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Non-Destructive Inspection on Resin Grouting Judgement for Repaired RC Member by Local Outlier Factor Method

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Abstract - This paper proposes a new non-destructive inspection method on resin grouting judgement using local outlier factor method (LOF) for the reinforced concrete (RC) member repaired by the internal pressure hardening (IPH) which is a kind of resin grouting repair technique. This inspection method is a type of machine learning uses hitting sound spectra as input data to judge the success or failure of resin grouting in the repaired RC member. The validity of this method is confirmed through a field experiment at repair site of RC slab member damaged by seawater chloride. In addition, the effect of number of teacher data used in the method is investigated on the evaluation indices such as true positive rate (TPR) and true negative rate (TNR).

***Keywords*:** Non-destructive inspection, Machine learning, LOF, Reinforced concrete, Resin grouting repair, Hitting sound

1. Introduction

The aging of social infrastructures such as concrete structures is an urgent issue, increases the need to enhance inspection methods in order to respond to aging. We must rely on the non-destructive inspection, in particular, since concrete structures are composed of a kind of adhesive called cement. Additionally, the current shortage of skilled workers increases demand for the non-destructive inspection method, facilitates adoption of AI technology and data science.

In the non-destructive inspection method that applies AI technology, the measurement data used for inspection take a variety of forms, such as images and hitting sounds, besides, many studies have been accumulated in recent years in Japan [1]-[4]. In these studies, various machine learning approaches have been employed such as self-organising maps [5], k-nearest neighbour algorithm, Neural network and so on. However, it can be said that their main focus is set on the determination of defects and deterioration of concrete members, but still few studies on judgement is required for success or failure on repairs of aging members.

On the other hand, the measure against the aging of structures is not only necessary to grasp the progress of aging, even in situations in which repair work with various repair methods is properly performed. Some new non-destructive inspection methods based on AI technology are needed to be developed for evaluation of repairing result. For example, the internal pressure hardening (IPH) method [6] employed in this study is a type of resin grouting repairing method, which fills voids occurred inside reinforced concrete (RC) members due to aging. In the operation of this repairing method, in order to repair the RC without cutting it, it is necessary to confirm in some non-destructive procedure the repair is completed whether all voids are reliably filled with resin. However, there have been few non-destructive inspection studies using AI technology in this regard.

From the viewpoint mentioned above, as a method to evaluate the success or failure of resin grouting by the IPH method, this study proposes a new non-destructive inspection method based on the local outlier factor (LOF) method [7] which is a type of machine learning, using hitting sound data which can be easily gathered at the repair site. Therefore, the purpose of this study is to confirm its validity experimentally. The LOF method uses only negative data as teacher data, therefore does not require positive data. To evaluate the success or failure of resin grouting, the LOF method requires only negative teacher data has an advantage, because voids remaining in the concrete have diversity when the grouting is not successful (positive), consequently their effects on the characteristics of the hitting sounds are difficult to predict. Then, we anticipate that the LOF method requiring only negative teacher data is applicable to the actual repaired RC members by IPH method.

An RC slab is chosen as subject of the test, which is an actual structure has deteriorated and has been repaired by the IPH method. Then, the hitting sounds recorded before and after the repair are used as input data for proposed machine learning method, to verify availability of the method. In addition, the effect of number of teacher data is investigated on various evaluation indices of the judgement results.

2. Repair by IPH method

The IPH method in this study which aims to be evaluated by AI technology is a type of resin grouting method. In this method, the covered concrete is used while it is preserved, drilled from the concrete surface to the position of the re-bar. A capsule for grouting epoxy resin is attached to the opening of the resulting hole, grouts the resin by the elongation force of the spring provided in it as shown in Fig. 1. At this time, the capsule also has the function of helping to reliably grout the resin into the void by stably replacing the air inside the concrete with resin. The resin filled in this way hardens inside the void to restore the solidity of concrete.

The non-destructive testing by hitting sound suggests that concrete with voids has different hitting sound characteristics from the non-deteriorated concrete without void, consequently the differences are appeared in the spectra of hitting sounds. It is expected that the hitting sound of concrete whose solidity has been restored by IPH method, will acquire same characteristics similar to that of hitting sound of non-deteriorated concrete, and that the success or failure of resin grouting into the void can be evaluated by judging the similarity with the hitting sound characteristics of non-deteriorated concrete.

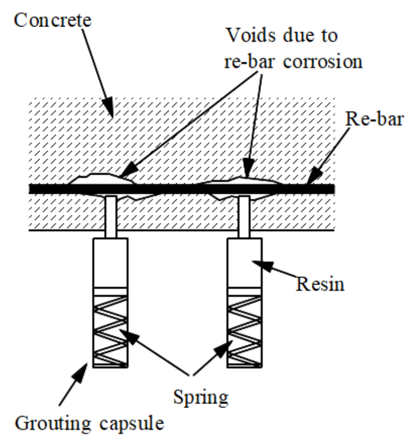

Fig. 1: Grouting by IPH method.

3. Proposed judgement method by LOF

The LOF [7] (local outlier factor) method which can determine the success or failure of filling voids with resin is a type of machine learning. In this study, a state in which the voids in concrete are filled with resin grouting normally is considered as negative, on the other hand, a positive state is defined as a state in which voids are remain unfilled.

The hitting sound is obtained as time history as shown in Fig. 2. This hitting sound is converted to the frequency domain spectrum by the Fourier transformation as shown in Fig. 3. Since this spectrum can be regarded as a vector quantity of order N, this can be represented as a single point in a N-dimensional feature space where each amplitude

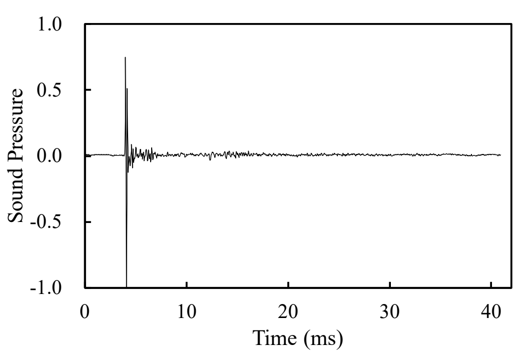

Fig. 2: Sample of hitting sound as time history.

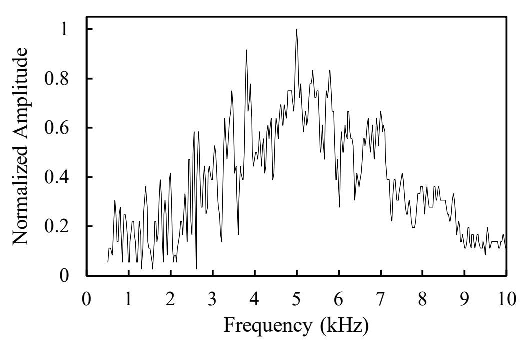

Fig. 3: Sample of hitting sound spectrum

value of this spectrum is a coordinate value. Specifically, the time history recorded for 40.96 ms at 100 kS/s (100,000 samples in 1 s) is converted by Fourier transformation, as the result, spectrum with frequency resolution 24.41 Hz is obtained. Since 380 amplitude values in the range from 500 Hz to 10 kHz are taken as coordinates of points in the feature space, the order N in the above description is 380.

Fig. 4 illustrates the concept of proposed method. LOF evaluates anomalies based on density of data. When data to be judged positive or negative are located in the same feature space, a data which has evaluated high density is predicted negative, in contrast, a data has low density is predicted positive. The local density is employed to represent the density of focused data. This local density is calculated as a reciprocal of the mean of distances between the test data and k selected nearest neighbour teacher data. In this study, the distance is defined as the Euclidean distance. Explaining with Fig. 4, assuming k to be 3, data B, C and D are nearest neighbours of the test data A, accordingly, the local density of the test data A is reciprocal of mean value of distance AB, AC and AD. Using the local density, the score value S of the test data A is calculated by following equation.

$$S = LD_T \,/\, LD_A \tag{1}$$

Where, LD_A is the local density of the test data A mentioned above, LD_T is the local density of the teacher data group. As for the local density of the teacher data group, although there is also a procedure to obtain as average value of the local density of each teacher data calculated separately, in this study, it is calculated as the average of the distances in all combinations between all teacher data for simplicity of calculation. If this score value S is smaller then preset threshold T, the test data is similar to teacher data group, thus it is judged to be negative. Else if S is greater than the threshold T, it is judged to be positive. The k value in this study is set to the smaller of 5 and the number of teacher data.

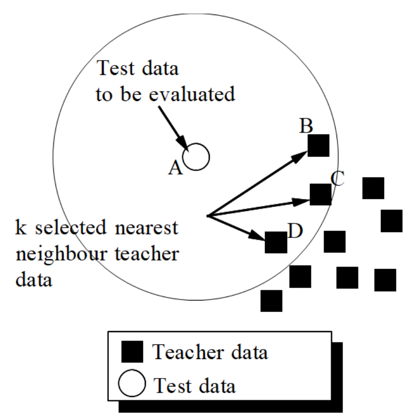

Fig. 4: Concept of LOF method.

Some other machine learning methods require both positive and negative teacher data. Although it is necessary to collect positive data for teacher data for these methods, collecting positive data with complex diversity is extremely difficult. Because, it is impossible to predict the effect of various voids occurred in concrete on spectrum of hitting sound. Therefore, we have no choice but to judge using positive data that are not clear whether they are actually positive or not with these methods. On the other hand, the LOF has an advantage in judging the success or failure of the resin grouting in voids whose diversity cannot be predicted, since it can performe only with negative teacher data.

Furthermore, LOF has a disadvantage that the threshold T compared to the score value S is a hyperparameter which must be artificially adjusted. To solve this problem, the threshold T is varied parametrically in this study.

4. Outline of the experiment

4.1. Target structural member

The RC structural member of the test is an RC floor slab of a road bridge whose completion year is un-known. Fig. 5 shows close-up view, and Fig. 6 shows a floor plan on the back side. Length of slab is almost 10.2 m, and, width is almost 4.9 m. Due to its construction near the coast, the corrosion of the reinforcing bars progressed, therefore the cover concrete in the grey shaded part in Fig. 6 is peeled off exposing corroded the reinforcing bars. During repair, at first the lost cover is reconstructed using with cross-section restoration materials, secondly the resin was grouted by the IPH method. The remaining

Fig. 5: Close-up view.

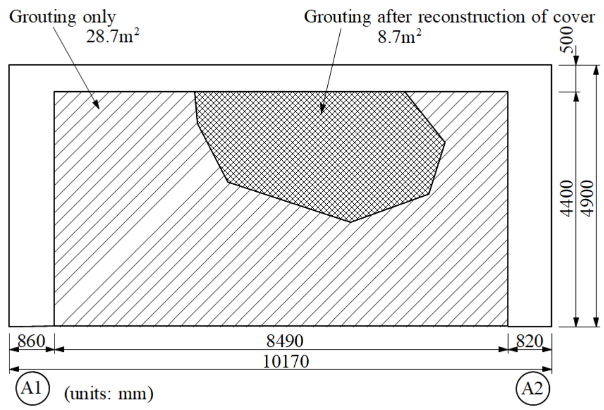

Fig. 6: Floor plan of RC slab.

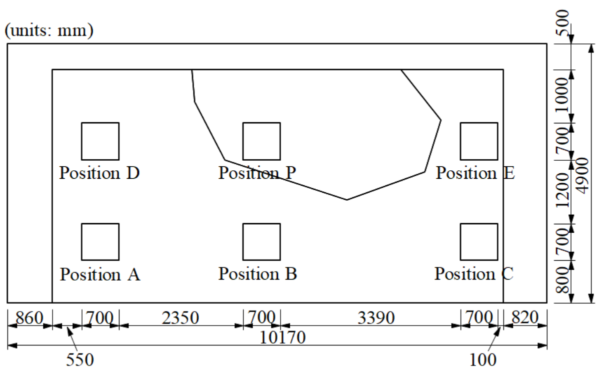

Fig. 7: Acquisition positions.

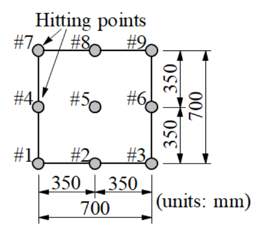

Fig. 8: Hitting points.

area is Fig. 6 is the part where the cover concrete left. In this part, the resin is grouted on the original cover concrete the cross-section reconstruction.

4.2. Acquisition of hitting sounds

Before the resin grouting, the hitting sounds used as positive data have been collected on the bottom surface of the slab. In the area cross-section reconstructed, the collection of sounds has been carried out after the reconstruction. After the resin grouting, hitting sounds have been collected again to use as negative data.

Fig. 7 shows acquisition positions of the hitting sound. Total of 6 acquisition positions are set. Five positions from A to E are locate in the remaining part of the cover concrete. Position P locates in the reconstruction part of the cover. These acquisition positions have the shape of square with a side of 700 mm. Each of 9 hitting points are set at these acquisition positions as shown in Fig. 8. Positive hitting sounds have been recorded once for each these hitting points as time histories. Therefore, the number of the hitting sounds recorded before the grouting is 54, multiplying 6 by 9. After obtaining the hitting sound, the grouting has been carried out by the IPH method, besides, another set of negative hitting sounds have been recorded for same hitting points. The hitting on the concrete surface has been performed manually using a plastic rod with a steel ball with diameter of 22mm attached to the tip.

5. Comparison of hitting sounds before and after resin grouting

In this section, we make an attempt to compare the score values before and after the resin grouting based on LOF. The data at acquisition position A are employed as the teacher data for the LOF method. All 9 negative data acquired at position A are used as the teacher data. We determined that this position A is the least affected by re-bar corrosion, because this position is the farthest from the reconstruction part of the cover. Fig. 9 represents the score value S_{pr} and

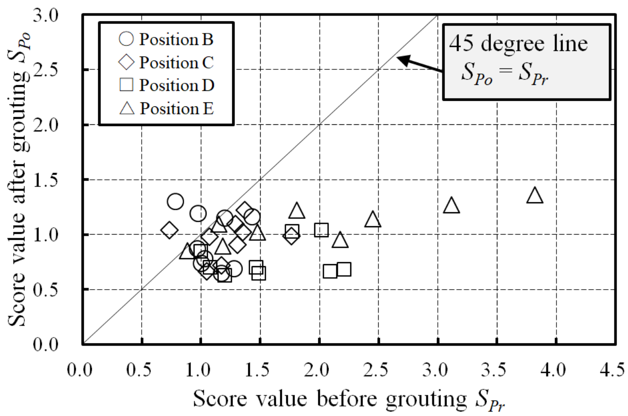

Fig. 9: Relationship between score value before and after grouting (Acquisition position B, C, D, E).

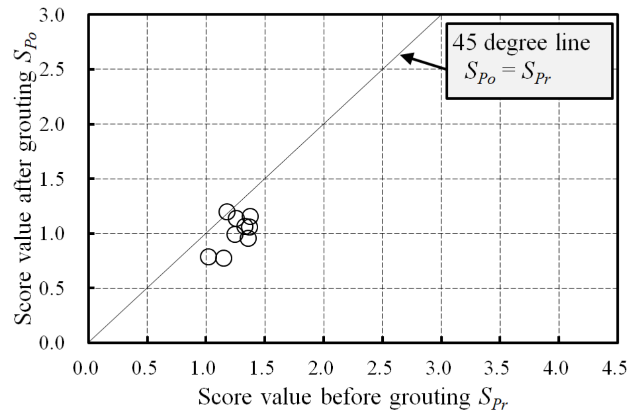

Fig. 10: Relationship between score value Before and after grouting (Acquisition position P).

Table 1: Positive test data.

Acquisition Position	Hitting Point	Score value: Before grouting S_{Pr}	Score value: After grouting S_{Po}
D	#5	1.767	1.031
D	#6	2.091	0.663
D	#8	2.206	0.686
D	#9	2.015	1.043
C	#3	1.764	0.984
E	#5	2.177	0.954
E	#6	2.449	1.144
E	#7	3.115	1.269
E	#8	3.820	1.363
E	#9	1.806	1.221

S_{po} at data acquisition position B, C, D and E. Where, suffix "*pr*" and "*po*" indicate the score values of the hitting sounds acquired before and after the resin grouting, respectively. Most of the dots, except for three, are plotted to the lower right of of the 45-degree line representing $S_{po} = S_{pr}$. From this, it can be seen that the score values are smaller for the hitting sounds after resin grouting than for the hitting sounds before resin grouting. This reduction in the score values indicates that the resin grouting causes the characteristics of the hitting sounds to become similar to the teacher data. Some of the score values of hitting sound are close to 4.0 at maximum before resin grouting, but after grouting, all score values, including those, are kept below 1.4.

Fig. 10 shows a comparison of the score values Spo and Spr at the acquisition position P locates in the reconstruction part of the cover. No dot is plotted on the upper left of the 45-degree line. The score value is reduced by the resin grouting at all nine hitting points (#1 to #9 in Fig. 8).

6. Judgement of success or failure of resin grouting

The focus of this section is on the possibility of judging success or failure of the resin grouting based on the proposed method.

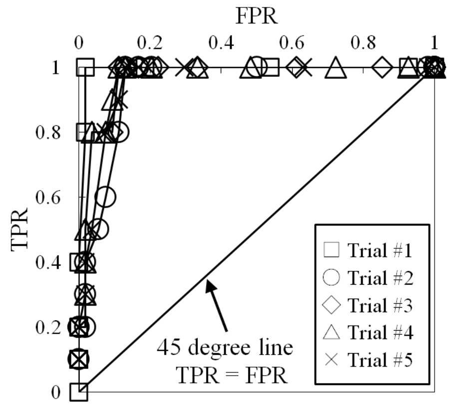

Fig. 11a: ROC curves
(number of teacher data: 2).

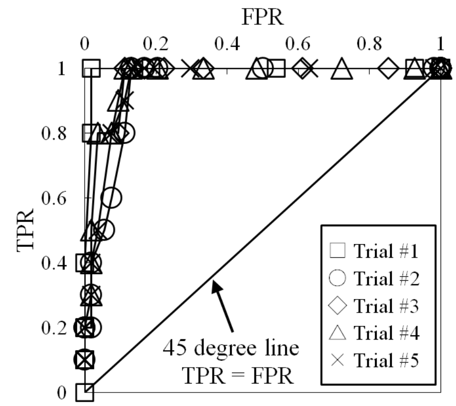

Fig. 11b: ROC curves
(number of teacher data: 6).

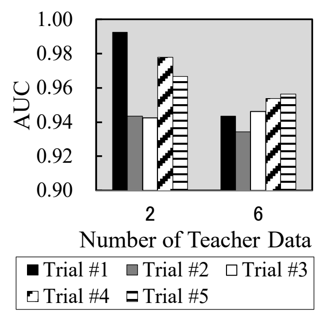

Fig. 12: AUC values
(number of teacher data: 2, 6).

Since the member used in this experiment are an actual structure in service, it was not possible to create defective with voids by intentionally failing the resin grouting. Therefore, data with score value before the grouting S_{pr} exceeding are extracted from the 36 hitting points on acquisition positions B, C, D, E to be set as positive test data with failure. of 10 data points with S_{pr} greater than 1.5 shown in Fig. 8. These data are summarized in Table 1, have score values S_{po} the grouting at most 1.363, hence are close to the negative teacher data in the feature space due to the effect of the On the other hand, negative data consists of 54 hitting sounds at 6 acquisition positions A, B, C, D, E, P gathered after the grouting. An attempt is made to distinguish a total of 64 points, 10 points of positive test data and 54 points of negative test data. The teacher data set uses 8 hitting sounds of an unreinforced concrete specimen to adopt negative data ensured no voids. The specimen is a square with sides of 300 mm and a thickness of 120 mm, consists from concrete with water-cement ratio of 57% and strength of 39 N/mm^2.

As explained in Section 3, negative/positive judgement based on the local outlier factor method is made by comparing the magnitude relationship between the score value S and the threshold value T, needs setting threshold value T in advance as a hyperparameter. A test data is presumed positive while S is greater than T, negative otherwise.

The receiver operating characteristic curve (ROC curve) is used to evaluate the judgement results on an assumption of the variation of the threshold T mentioned above, has an orthogonal coordinate with evaluation indices the true positive rate (TPR) as y-axis and the false positive rate as x-axis. Fig. 11a and 11b represent the ROC curves under deferent judgement conditions. In Fig. 11a, number of teacher data is set to 2, and in Fig. 11b it is set to 6, respectively. These figures show the results of each five trials. In each of the trials, as training data, 2 or 6 data are randomly selected from 8 prepared data set. The upper left corners of the ROC curves express the ideal judgement results in which TPR is

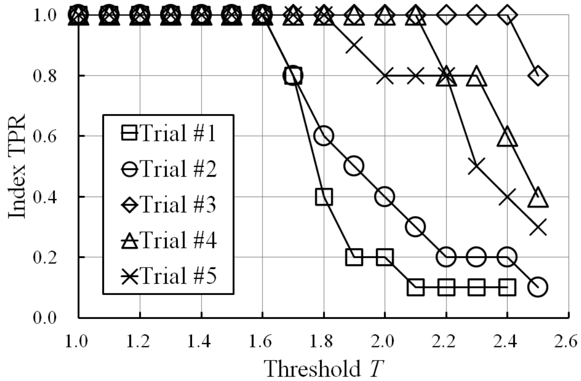

Fig. 13a: Relationship between TPR and threshold T (number of teacher data: 2).

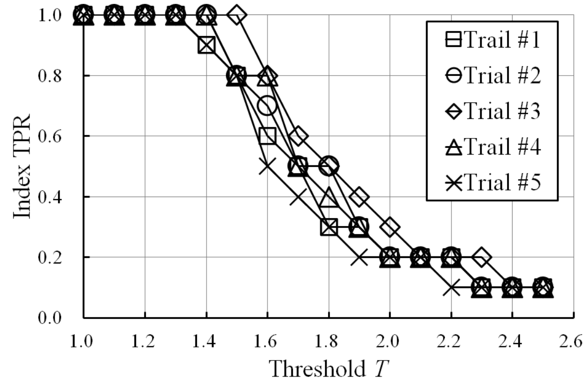

Fig. 13b: Relationship between TPR and threshold T (number of teacher data: 6).

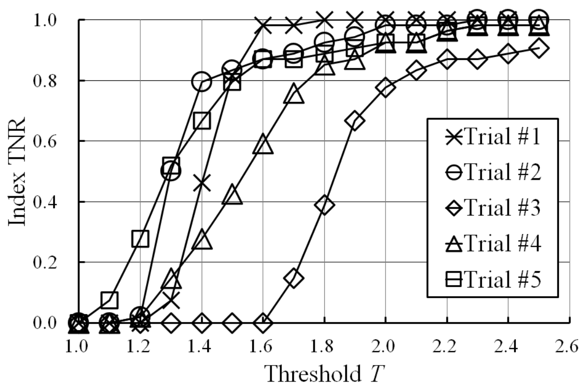

Fig. 14a: Relationship between TNR and threshold T (number of teacher data: 2).

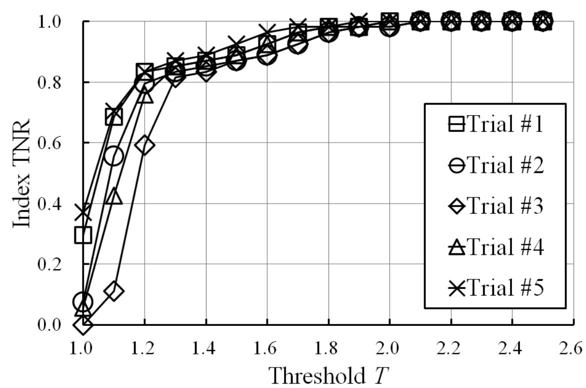

Fig. 14b: Relationship between TNR and threshold T (number of teacher data: 6).

1.0 and FPR is 0.0. Although the ROC curves do not match these corners in all trials in Fig. 11a and 11b, they capture the the neighbours of the corners. Observing at the Area Under the Curve value (AUC value), which is a quantitative evaluation evaluation of the ROC curve, the values of the ROC curves in both figures exceed 0.9 in all trials (Fig. 12). confirming the the high performance of the proposed method. The high performance of the proposed method as a learner is indicated, accordingly its applicability to judging success or failure of the resin grouting is confirmed.

Secondly, the relationships between the threshold value T and the evaluation indices are considered from the perspective of the number of teacher data. The relationships between the threshold T and the true positive rate TPR are shown in Fig. 13a and 13b, and the relationships between the threshold T and the true negative rate (TNR) are shown in Fig. 14a and 14b, respectively. When the number of teacher data is 6, the tendencies of TPR and TNR for the threshold T are similar in all trials, moreover the threshold T at which they start to decrease is almost the same regardless of the trials (See Fig. 13b and Fig. 14b). While, when the number of teacher data is 2, the tendencies of the indices differ substantially with each trial (Fig. 13a and Fig. 14a). In practical terms, the judgement is required to keep TPR high to prevent the false negatives, which are type II errors. From this point of view, if the number of teacher data is 6, the threshold T must be below 1.4 in order to keep TPR above 0.9 in all trials (Fig. 13b), consequently TNR is guaranteed to be 0.8 or higher (Fig.14b). Conversely, in the case of the number of teacher data is 2, although upper limit of the threshold T is 1.6 in order to keep TPR above 0.9 in all trials

(Fig.13a), TNR will have a wide range of values from 0.0 to 1.0 at this threshold (Fig. 14a). A judgement result with a TNR value of 0.0 means that all actual negative data become false positives. In the local outlier factor method, the threshold T is a hyperparameter that must be set in advance by humans, so the trends of TPR and TNR need to be stable for each trial. The result of this study suggests that increasing the number of teacher data is effective in keeping both TPR and TNR high.

7. Conclusion

This paper proposes a new non-destructive inspection method featuring LOF on judgement of resin grouting for the RC member repaired by the IPH method. Changes in score values output by the proposed method have been certified by comparing data before and after grouting. A study focusing on AUC has confirmed the validity of the proposed method in judging the success or failure of resin grouting. In addition, the need to increase the number of teacher data has been recognized in the judgement, considering the relationship between the evaluation indices and threshold.

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