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Effect of Mislabeled Data on Judgement Results for Re-bar Corrosion by Impact Sound Based on Neural Network

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Abstract **-** The purpose of this study is to examine the effect of mislabeled data in the training data on the judgment results for reinforcement corrosion by the impact sounds of a steel ball colliding based on a neural network. For this purpose, the impact sounds of RC specimens with different corrosion levels were recorded, and the effects of contaminating with data in which corrosion has progressed beyond the target corrosion level into the positive training data were examined. As a result, it was found that the true positive rate decreased as the contamination rate increased when mislabeled data in the judgement the corrosion level of 1% was included. In addition, in the judgement of the corrosion level of 3%, the true positive rate tends to reduce when mislabeled data is included, but it was clarified that it is less affected by contaminating with the mislabeled data than the judgement of the corrosion level of 1%.

Keywords**:** Non-destructive inspection, Reinforced concrete, Rebar corrosion, Impact sound, Neural network

1. Introduction

In recent years, the studies using machine learning have attracted attention as non-destructive inspection techniques for RC structures. One of them is the use for hammering test, and many studies have been conducted mainly for detecting deformation such as loose part and stripping [1]-[5]. In addition, we have also proposed a method for determining the presence or absence of rebar corrosion that combines hammering test and machine learning [6], [7]. Many of these methods are premised on the collecting of positive training data. Considering application to the inspection of existing structures, it is difficult to collect data in the early stages of deterioration, especially when no appearance deformation is observed, and it is assumed that data which is inconsistent the level of degradation of the data to be inspected, i.e. mislabeled data, will be collected. It is also conceivable that the contamination of these mislabeled data may have an adverse effect on the inspection results, but there are few studies that focus on this. Accordingly, this study aimed to examine the effect of contamination with mislabeled data in the positive training data on the judgment results of rebar corrosion by the impact sounds of a steel ball colliding based on a neural network.

2. Experimental Procedure

2.1. Materials

Fig. 1 shows a layout of test specimens. The shape of these specimens is rectangle with dimensions of 300 mm×300 mm×120 mm, which models a part of a RC wall, and has four D13 (SD295A) reinforcing bars with a space of 63 mm inside. Concrete cover thickness is 77 mm on the colliding surface side where the impact sounds are recorded, and 30 mm on the opposite side. Table 1 shows the mix proportion of concrete. Eight specimens are prepared with the same mix proportion and subjected to water-curing for a month. The compressive strength is 34.8 N/mm2 (material age 28 days). Corrosion method of reinforcing bars is electrolytic corrosion. The target corrosion level is set to 1%, 3%, and 6%, and the energization time spent on the electrolysis is set to 28.2 hr. per 1% corrosion level with reference to previous study [8], [9]. Four specimens (No. 1~4) are corrosion specimens that are subjected to electrolytic corrosion, and the remaining four (No. 5~8) are controlled specimens that are not electrolytically corroded.

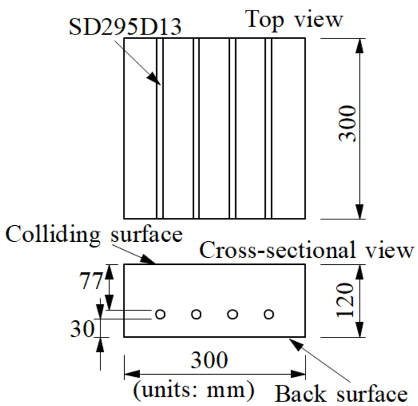
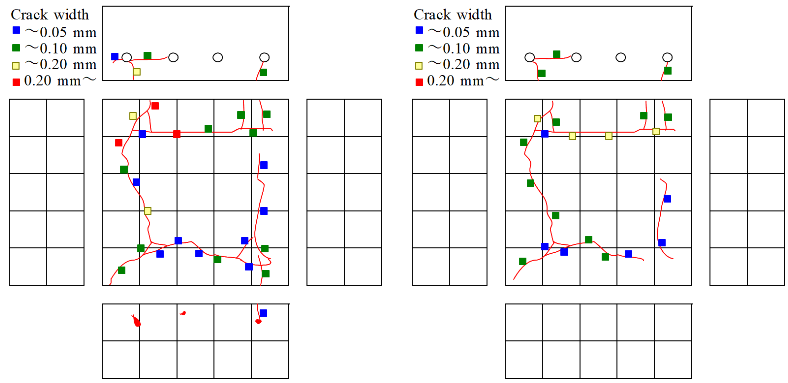


Fig. 1: Specimen specifications



(a): Corrosion level of 3% (b): Corrosion level of 6%

Fig. 2: Corrosion crack distribution (specimen No.1)

Table 1: Mix proportion

Maximum aggregate size G_{max} (mm)	Water cement ratio W/C (%)	Amount of air (%)	Weight per Unit Volume (kg/m^3)				
			Water W	Cement C	Sand S	Gravel G	AE agent A
20	60	3.0	175	292	680	1060	3.5

No corrosion cracks were observed on the surface of any specimen with a corrosion level of 1% after electrolytic corrosion. However, at the corrosion levels of 3% and 6%, corrosion cracks were observed only on the back surface and some side surfaces where the concrete cover thickness was small. On the other hand, no corrosion cracks were observed on the colliding surface on the opposite side of any specimens. Fig. 2 shows an example of the corrosion crack distribution on the back surface of the specimen at the corrosion level are 3% and 6%. Corrosion cracks with a width of less than 0.2 mm were commonly observed for all specimens at the corrosion level of 3%, and at the final corrosion level of 6%, the crack width that occurred at a corrosion rate of 3% increased only slightly.

2.2. Recording Impact Sound

In this study, drop collision of a steel ball was employed as the impact method considering the reproducibility of the experiment. As shown in Table 2, a steel ball with a diameter of 20 mm and a mass of 31 g was dropped from a height of 810 mm. The impact position was the range in the center of the colliding surface (50 mm ×50 mm). The specimens were placed on the floor with the colliding surface facing up, with 60 mm thick polystyrene foam was interposed between the specimen and the floor to eliminate the influence of the support conditions.

Table 2: Drop collision conditions of a steel ball

Diameter (mm)	Mass (g)	Drop height (mm)	Kinetic energy (J)	Momentum (kgm/s)	Collision velocity (m/s)	Maximum impact force (N)	Contact time (μs)
20	31	810	0.246	0.123	3.98	4361	91

The impact sounds at the time of colliding were recorded by a microphone (sensitivity 50 mV/Pa) installed at a position 300 mm above the colliding surface. The sound pressure output as a voltage from the microphone was A/D converted by a data logger with a sampling rate of 100,000 samples per second and recorded as the time -domain responses. In this study, the sampling length is 40 ms. The impact sounds were recorded four times in total, before the electrolytic corrosion and after the corrosion levels of 1%, 3%, and 6%.

2.3. Judgement for Rebar Corrosion Based on Neural Network

2.3.1. Neural Network Model

High-precision analysis is possible by using neural network models with multiple intermediate layers, but they require a huge amount of training data. In this study, because the number of data samples that can be used for learning is limited due to sample collection in the laboratory, the neural network model with a minimal configuration consisting of the input layer, one intermediate layer, and the output layer is adopted. The number of nodes in the intermediate layer is set to 8, and the number of epochs is set to 400. As the learning method, back propagation and gradient descent are adopted, in which the node errors of intermediate layer are calculated in order from the node errors of output layer, and the weight of the joint is updated based on the errors. In addition, the activation function is used the sigmoid function.

2.3.2. Feature

The recorded time-domain responses of sound pressure were converted into spectra by discrete Fourier transform, and then normalized so that the maximum value became 1.0. Since Fourier transform is performed on the time-domain responses cut into the sampling length of 40 ms, the frequency resolution is 25 Hz. Because it is concerned that S/N ratio will be low at high frequencies, cutoff frequency on the high frequency side is set to 5000 Hz. In addition, since the band below 500 Hz is removed from the analysis to prevent the influence of DC offset and spectral leakage, one spectrum has 181 features in the range of 500 to 5000 Hz. Fig. 3 shows an example of the spectra at each corrosion level including before electrolytic corrosion. As a general trend, the entire waveform shows similar trends at corrosion levels of 0% and 1%, and at corrosion levels of 3% and 6%, the maximum peak frequency is smaller than at corrosion levels of 0% and 1%. Comparing the corrosion levels of 3% and 6%, the difference between the two is remarkable in the band after the maximum peak frequency.

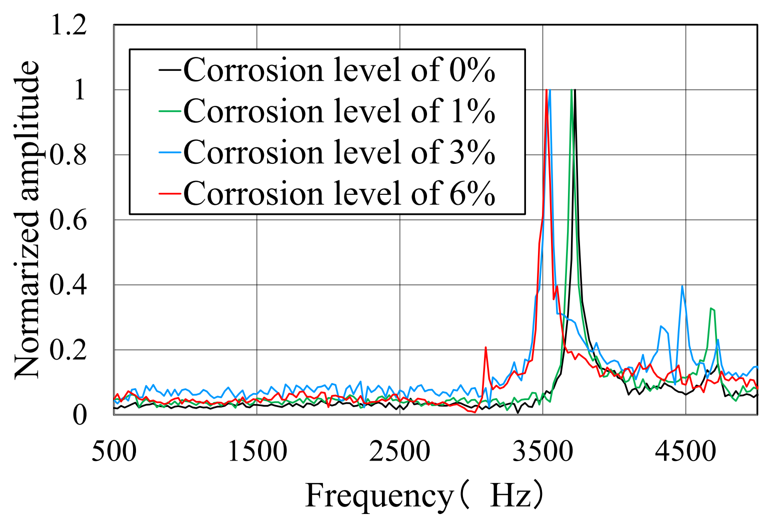


Fig. 3: Spectra for each corrosion level

2.3.3. Data Set

As shown in Table 3, the impact sound data can be divided into 7 categories according to the presence or absence electrolytic corrosion and the difference in recording occasion. In each category, because 16 impact sounds are recorded each specimen, one category consists of 64 input data. Since there are 7 categories from C_0 to N_3, the entire category is data group consisting of 448 data. From this data group, training data and test data are randomly selected while avoiding duplication between both data. At this time, the data with a different corrosion level from the positive test data to be judged is contaminated into the positive training data used for learning. Table 4 shows the number of impact sound data selected. For each judgement, the learning is performed using a total of 96 training data, and then the judgement is performed using a total of 128 test data.

Table 3: Classification of impact sound data

Category	Recording occasion	Actual conditons	Target specimens
C_0	Before electrolytic corrosion (Corrosion level of 0%)	Negative	Corroded specimens No.1~4
C_1	As of target corrosion level of 1%	Positive	
C_3	As of target corrosion level of 3%		
C_6	As of target corrosion level of 6%		
N_0	Same as C_0	Negative	Non corroded specimens No.5~8
N_1	Same as C_1		
N_3	Same as C_3		

Table 4: The number of impact sound data selected

Contamination rate of mislabeled data	Number of data				
	Test data		Training data		
	Positive	Negative	Positive		Negative
			Labeled	Mislabeled	
0%	32	96	32	0	64
20%	32	96	26	6	64
50%	32	96	16	16	64
80%	32	96	6	26	64
100%	32	96	0	32	64

2.3.4 Judgement and Evaluation Method

Rebar Corrosion is judged by this neural network based on the amplitude of the output value from only one node on the on the output layer for the input of the spectra to the input layer. The output value is in the range of 0.0 to 1.0. process, 1.0 1.0 is set as the output value for training data presence of corrosion, and 0.0 is set for absence. In judging process of the test test data, the output value is equal or more than 0.5 interpreted to be present corrosion, and less than 0.5 to be absent. There There are two predicted conditions: Predicted Positive, which determines that there is corrosion, and Predicted Negative, which determines that there is no corrosion. All 128 test data are judged as either. However, these positive and negative predictions are not limited to that correspond to the actual positive and the actual negative, which are the presence or absence of corrosion, and misjudgement is unavoidable. The test data is hence classified into one of the four categories True Positive, False Negative, False Positive, and True Negative.

2.3.5 Judgement Conditions

In this study, the effects of the contamination with the mislabeld data in the positive training data used for learning on the judgment results is examined. The focus is on the judgement of the corrosion levels of 1% and 3%, which are the early stages of rebar corrosion. As shown in Table 5, the data categories C_3 or C_6 are contaminated into the positive training data at 20%, 50%, 80%, and 100%. A total of 14 cases were judged, including the type without contamination for comparison. In this study, the cross-validation was adopted to evaluate the performance of the neural network model, and each type was tried four times.

Table 5: Judgement conditions

Type	Category of test data (Table 3)	Contamination of mislabeled data		
		Category (Table 3)	Number	Rate
C_1-0	Positive C_1 Negative C_0, N_0, N_1	−	0	0%
C_1-20C_3		C_3	6	20%
C_1-50C_3			16	50%
C_1-80C_3			26	80%
C_1-100C_3			32	100%
C_1-20C_6		C_6	6	20%
C_1-50C_6			16	50%
C_1-80C_6			26	80%
C_1-100C_6			32	100%
C_3-0	Positive C_3 Negative C_0, N_0, N_3	−	0	0%
C_3-20C_6		C_6	6	20%
C_3-50C_6			16	50%
C_3-80C_6			26	80%
C_3-100C_6			32	100%

3. Judgement Results

3.1. Judgement of C_1

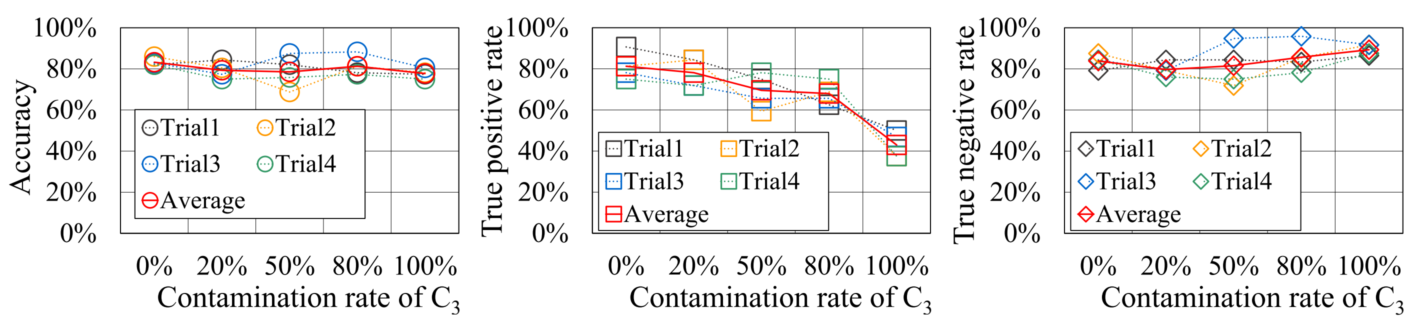
3.1.1. Contamination of C_3

Fig. 4 shows the Judgement result of C_1 in the case of contaminating with C_3 in the positive training data. For comparison, the result of the judgement without contamination of C_3 ("C_1-0" in Table 5) are also shown. Fig. 4(a) shows that although there are differences in each trial, the accuracy gradually decreases as the contamination rate of category C_3 increases compared to 0%. This can be said to be due to the significant drop in the true positive rate shown in Fig. 4(b). In the judgement of C_1, the true positive rate was greatly affected by the contamination of C_3, and there was a tendency for the number of false negative to rise.

3.1.2. Contamination of C_6

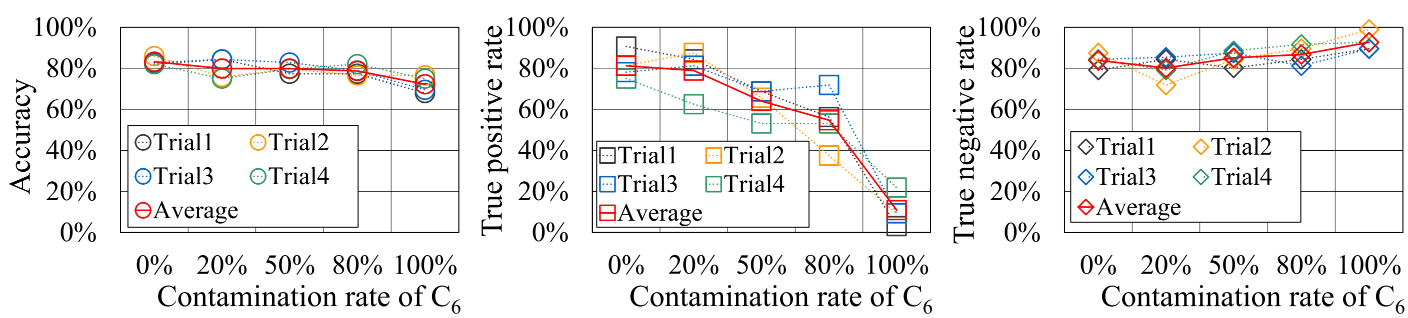
Next, Fig. 5 shows the judgement result of C_1 in the case of contaminating with C_6, which is corroded than C_3 in the positive training data. As can be seen from the figure, the accuracy goes down as the true positive rate decreases as the contamination rate of C_6 increases, the same as the case where C_3 is included. Compared to Fig. 4, the drop in the true positive rate is greater as the contamination rate rises, and a reduction is particularly conspicuous when the contamination rate in C_6 exceeds 50% (Fig. 5(b)).

From the above, it can be said that it is necessary to collect training data that is consistent with the corrosion level of the test data as much as possible in the judgement of the early stage of corrosion C_1 (corrosion level of 1%) for the purpose of the screening inspection. However, in the judgment of category C_1 performed in this study, even in the ideal



(a): Accuracy (b): True positive rate (c): True negative rate

Fig. 4: Judgement of C_1 (Contamination of C_3)



(a): Accuracy (b): True positive rate (c): True negative rate

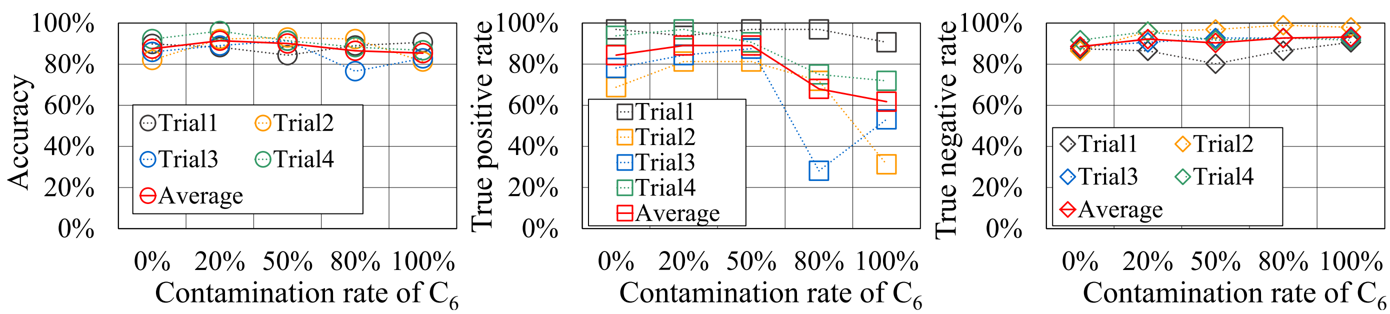
Fig. 5: Judgement of C_1 (Contamination of C_6)

judgement conditions "C_1-0" with a contamination rate of 0%, the true positive rate is about 80%. It should pay attention that even if contamination can be avoided, about 20% will be judged as false negative.

3.2. Judgement of C_3

Fig. 6 shows the Judgement result of C_3 in the case of contaminating with C_6 in the positive training data. The figure shows that although there is a variability in each trial, both the accuracy and the true positive rate maintain values equivalent to those of the judgement conditions" C_3-0" up to 50% of the contamination rate. Therefore, it can be said that the influence of the contamination with the mislabeled data is less than the judgement of C_1.

Based on the above, it is possible that even if the mislabeled data is contaminated in the judgement of corrosion level of 3%, it can be determined with the same accuracy as when there is no contamination if the contamination rate is low. However, further investigation is necessary in the future because there is variation in each trial and the recording conditions for the impact sounds are limited.



(a): Accuracy (b): True positive rate (c): True negative rate

Fig. 6: Judgement of C_3 (Contamination of C_6)

4. Conclusion

In this study, the effect of mislabeled data on the judgement results was investigated in the judgement method for rebar corrosion by using the impact sounds based on a neural network. The findings obtained are shown below.

In judging the corrosion level of 1%, when the corrosion levels of 3% and 6% were contaminated in the positive training data, it was found that the higher the contamination rate, the more the true positive rate tended to decrease. When collecting positive training data, it was found desirable to collect data with a similar corrosion level consistent with that of the test data.

In the judgement of the corrosion level of 3%, the true positive rate decreased due to the contamination of mislabeled data, but it was confirmed that it was less affected than the judgement of the corrosion level of 1%.

This study was an investigation under limited conditions. It is necessary to accumulate a large amount of data through experimental studies that consider a wide range of conditions, such as the dimensions of the specimens, the number and position of rebars, and the corrosion method so as to target general structural members.

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