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Smart non-destructive test of a concrete wall using a hammer

Atsushi Ito, Masafumi Koike, and Katsuhiko Hibino

***Abstract*—Large concrete structures such as buildings, bridges, and tunnels are aging. In Japan and many other countries, those built during economic reconstruction after World War II are about 60 to 70 years old, and flacking and other problems are becoming more noticeable. Periodic inspections were made mandatory by government and ministerial ordinance during the 2013-2014 fiscal year, and inspections based on the new standards have just begun. There are various methods to check the soundness of concrete, but the hammering test is widely used because it does not require special equipment. However, long experience is required to master the hammering test. Therefore, mechanization is desired. Although the difference between the sound of a defective part and a normal part is very small, we have shown that neural network is useful in our research. To use this technology in the actual field, it is necessary to meet the forms of concrete structures in various conditions. For example, flacking in concrete exists at various depths, and it is impossible to learn about flacking in all cases. This paper presents the results of a study of the possibility of finding flacking at different depths with a single inspection learning model and an idea to increase the accuracy of a learning model when we use a rolling hammer.**

***Keywords*—Hammering test; Non-destructive test; Neural network; Transfer learning**

I. Introduction

IN recent years, social infrastructures such as buildings, bridges, and roads have been aging, and the demand for inspection is expected to increase [1]. According to the Japanese government report, at the end of 2022, approximately 1,257,000 condominium units were 40 years old or older. This number is expected to increase by 2.1 times in 10 years and 3.5 times in 20 years [2].

Infrastructure inspection encompasses a range of maintenance tasks, necessitating meticulous diagnosis and assessment of structural integrity and seismic resilience. Modern techniques involve using robots and drones to inspect areas inaccessible to humans, such as expansive bridges and high-rise walls, often necessitating scaffolding [4]. In cases where visual inspection is impossible, like within building walls, a common method involves detecting changes in sound through hammering. Despite being a cost-effective technique, it demands expertise to discern sounds indicating structural issues, making judgments subjective and potentially inconsistent.

Despite its affordability, this testing method demands expertise in differentiating sounds originating from defective areas. However, judgments are subjective and can vary due to individual perceptions. Sound testing is not limited to concrete walls but extends to tile walls commonly found in apartments, numbering approximately 6.65 million in Japan [3]. Streamlining and simplifying hammering tests are vital to inspect this substantial number of buildings efficiently.

Figure 1 shows several types of buildings and structures.

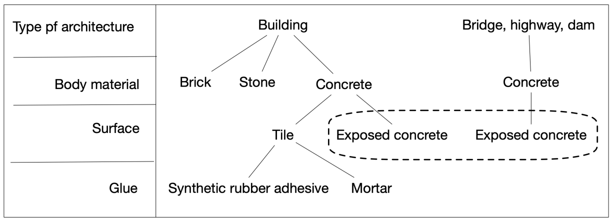

Fig. 1. Types of structure and surface

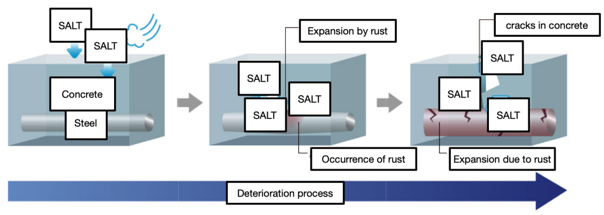

Fig. 2. Flacking caused by salt

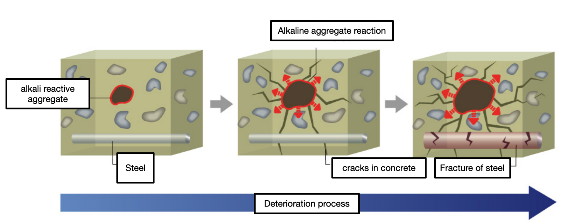

Fig. 3. Flacking caused by alkaline aggregate reaction

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A. Ito is with Faculty of Economics, Chuo University, Tokyo, Japan (ORCID: 0000-0002-9686-4019, e-mail: atc.00s@g.chuo-u.ac.jp).

M. Koike is with Department of Engineering, Utsunomiya University, Tochigi, Japan (e-mail: koike@is.utsunomiya-u.ac.jp).

K. Hibino is with Port Denshi Corporation, Tokyo, Japan (e-mail: hibino@port-d.co.jp).

The structure's body is often made of concrete, although in some cases, it may consist of stone or brick, which is the subject of this paper. Two surface patterns exist. Large structures are bare concrete, but condominiums and commercial buildings are often covered with tiles to decorate and protect the concrete. In the past, tiles were often applied with mortar, but in recent years, tiles are increasingly being applied with adhesives. In this paper, our focus is on a structures with exposed concrete surfaces.

Figure 2 (caused by salt) and Figure 3 (caused by alkaline aggregate reaction) show two major reasons that cause flacking in the concrete constructions. In both cases, small clacks caused the inside of a concrete wall to grow and increase according to the year. Finally, small clacks cause flacking, and in the worst case, some portion of concrete falls.

In this paper, we discuss the outline of the research on the hammering test of concrete walls. There are differences between tile and concrete walls, as shown in Table I. A significant difference is that the tiles' flaking (cavity) location is almost the same depth, a few millimeters down. However, concrete walls vary from 20 mm to 100 mm or even more in some cases. For this reason, we made test blocks with flacking with different depths of flaking (25mm and 55mm). In contrast, concrete walls do not vary in material and texture from place to place, but the depth at which flacking varies. However, developing a learning model using training data of multiple depths of flacking takes much work. Notably, differences between tile and concrete walls, detailed in Table I, are significant. Tiles typically exhibit consistent flaking depths, a few millimeters down, whereas concrete walls vary widely, ranging from 20 mm to 100 mm or even more in certain cases. We created test blocks with different flaking depths (25mm and 55mm) to address this variation.

In the rest of this paper, we explain the related works in section 3 and the research questions in section 4. In section 5, the result of the research of the possibility of realizing the one learning model can be used for the flacking of different depths. Section 6 explains the trial result to solve the problem of using a rolling hammer to investigate concrete walls. We conclude this paper in section 7.

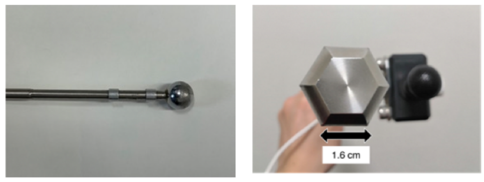
II. Hammering test and AI

There are two devices and an inspection method to find the flacking of concrete walls. As shown in Figure 4, two devices are used for hammering tests: one is a small hammer (left), and another is a rolling hammer (right).

The rolling hammer has a metal hexagonal ball. The gap between the two edges measures 1.6 cm. A hammering sound is generated by the rolling action of this device along the wall. The sounds are captured using a microphone positioned near the rolling ball.

In Figure 5, an instance of a hammering sound obtained with a KoroKoro is illustrated. The advantage of using KoroKoro lies in its ability to strike a wall approximately 15 times per second (roughly every 0.07 seconds). In contrast, a standard hammer yields a hammering sound about once per second.

So, we have used neural networks (NN) and Transfer Learning (TL) [9] for the hammering test to check the



Small Hammer Rolling Hammer

Fig. 4. Two devices for hammering test

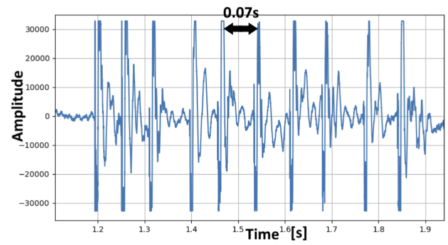


Fig. 5. Recorded sound by using a rolling hammer

injured part by using the hitting sound. We targeted a tile wall and demonstrated our approach's effectiveness for tile walls commonly used in apartments [10].

The TL is a way to develop a learning model quickly by modifying the last layer of the existing learning model and is used frequently in many applications. One of the famous environments to use TL is a Teachable Machine [7] [8]. The Teachable Machine uses MobileNet [19] as the basis of the learning.

The TL offers a rapid approach to developing learning models by adjusting the final layer of an existing model. It finds widespread application in various fields. A well-known example of TL implementation is the Teachable Machine [7] [8], which utilizes MobileNet [19] as its foundational learning framework.

Concrete walls, while consistent in material and texture across different locations, vary significantly in flaking depth. Designing a learning model utilizing training data from various flaking depths demands substantial effort.

Therefore, this paper presents the findings of a study aimed at constructing a learning model unaffected by the depth of flaking. And devices for the hammering test are different. We can use both a small and rolling hammer for the concrete since they can cause a strong impact. On the other hand, we can use a small hammer for a tile wall but not to make an impact. We slide a small ball on the top of a small hammer. We cannot use a rolling hammer since a strong impact sometimes breaks a tile.

III. Related Works

Significant research has been conducted on AI-applied hammering testing in the mentioned scenario. In their study [11], various algorithms, including SVM and DT, were compared. The SVM method exhibited a worst-case predictive value of 72% and a best-predicted value of 99%. Another study [12]

TABLE I
DIFFERENCE OF CHARACTERISTICS BETWEEN WALLS MADE BY TILE AND CONCRETE

Features	Tile	Concrete
Finish of the surface	Surface textures are different Between tiles, there is mortal part The size of each tile is almost the same	Smooth Flat
Location of flacking	Between a tile and wall	Inside concrete
Depth of flacking	Tile thickness is about the same	The depth of flaking varies a lot
Flacking size	Smaller than the tile size	The size of flaking varies a lot
Effect of Rolling Hammer	Sometimes Rolling Hammer is trapped between tiles and slips on the surface	Rolling Hammer roles smooth and uniformly

utilized a camera and SVM for hammering tests, achieving an F-measure of approximately 0.73.

At the product level, tools like T.T.Car [5] and AI Hammering Test Checker [6] employ hammering tests. T.T.Car creates a problem area map by moving along measurement lines drawn on the road but cannot inspect wall surfaces. AI Hammering Test Checker records hammer sounds from a microphone and employs a machine learning function to detect flaking or peeling inside concrete walls using the k-mean method as an ML algorithm. However, its accuracy does not exceed 80%, whereas the accuracy reaches 90% when using NN and Transfer Learning [9].

There are various methods for the inspection of structures, including those using microwave ([13]), robots ([14]), and ultrasonic waves ([17]). In reference [15], various techniques related to nondestructive inspection of tunnel linings are presented.

The application of machine learning to structural inspection has gained momentum in recent years. Reference [11] compares the effectiveness of applying machine learning algorithms such as Support Vector Machine (SVM) and Decision Tree (DT). In the case of SVM, the performance is 99% when it is good, but when it is bad, it is about 72%. According to the [12], in the case of multimodal, images and percussion are combined, and a decision using SVM is put into it. The F value, in this case, is shown to be about 0.73. In addition to our work ([9]), other deep learning applications include the development of a technique for detecting cracks in concrete [16] and the use of transition learning to detect cracks in masonry walls [18].

T.T.Car [5] and AI hammering test checker [6] are among those that have been commercialized. T.T.Car moves along a line drawn on the road and detects normal areas and areas with floaters or cracks while performing a hammering test. AI hammering test checker collects hammering sounds of normal locations collected by a microphone and uses the k-mean method to construct a decision logic for each use. However, its accuracy could be higher, around 80%. On the other hand, by using neural networks and transition learning, which we have been doing, it has been shown that an accuracy of about 90% can be achieved [9].

IV. Research Questions

There are several difficulties in performing hammering tests.

1) The sound caused by the flacking part is small, and usually, the sound of the healthy and flacking parts is not large. Many experiences and training are required.
2) If a hammer hits a wall hard, the returned sound is large, but sometimes the hammer destroys or creates another problem in a wall. So, it is required to make an impact not so hard.
3) Many large buildings and constructions face large streets. The road noise is large, and it is difficult to listen to small sounds caused by the flacking part. The night operation at the high wall is dangerous, so we must inspect the wall in the daytime.

So, we need to develop a technique to inspect a wall using AI.

This paper examines the following issues in the acoustic inspection of concrete structures.

1) Can a learning model work for the flacking at different depths?
2) Can we prevent the loss of accuracy in the case of continuous data acquisition, as in the case of a rolling hammer, instead of using a small hammer?

For this purpose, the following experiments were conducted.

1) With a specimen with delamination at 55 cm and 25 cm can the model learned with one recognize the other?
2) Analysis of the data acquired when using the rolling hammer and how to respond to the data.

In this experiment, data is obtained using a small hammer and a rolling hammer, as shown in Figure 6, then manually separated into normal (healthy) and flacking parts. The specimen is structured as shown in Figure 8 and Figure 10 with a circular flacking area and a normal area around it. When acquiring data from these parts, if a small hammer is used, the normal and abnormal parts are disjointed, and the data from the normal and flacking parts are independent, as shown in Case 1 of Figure 7. It means that the obtained learning model is stable.

In contrast, when using a rolling hammer, the hammer passed the normal and flacking parts through the boundary of the normal and flacking portions, as shown in Figure 8. Therefore, as shown in the Figure 8 and Figure 9, some places show normal and flacking responses. As shown in Case 2 of Figure 7, parts of the response are difficult to distinguish between the two, even when creating data for learning. It means that the learning data set is not disjoint, and such data may cause the learning model to contain noise, lower the percentage of correct answers, and not be stable. This kind of data is thought to cause the learning model to contain noise and lower the rate of correct answers.

Chapter 4 below describes our experiments' results on responses to different depths' flackings. In Chapter 5, we describe the results of our investigation into data handling at the boundary between normal and flacking areas.

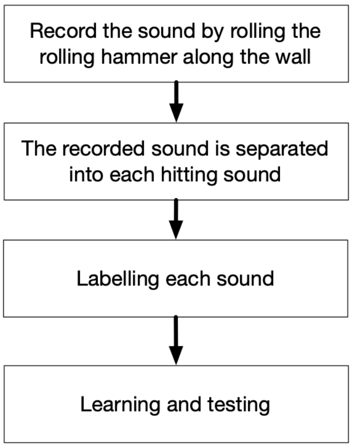


Fig. 6. A flow for experiment

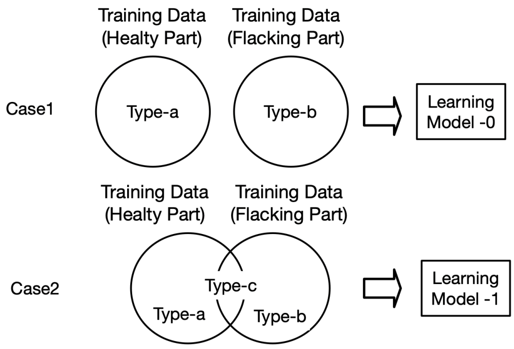


Fig. 7. The effect of the boundary to create a learning model

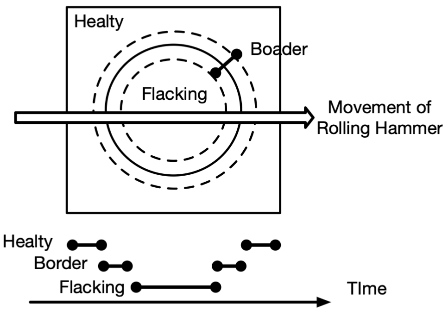


Fig. 8. The border data between the normal part and flacking part

V. ADAPTING DIFFERENT DEPTH OF FLACKING

This section presents the outcomes of validating the accuracy of the hammering test conducted on the sample illustrated in Figure 11.

The test performed on the specimen with flaking 55 mm below the surface is outlined as follows.

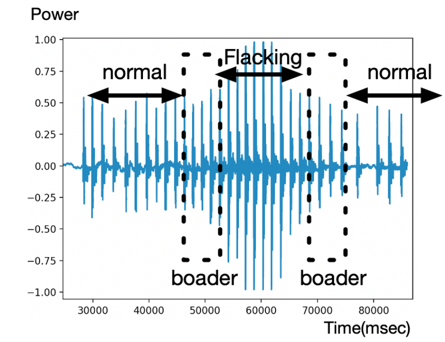


Fig. 9. The wave caused by rolling hammer

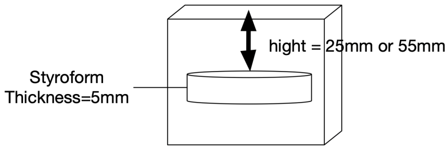


Fig. 10. The structure of specimen

– Extract data randomly from the hammering result. For developing the learning model, we used 56 training and 8 test data.
– Perform training with 150 epochs using Transfer Learning (Teachable Machine [7] [8]).
– Perform the test using four normal and four flacking.

We achieved an accuracy of 91.2% for the 55mm flaking depth, as illustrated in Figure 12. Subsequently, we assessed the versatility of the learning model for specimens with 25mm flaking depth, employing 10 test samples from a specimen with flaking at 25mm. The accuracy, depicted in Figure 12, stood at 97.3%.

These results indicate that the learning model designed for a 55mm flaking depth specimen has the capability to test data from various flaking depths. The learning model was developed using Teachable Machine.

VI. ADAPTING ROLLING HAMMER

Then, we evaluated the model as explained in the previous section using the test specimens in Figure 13 and used a rolling hammer to detect the flacking. This specimen has flacking at 40mm, 60mm, 80mm, and 100mm deep.

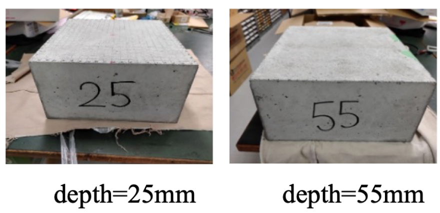


Fig. 11. The specimen for the test of depth

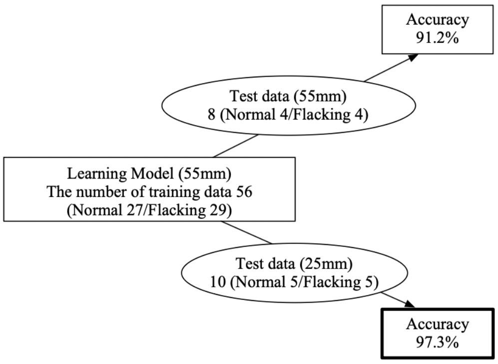


Fig. 12. The result of use one learning model to different specimen

We conducted tests and gathered data from the concrete block. Regrettably, the outcome fell below expectations (around 50%). Consequently, we meticulously analyzed the hammering sound data to discern the cause behind this unexpected result.

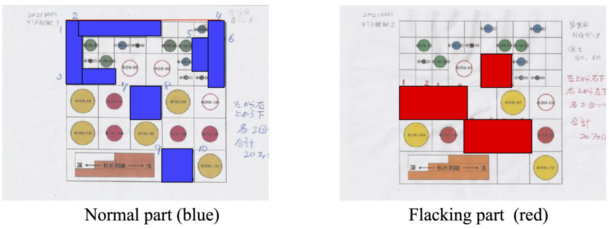


Fig. 13. Different sample

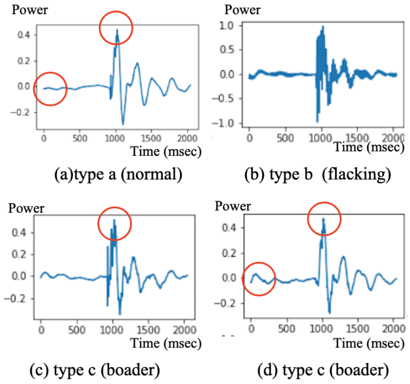


Fig. 14. Comparison of sound (wav) of normal and flacking part

Figure 9 displays the output from a rolling hammer. The sound produced by a normal section (shown in the figure's center) was smaller than that of the flaking part. Although the power of the peak remained consistent, the flaking section exhibited a larger and non-uniform peak. In this scenario, the actual flaking area is at the center (marked by the loud sound), while the surrounding regions (flatter portions) are normal. Consequently, the sound's intensity plays a crucial role in distinguishing flaking.

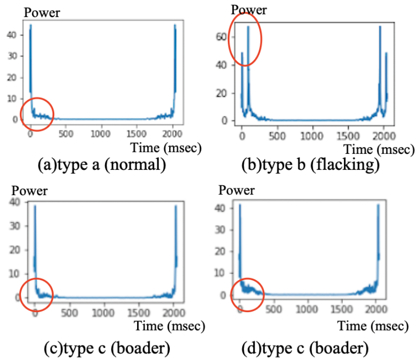


Fig. 15. Comparison of FFT of normal and flacking part

We labeled each sound caused by hitting as normal or flacked. However, as shown in Figure 9, between the normal part and flacking part, there is a sound caused by the border between the normal part and the flacking part. As shown in Figure 9, if a hammer hits the border between the normal part and the flacking part, it is not easy to distinguish the sound that comes from the normal part or the flacking part. In the following part of this paper, we call the sound of the normal part type a, the flacking part type b, and the border part type c.

A. Analyse the sound data

Figure 14 displays typical patterns of hammering sound data in WAV format, showcasing four distinct types.

Data from the normal section (type a), the flaking area (type b), and the boundary between the normal and flaking sections (type c) exhibit varying characteristics. The sound from the flaking section (type b) is louder, with a peak at 1.0, in contrast to the normal section (type a), where the sound registers at 0.4 to 0.5. This discrepancy arises because the concrete in normal areas is solid and does not vibrate, while the flaking section, having a cavity, produces a louder, more musical sound. Additionally, the flaking part's waveform is thicker due to the presence of vibration sounds within it.

We also examined the sound from the border region (type c). The sound's peak resembles that of type a and type c. However, type c exhibits some vibrations caused by the flaking part. The waveform of type c includes some noise in comparison to type b but remains indistinct.

B. Analyse the waveforms of FFT

The waveforms obtained after the Fast Fourier Transform (FFT) were compared, as depicted in Figure 15. Typically, the flaking section (type a) exhibits two peaks, attributed to the cavity reflecting vibration sounds within the wall. In contrast, the normal section (type b) lacks a second peak. However, identifying the border section poses a challenge. This area displays distinct characteristics, including additional vibrations, although they are smaller than those in type a. Distinguishing these nuances proves to be difficult.

C. Removing data of border for learning

Distinguishing type c data as flaking proved challenging. Therefore, we manually removed such data to enhance the quality of our learning model. Utilizing the Teachable Machine, we developed the model, the results of which are presented in Table II. The right column indicates the outcome of the learning model created without type c data.

Upon eliminating type c data, the learning model exhibited improved accuracy.

TABLE II
TRIAL WITHOUT TYPE3 C DATA

	type c included	type c removed from learning data
The number of learning data (Normal/Flacking)	40 (20/20)	40 (20/20)
The number of test data (Normal/Flacking)	20 (10/10)	20 (10/10)
Accuracy	90%	95%

VII. CONCLUSIONS

In Japan and worldwide, social infrastructure such as roads, bridges, dams, and other buildings constructed immediately after World War II are aging, and accidents involving concrete spalling are becoming more common. Also, the number of peeling tiles attached to residential buildings for decoration is increasing. Therefore, we have been studying techniques to inspect them.

This paper shows that the model learned on a 25 mm deep crack can also be used on a 55 mm deep crack. This result demonstrated the versatility of the learning model and the practicality of using neural networks for hammering tests. The accuracy obtained from our experiment was over 90%. This result was better than the accuracy of AI Hammering Test Checker [6] that used the k-mean method. However, this result was obtained in the limited number of test data. Improving the training data's accuracy is necessary to construct a more versatile learning model. We showed that the accuracy can be increased by eliminating data at the boundary between abnormal and normal areas.

For future work, we intend to verify the model's usefulness by testing it on various specimens and concrete structures. Another issue to be addressed for practical application is the development of technology to locate flacking areas accurately. In addition, while we used recorded data for the research, real-time processing is required to use this system in the real field. The construction of software to handle this is also an issue.

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