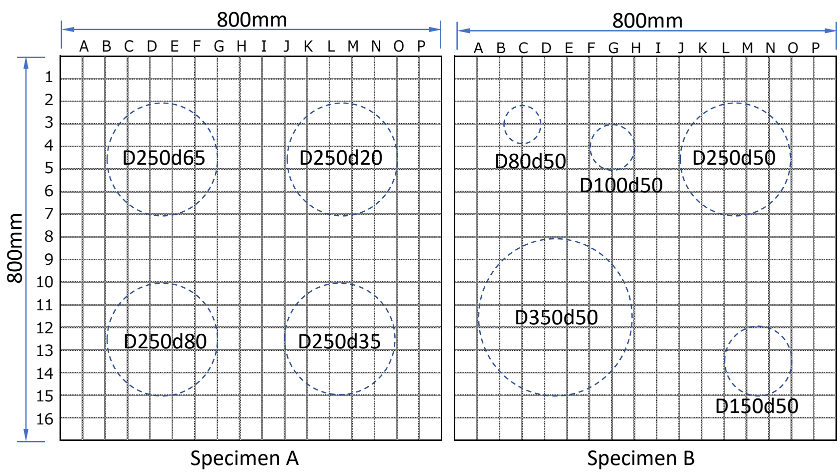


Figure 2: Arrangement of voids

defect-free area near the center of the specimens, G7 to J10 of specimen A, and I8 to O11 of specimen B. Also, considering the influence of the voids or border of specimen, impact sounds were obtained from the edges of the specimens, rows No.1, 16 and columns A, P, where the concrete is not constrained.

As a spectrogram by the short-time Fourier transformation shows the change of the frequency distribution in time series, it is important how should be taken the picture shall be important. Auditory characteristics of impact sound are thought to appear in both frequency distribution and its change in time. In a human judgment, influence factors (e.g. ambient noise, shape or boundary of concrete, echo or attenuation by surrounding environment) may be corrected unconsciously. Generally, it can be inferred that the higher the resolution of the image, that is, the more the information amount can express the characteristics of the sound more, the better the estimation accuracy will be.

On the other hand, in the short-time Fourier transform, the time resolution and the frequency resolution are a trade-off. There is much room for discussion on data processing that is most suitable for impact-echo survey including these. In this paper, however, this argument is omitted, focusing on confirming the applicability of machine learning by spectrogram to defect estimation, the image was cut out large portions of image gradation change. From this point of view, a range of about 125ms from the start and a frequency up to 5.5kHz was converted into a 28 by 28pixels grayscale image. MATLAB software version R2018a was used for spectrogram conversion and machine learning process.

For machine learning, a simple convolutional neural network architecture for image classification was defined by using MATLAB's Neural Network Toolbox.

200 training data were prepared for 11 classes consisting of 9 kinds of void type and 2 types no void (Center and Edge). 15% randomly extracted out of each 200 data were kept as verification data and the remaining 1,870 images were used as training data. Verification data was not used for network updating and periodically verified that over-fitting did not occur during learning.

3.3 RESULTS OF MACHINE LEARNING

Table 1 shows an example of the confusion matrix of estimation results. Here, the aggregation of responses classified by the neural network after learning is shown for 30 sets of verification data given for each instance shown in the leftmost column. The overall accuracy shows a very high value of 96.7%. Since the input data given here is verification data which is not used for training, the high accuracy with verification data can deny an over-fitting.

However, it is considered that the impact sound has very high auditory similarity in the same instance due to the uniform circular void, and the same tendency shall be observed in the spectrogram and the feature values. Therefore, it is important to note that the data in this study is particularly small in variation and to note that the classifier is specialized for the test specimen.

Even though, it should be noteworthy that the discriminator surely identified small

Table 1: Confusion matrix

Actual / Predicted	D100 d50	D150 d50	D250 d20	D250 d35	D250 d50	D250 d65	D250 d80	D350 d50	D80 d50	Center	Edge	Accuracy
D100d50	29	1	0	0	0	0	0	0	0	0	0	96.7%
D150d50	0	30	0	0	0	0	0	0	0	0	0	100.0%
D250d20	0	0	30	0	0	0	0	0	0	0	0	100.0%
D250d35	0	0	0	29	0	0	0	0	0	0	1	96.7%
D250d50	0	1	0	0	29	0	0	0	0	0	0	96.7%
D250d65	0	0	0	0	0	29	1	0	0	0	0	96.7%
D250d80	1	0	0	0	0	4	25	0	0	0	0	83.3%
D350d50	0	0	0	0	0	0	0	30	0	0	0	100.0%
D80d50	0	0	0	0	0	0	0	0	30	0	0	100.0%
Center	0	0	0	0	0	0	0	1	0	29	0	96.7%
Edge	0	0	0	0	0	0	0	1	0	0	29	96.7%
											Total	96.7%

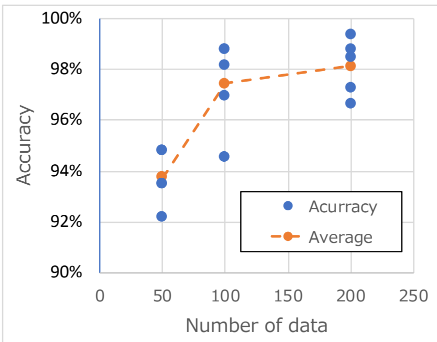


Figure 3: Accuracy and number of training data

diameter or deep void (e.g. D80, d50) and no-void (Center, Edge) point which is auditory very similar and cannot be discriminated from their impact sounds.

Figure 3 shows the relationship between the number of training data and accuracy obtained. Training was done 5 times in each number of training datasets, and the number of training data was changed from 50, 100, to 200. It was observed that the average accuracy was not improved a lot over 100 training data. Therefore, 200 training data seems to be adequate for this study.

3.4 RESULTS AND DISCUSSION OF INDOOR TEST

For evaluation of the discriminator, impact sounds were recorded at each cross point of lines marked in 50mm pitch on the surface of the specimens. Collected sounds were converted into spectrograms and pixelized in the same manner as training data.

Figure 4 shows the estimation result by the discriminator. The hatched part of the dense orange is the point where the void is located beneath, the hatched part of the thin orange is the boundary of the void. Symbols in the cell indicate estimation results. In the figure, “@” indicates that the discriminator correctly answered the diameter and the depth of the void, “o” indicates that correctly distinguish if there is a void or not, and “x” indicates the presence or not of void was incorrect. Regarding the boundary part, both the prescribed void specification and also no void were taken as correct answers.

Looking at the estimation results of the void-area (dense hatched part), in the shallow void (right side of the A specimen) and the relatively large void (lower left of the B specimen), the diameter and depth are correct in many regions. However, the correct answer rate is low in the deep voids (left side of the A specimen) and small voids (upper left of the B specimen). From this, it can be inferred, as same as the auditorily similar for human, the impact sound of the deep or small void is difficult to distinguish for the discriminator.

The overall correct answer rate by adding “@” and “o” was 91%, which is lower than the accuracy of around 98% obtained in the verification phase of machine learning. Although the cause of this is not clear, since the impact sound of the training data was collected at one time, the variation of impact sound is very small. Also, the evaluation data was obtained only 1 impact sound recorded at another time. Because of the condition above, it is possible that the difference of recording condition or environmental condition may affect the impact sound to

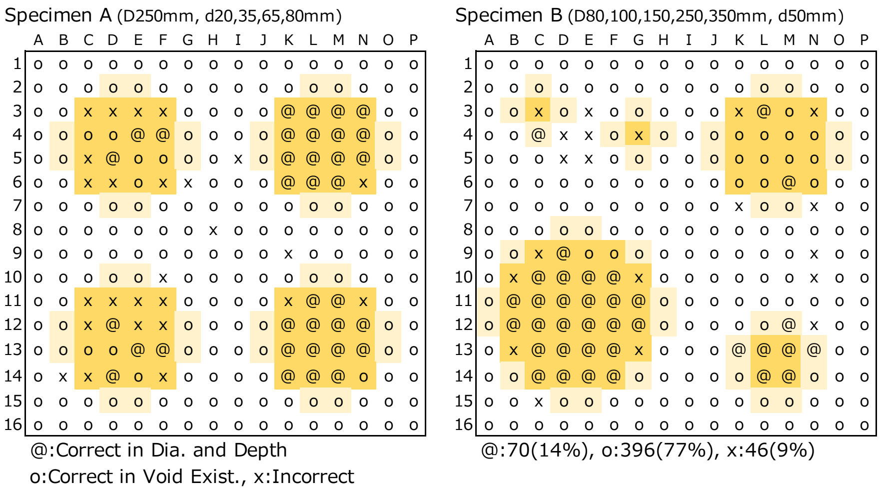


Figure 4: Result of estimation by machine learning

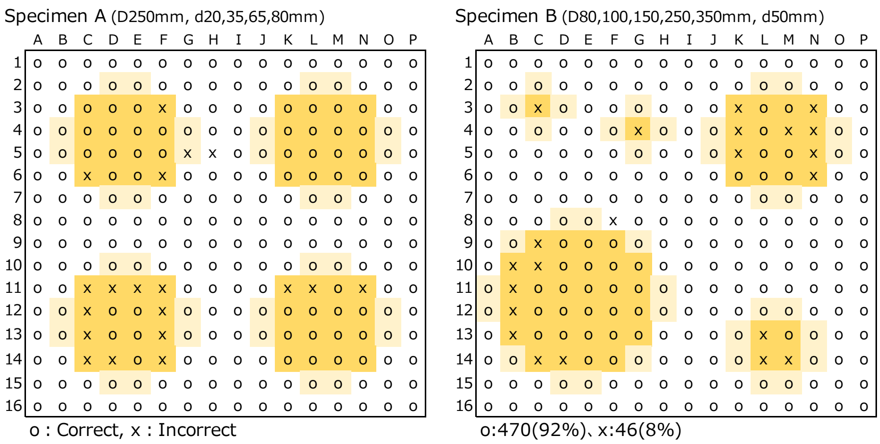


Figure 5: Result of estimation by a human expert

cause the wrong judgment.

About this, it is thought that there is a possibility of improving the correct answer rate by giving a variation to the impact sound recording condition, or giving a plural impact sounds at the time of evaluation.

Also, this time, the training data of no-void was set to the 2 types, named Center and Edge. This was set as a matter of convenience, because the vibration characteristics of the edge where the side of the specimen is released and the center of the test specimen are different even at the same no void condition. The influence of structural boundary conditions on the impact sound also occurs in the actual structure. And it is considered that some measures are necessary such as considering the influence of the boundary separately in order to make an appropriate estimation. Specifically, using multi-modal machine learning may be the solution, for example, introducing edge distance as a parameter, as if the human naturally compensates the influence of the structural boundary to the impact sound. It is considered that the presence or absence of the void at the edge may be properly estimated by this way.

As a comparison with conventional impact-echo survey, a blind test was conducted by an expert of the method. As shown in Figure 5, the result is almost the same tendency as the estimation by the discriminator shown in Figure 6. Also, the correct answer rate was almost the same as 91% by machine learning ("@" and "o"), and 92% by an expert ("o"). When viewed individually, it can be seen that the correct answer rate decreases in the "deep voids" and "small voids" by the expert and also by the discriminator. However, it is considered that it is meaningful to be able to make a stable judgment by machine learning without a human expert because the judgment by a person is largely affected by the skill of individual or the differences of the environment.

In this test, as an auditory feature of the impact sound of the void part, those with a shallow or large diameter are clearly different from the no-void part and sounds are easily distinguishable. But void part with deep or small diameter was extremely difficult to distinguish from the no-void part. However, it was shown that even if almost no difference in the impact sound was felt for human, it was possible for discriminator to recognize and distinguish the characteristics of the impact sound. From this, it is thought that by improving training data and learning conditions, it will be possible to estimate defects in concrete more accurately than the judgment of the human expert.

4 FIELD TESTS

A deterioration investigation was carried out on a concrete pier about 30 years after construction in Japan. The pier has a concrete cover of around 80 mm, but due to salt damage, corrosion of the rebar has progressed, and flaking of concrete has occurred over a wide area (Figure 6). In the survey, the results of impact-echo survey and visual observation on the bottom surface of the concrete slab were done. The result was compared with the estimation by neural network generated from impact sound data separately acquired on site.

In the process of the deterioration survey, it was judged by the impact-echo survey expert that there is flaking in the area shown by blue marking or blue hatching, in the photograph and sketch of Figure 8. On the other hand, in the same pier, 334 impact sounds were recorded from the area where there is clearly a defect such as flaking from impact sound and also the area where it is normal from impact sound. These impact sounds were converted into spectrograms and given as training data to create a neural network. With this network, for

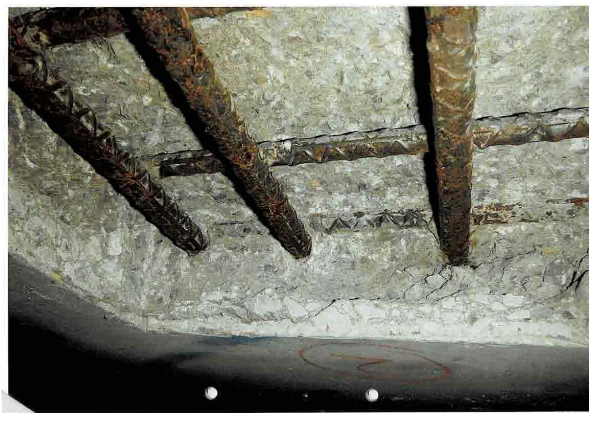
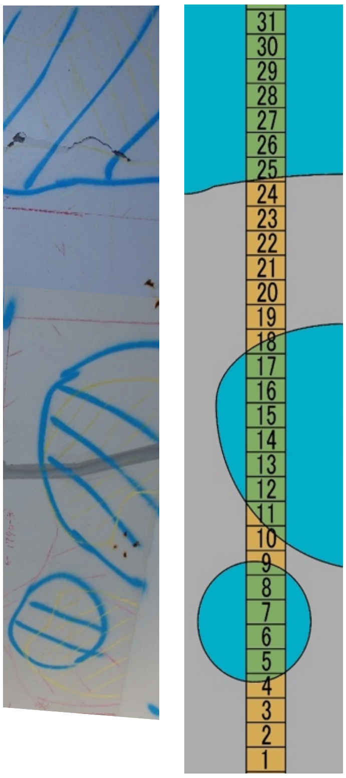


Figure 6: State of deterioration on the bottom surface of concrete slab



No.	Rate
31	0%
30	10%
29	40%
28	40%
27	90%
26	0%
25	0%
24	0%
23	0%
22	0%
21	0%
20	0%
19	0%
18	0%
17	0%
16	80%
15	60%
14	20%
13	10%
12	0%
11	10%
10	10%
9	10%
8	0%
7	0%
6	0%
5	10%
4	0%
3	0%
2	10%
1	0%

Photo Sketch Estimation

Figure 7: Expert's diagnosis and estimation by the neural network on site

each of the 31 sections set on the lower surface of the slab, shown in Figure 7, estimation was made for each of 10 impact sounds per section. In each section, the percentage of the number of times that there was a defect was shown in Figure 7. From this result, it can be seen that the area determined as defect by machine learning is roughly included in the area that the expert judged as defect.

The reason that the area of defect determined by machine learning is narrower than the expert's judgment is that the impact sounds for training data of defect were taken from the area only where a severe flaking is occurred. We took the sound in the area where we can surely estimate from the impact sound that there is defect, and used it as training data for defect. Therefore, it is considered that the determination of the presence of defects is more severe tendency than the determination of the expert (a minor defect is not determined as defects). In order to solve this, it is necessary to create a neural network based on appropriate training data with a real structure or a full-size model, etc. If this can be done, it is considered that the state of the defect can be estimated with the same accuracy as in the indoor test at least.

5 DISCUSSION AND FUTURE ISSUES

For example, when we conduct an impact-echo survey to a concrete structure with thick cover, it is necessary to apply a relatively big striking energy in order to capture the response of the defect locating deep inside from the surface. However, considering the automation of impact-echo surveys by self-propelled robots and the like, it is difficult to give an impact remotely and automatically with big energy. To meet this demand, it is required to obtain the response of deep defect with as small energy impact as possible. According to the result of this study, it was shown that machine learning can recognize differences of impact sound that are indistinguishable to humans. This suggests that this method may be effective for automation/advancement of impact-echo survey.

Also, in impact-echo survey by a human expert, it is inevitable that fluctuations in the estimation accuracy due to the inspector's skill or effect of environmental conditions. Therefore, when we repair a concrete structure, usually chipping work will be done wider than the area judged to be defect. If this can be estimated with high accuracy by machine learning, it can be expected to reduce extra chipping work.

The flaking and defects caused by the deterioration of the concrete structure develop initially from fine cracks. It is considered that detecting this initial crack is important for improving preventive maintenance efficiency. According to this method, a high precision of impact-echo survey can be expected, so it is considered possible to detect fine defect like initial crack.

Although the applicability of this method could be confirmed in the field test, it was also confirmed that the accuracy of the training data is directly related to the discrimination accuracy. Since it is difficult to confirm the degree of deterioration in actual structures, in order to acquire correct training data, it is necessary to acquire training data on a full-sized specimen that can clearly indicate the state of deterioration.

In this test specimen, uniform circular voids with a thickness of 10 mm were created, but the timbre differs from that of impact sounds that can be affected by flaking or crack of actual concrete structures. It is also important to reproduce the defect more realistically in future tests.

In this study, we confirmed the applicability of machine learning, but it was confirmed that impact sound can be determined with a certain accuracy by capturing the characteristics of impact sound even with extremely small image data of 28 by 28pixels. Although omitted in this paper, it is thought that it is possible to construct a more appropriate general-purpose neural network for impact-echo evaluation by performing pre-processing of data, supervising method, parameter optimization and the like. For this purpose, an actual structure with various features and data in real environment are necessary.

6 CONCLUSIONS

The following conclusions were obtained from this series of experiments and field tests.

1. By machine learning based on the image recognition of impact sound spectrogram, it could be confirmed that there is a possibility that the state of the defect in concrete can be estimated.

2. It was confirmed that the feature extraction of impact sound by spectrogram may be possible even with very small data such as a 28 by 28 pixels grayscale image.

3. The discrimination of the impact sound by the image recognition of the spectrogram may be able to recognize the difference of the level which cannot be discriminated by a human.

4. It was shown that this method will be applicable to on-site impact-echo survey by acquiring appropriate training data.

This study confirmed the possibility of estimating the state of internal defect in concrete by image recognition of spectrogram in impact-echo monitoring method. In the future, along with the sophistication of impact-echo sound exploration, the application of machine learning to other exploration methods, data collection of environmental information/design information, etc. and the data of actual structure are accumulated, based on the deterioration progress prediction and the life expectancy. We will study the application of neural network to comprehensive evaluation of soundness of structure.

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