Flaking Concrete Detection
with Hammering Inspection Methodology based on Machine Learning

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ABSTRACT
Recently, efficient infrastructure maintenance methodologies have been required in Japan, because the number of aged infrastructures, such as bridges, roads, and tunnels, are increasing drastically. Actual maintenance works consist of a visual inspection, hammering test and paper based archiving. However, there are technical issues, such as a rapider education for professional inspection, infrastructure evaluation cost improvement, and shortage of skilled engineers for infrastructure maintenance. In this paper, we aimed to propose an inspection methodology based on machine learning for concrete structure maintenance using Geographic Information Systems (GIS). We also focused on a hammering test for flaking concrete detection as GIS attribute data acquisition on site. The hammering inspection methodology can evaluate health a condition of concrete surface with hammering sounds. In this research, we have applied a machine learning methodology with k-nearest neighbor (k-NN) algorithm for concrete hammering inspection works.

1. INTRODUCTION

The Japan Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has reported that there are many infrastructures, such as 700,000 bridges, 10,000 tunnels, 10,000 revetment, 450,000 km sewage pipes, and 5,000 quay walls which are 50 years old or older in Japan. The ratio of the number of aged bridges in Japan is 18% in 2013. The ratio of the number of bridges in Japan will increase drastically, as shown in Figure 1.

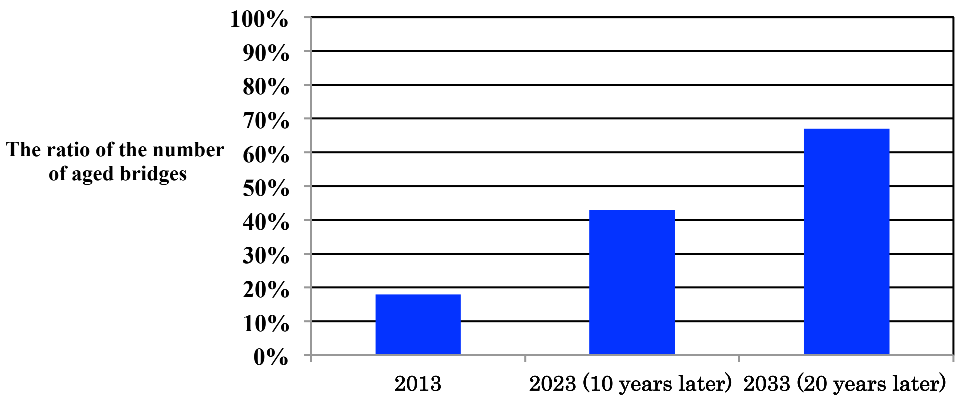

Figure 1. The ratio of the number of aged bridges in Japan

Moreover, the ratio of the number of municipal offices in engineers for structure maintenance is 68%, as shown in Figure 2. These facts mean that many bridges are managed by municipal governments. In many municipal governments, it is not easy to increase annual budgets due to social issue, such as decline, population ageing and shrinkage of the working population. Thus, many infrastructures are required to be applied lower cost methodologies for maintenance works. Currently, actual maintenance works consist of a visual inspection, hammering test, and paper based archiving. However, the number of inspection engineers is decreasing because many inspection engineers are going to be higher ages. Based on these situations, we have developed a hammering inspection methodology with machine learning algorithm and GIS for lower cost infrastructure inspection works. In concrete deterioration detection, there are many features, such as cracks, free lime, floating, scaling, peeling and flaking. Photogrammetry and laser scanning can measure many features on concrete surfaces. However, it is not easy to detect some features in invisible parts, such as flaking parts. In this paper, we have focused on a flaked concrete detection using sound data.

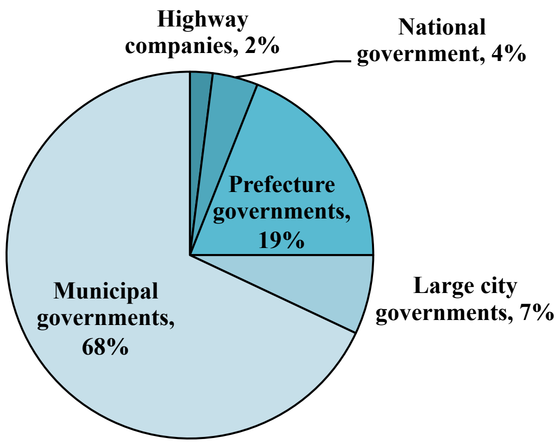

Figure 2. Infrastructure maintenance administrators in Japan

1.1 Hammering inspection

A hammering inspection is one of popular inspection methodologies on site. There are two types of hammering inspection. The first is a hammering sound evaluation with the act of attentive hearing by inspection engineers. The results depend on inspector's experience and skills. The second is a hammering sound evaluation using a microphone. Firstly, the sounds are generated by hammer striking on concrete surfaces. Then, the sounds are acquired by the microphone. Although this methodology can evaluate concrete condition quantitatively, expensive hardware products and professional skills are required.

1.2 Machine learning

Machine learning is the science of getting computers to act without being explicitly programmed. The machine learning is incredibly powerful to make predictions and calculated suggestions based on large amounts of data. In our research, we apply the machine learning to the hammering inspection. The sounds of flaked parts have differences in each concrete structure. The machine learning has an advantage to cover differences of each concrete structure. There are various machine learning algorithms, such as support vector machine, k-means, and k-NN (Gongde et al., 2003).

2. METHODOLOGY

A hammering inspection is the most popular inspection methodology to detect flaking parts on concrete surfaces. However, there are three technical issues. The first issue is that the hammering test requires many inspectors because of a great number of aged structures. The second issue is that the quality of hammering test depends on inspector's experience and skills. The third issue is that conventional approaches require an expensive microphone and hardware products. Thus, it is not easy for municipal governments to apply the conventional approaches. Therefore, we have proposed an approach using lower cost and more simple hardware products. Our methodology consists of three parts, as shown in Figure 3. The first is sound data acquisition. The second is sound data evaluation with a machine learning software. The third is location-based inspection data management.

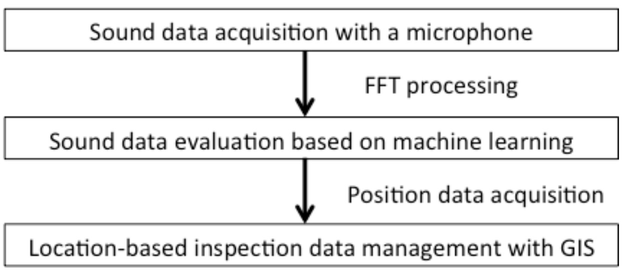

Figure 3. Processing flow of our methodology

2.1 Sound data acquisition

We strike a concrete surface using a hammer to generate sounds from a concrete the surface. The generated sounds are acquired with a microphone. The microphone is required a dynamic range from 0 kHz to 10 kHz, and acoustic pressure from 0 dB to 10 dB.

2.2 Sound data evaluation

The acquired sounds from 0 kHz to 10 kHz are evaluated, because significant frequency exists in a range lower than 10 kHz when flaking parts are detected from hammering sounds (Taketo et al., 1996). We evaluated the acquired sound into 390 dimensions related to dominant frequency to improve the accuracy of evaluation. We have developed a software product to evaluate flaking concrete surface with machine learning. We selected the k-NN algorithm, because the k-NN algorithm has an advantage to achieve a rapid training data correction on site. Generated sounds by a hammer tend to be diffused. Thus, we applied Fast Fourier Transform (FFT) algorithm to find dominant frequencies of measured objects. The dominant frequencies were grouped into 390 parts between 0 kHz and 10 kHz uniformity. Each group was integrated into 390 dimensions for a concrete condition evaluation. We converted the concrete condition with the k-NN into binary results consisted of "good" and "bad". The "good" indicates that the measured concrete surface is healthy. On the other hand, the "bad" indicates that the measured concrete surface has a flaking part.

2.3 Location-based inspection data management

Generally, the acquired inspection data are managed by papers or spreadsheets without position data. However, it is not easy to achieve efficient data management for inspection data evaluation. Thus, we focus on GIS to improve data management of infrastructure inspection and maintenance, as shown in Figure 4.

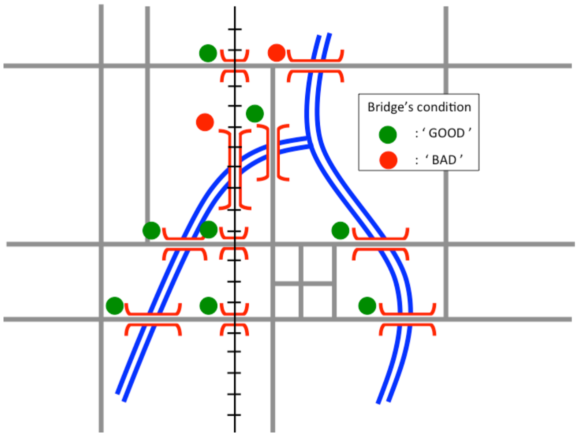

Figure 4. Location-based bridge inspection

3. EXPERIMENTS

We conducted two experiments. In the first experiment, we prepared a reference test piece and nine flaking test pieces, as shown in Table 1. The size of each prepared test piece was 300 mm width × 300 mm height × 100 mm depth. The each test piece had two round steel bars with 16 mm diameter. The bars were set in parallel at 50 mm depth from the concrete surface. Moreover, an interval between bars was 100 mm.

Table 1. Test pieces in experiment 1

	Part of flaking length		
	50 mm	100 mm	150 mm
A. Full flaked (between bar and concrete surface)	A-50	A-100	A-150
B. Flaked part is 25mm depth	B-50	B-100	C-150
C. Flaked part exists between rounded bars	C-50	C-100	C-150

In the second experiment, we prepared a reference test piece. The prepared reference pieces were 21 pieces that have flaking part from 0 kHz to 10 kHz, and three pieces that have flaking part over 10 kHz, as shown in Table 2. The size of each test piece was 150 mm width × 150 mm height × 150 mm depth. We made an assumption that flaking part of concrete was vibrated in a primary inherent vibration mode that is calculated by the following formula.

$$f = \left(\frac{\pi}{L}\right)^2 \times \frac{1}{2\pi}\sqrt{\frac{EI}{\rho A}} \quad \text{[Hz]} \qquad (1)$$

where, 'f' is an inherent frequency [Hz], 'L' is a side of flaking part [m], 'E' is an elastic parameter [N/m^2], 'I' is geometrical moment of inertia [m^4], 'ρ' is a test piece density [kg/m^3], and 'A' is a test piece area [m^2]. Each test piece was sealed to simulate flaking parts with polyethylene sheets (1 mm thickness).

Table 2. Dominant frequency of flaking part of test pieces in experiment 2 (bright grayed parts indicate reference pieces that have flaking part from 0 kHz to 10 kHz, and dark grayed parts indicate reference pieces that have flaking part over 10 kHz

Size \ Depth	10 mm	20 mm	30 mm	40 mm	50 mm
10 mm×10 mm	153.29	306.59	459.88	613.18	766.47
20 mm×20 mm	38.32	76.65	114.97	153.29	191.62
30 mm×30 mm	17.03	34.07	51.10	68.13	85.16
40 mm×40 mm	9.58	19.16	28.74	38.32	47.90
50 mm×50 mm	6.13	12.26	18.4	24.53	30.66
60 mm×60 mm	4.26	8.52	12.77	17.03	21.29
70 mm×70 mm	3.13	6.26	9.39	12.51	15.64
80 mm×80 mm	2.40	4.79	7.19	9.58	11.98
90 mm×90 mm	1.89	3.79	5.68	7.57	9.46
100 mm×100 mm	1.53	3.07	4.60	6.13	7.66

[kHz]

3.2 Measurement system

Figure 5 shows our developed measurement system in hammering inspection experiments. The measurement system consists of four equipments: an inspection hammer with steel ball (20mm diameter), inspection machine with microphone (PDC-100, Port Denshi Co., Ltd), and machine learning software (Smart Machine Co., Ltd) on PC (Macbook, 1.3 GHz). The inspection machine was connected with the PC and microphone. The microphone was attached to a stick to keep a distance from a concrete surface to microphone in sound data acquisition.

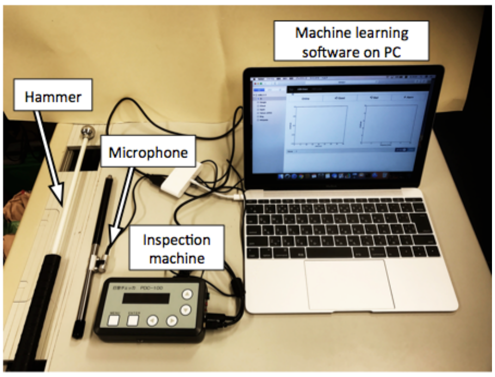

Figure 5. Measurement system

3.3 Training data acquisition

Firstly, we hammered reference test pieces to acquire training data. We evaluated the number of training data with four cases, as shown in Table 3. After the training data acquisition, we hammered reference pieces 10 times in a set, and we prepared five inspection sets for each case. Thus, we hammered 50 times for each case in total. Moreover, we prepared four types of training dataset, such as two training data (minimum), five training data (medium), nine training (large), and 13 training data (maximum).

Table 3. Success rate of each training data

	The number of training data			
	2	5	9	13
Experiment 1	100.0%	97.5%	97.5%	87.5%
Experiment 2	100.0%	70.0%	70.0%	97.5%

3.4 Results in primary experiment

Although it is not enough to detect flaked parts, the two training data provided 100% success rate. In our experiment, we used the nine training data for the first experiment. Moreover, we used the 13 training data for the second experiment to distinguish 'good' from 'bad'.

4. Results

We defined a ratio between the number of succeeded results and the number of true data as the success rate of flaking concrete detection. Moreover, we summarized the success rate of flaking concrete detection in each experiment.

4.1 Experiment 1

Table 4 shows the success rate of flaking concrete detection. The results were 100% in all cases in the first experiment. The C-50 had the smallest flaking part in these nine flaking pieces. The flaked size in C-50 was 116 mm width×84 mm height and 50 mm depth. The dominant frequency was 5.7 kHz approximately. Thus, all pieces prepared in experiment 1 were within a range of evaluation.

Table 4. Results in experiment 1

	Flaking length		
	50 mm	100 mm	150 mm
A. Full flaked (between bar and concrete surface)	(A-50) 100%	(A-100) 100%	(A-150) 100%
B. Flaked part is 25mm depth	(B-50) 100%	(B-100) 100%	(B150) 100%
C. Flaked part exists between rounded bars	(C-50) 100%	(C-100) 100%	(C-150) 100%

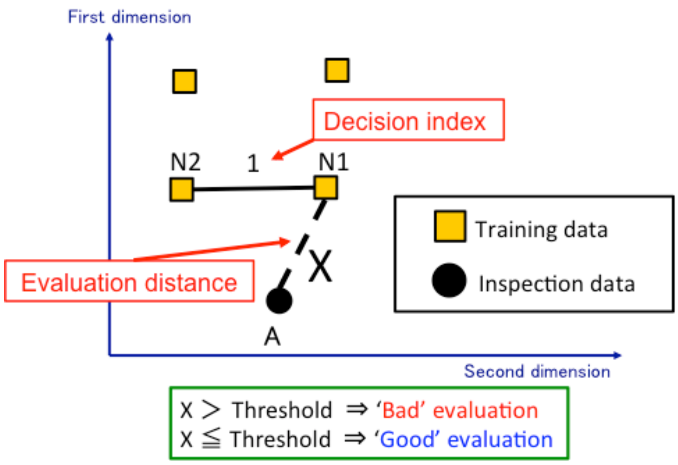

Figure 6. Inspection data evaluation

4.2 Experiment 2

Table 5 shows results in the second experiment. 21 samples were correctly evaluated under 10 kHz. The other samples failed to be evaluated, because estimated dominant frequencies existed over 10 kHz. The microphone could cover within 10 kHz. Thus, the threshold value for our hammering sound evaluation was set at 10 kHz. We set 1.2 times distance of decision index as the threshold value in experiment 1 and 2. The decision index is a distance from N1 to N2, as shown in Figure 6. The vertical axis indicates the first dimension, and the horizontal axis indicates the second dimension. The N1 and N2 are the nearest two training data from the inspection data (A). Moreover, we categorized 'good' and 'bad' with the evaluation distance. The evaluation distance is a distance from the inspection data (A) to the nearest training data N1. When the evaluation distance was more than 1.2 times of decision index, we categorized the result as 'good'. On the other hand, when a result was less than 1.2 times of decision index, we categorized the result as 'bad'. Test piece data under 10 kHz dominant frequencies were from 2.6 to 12.7 times of decision index. However, test piece data over 10kHz area were from 1.2 to 1.5 times of decision index approximately.

Table 5. Results in experiment 2

Depth \ Size	10 mm	20 mm	30 mm	40 mm	50 mm
10 mm×10 mm			60%		
20 mm×20 mm					
30 mm×30 mm				60%	
40 mm×40 mm	100%				
50 mm×50 mm	100%				30%
60 mm×60 mm	100%	100%			
70 mm×70 mm	100%	100%	100%		
80 mm×80 mm	100%	100%	100%	100%	
90 mm×90 mm	100%	100%	100%	100%	100%
100 mm×100 mm	100%	100%	100%	100%	100%

5. DISCUSSION

We have confirmed that the proposed hammering inspection could show a simple result, such as 'good' and 'bad' with the k-NN. The hammering inspection methodology could evaluate all flaking test pieces when dominant frequencies were estimated under 10 kHz. However, when dominant frequencies were estimated over 10 kHz, it is difficult to evaluate flaking test pieces theoretically. However, it was possible to evaluate flaking test pieces from 30% to 60%. Firstly, we would change the threshold from 1.2 to 2.0 times of decision index, because the test piece data under 10 kHz dominant frequencies were from 2.6 to 12.7 times of decision index. Moreover, test piece data over 10 kHz area were from 1.2 to 1.5 times of decision index approximately. The dominant frequencies depend on the size of test pieces and hammering power. Thus, we would conduct an experiment using bigger test pieces to evaluate our machine. Moreover, we would clarify the mechanism to improve our evaluation precision.

6. CONCLUSION

In this paper, we proposed the hammering inspection methodology based on machine learning. We have evaluated that our proposed methodology can evaluate flaking concrete test pieces with the k-NN algorithm. Moreover, we have confirmed that our proposed methodology can evaluate flaking concrete test piece under 10 kHz correctly. Our proposed methodology would be improved with better parameters, such as the number of training data and thresholds for evaluation processing.

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