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Experimental data augmentation of acceleration signals for localization of metal sphere impact in a rectangular plate

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1. Introduction

Loose Part Monitoring System (LPMS), which is a component of the NSSS Integrity Monitoring System (NIMS), is employed to monitor impact signals and analyze the location and mass of metal loose parts within the primary systems of nuclear power plants. Localization algorithms are based on the time difference of arrival at three acceleration sensors [1]. To enhance localization accuracy, precise estimation of the time differences in arrival for impact signals from metal loose parts between accelerometers is necessary. And the wave propagation speed of structure from impact signals is also important. In cases where a metal loose part impact event alarm occurs in the loose part monitoring system of the primary system in nuclear power plants, rapid signal analysis and timely reporting to the regulator are of very importance. Experts in the relevant field conduct data analysis to assess the impact signals. Recently, research has been conducted in the field of nuclear power plant structural integrity using fault simulation testbeds and finite element models to apply artificial intelligence technology [2], [3].

However, simulating high-temperature and high-pressure environments is difficult, and simulating various fault conditions for the application of deep learning models is also challenging. As a result, acquiring sufficient training data is extremely difficult. For the simulation of metal loose part impact data, an impact testbed with three accelerometers is being used to produce impact data. However, performing tests thousands or tens of thousands of times by humans for generating artificial intelligence training data is highly inefficient and prone to human errors. Therefore, in this paper, to augment the data for training artificial intelligence models, an array of accelerometers at measurement points on a square testbed and accelerometer pairing between points have been used to generate hundreds of thousands of data in a short period of time. To evaluate the learning performance of the artificial intelligence model as the number of data points increased, To evaluate the learning performance of the artificial intelligence model as the number of data points increased.

2. Methods and Results

In this section, we presented the conventional experimental method, the experimental method using the accelerometer array, the augmentation method through data pairing, and the errors of the artificial intelligence model based on data augmentation.

2.1 Metal sphere impact test setup in a rectangular plate

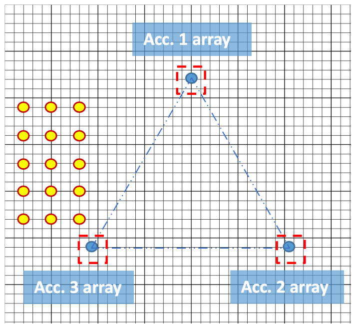

Fig. 1. Test setup for metal sphere impact

The test setup for the rectangular plate metal sphere impact test is shown in Fig.1. Three accelerometers were positioned in a triangular arrangement at the locations indicated by blue circles. The yellow circle in Figure 1 represents the impact test location for the metal sphere, and a flexible wire was used to connect a 12g metal sphere for the impact test. The grid spacing is 50mm, and the size of the plate is 2m x 2m. Impact tests were conducted 40 times at each point with a flexible wire length of 300mm and an elevation angle of 40 degrees. For data augmentation, a total of 27 accelerometers were mounted in the designated regions of red squares shown in Fig.1. Each of these regions contained a 3x3 grid of uniaxial accelerometers positioned at the vertex area of the triangle. The measurement system and accelerometer data acquisition were performed using NI PXIe and NI LABVIEW, and the data sampling rate, acquisition time, and pre-trigger conditions are shown in Table 1 below.

Table I: Signal acquisition condition

Sampling frequency	200kHz
Measuring time	100ms
Pre-trigger time	15ms

2.2 Acceleration signal pairing and data augmentation

For the localization of the impact of the metal sphere, a minimum of 3 accelerometer signals are required. In this case, one signal from each accelerometer array position is necessary. Considering the scale of the localization in operating nuclear power plants, an estimation accuracy of a few centimeters was considered. As shown in Figure 1, by utilizing combinations of accelerometer arrays with 9 sensors each at mounting positions 1, 2, and 3, a total of 729 datasets were obtained from a single impact test. Using this approach, a total of 262,440 datasets were acquired 15 positions.

2.3 Train and validation of applied AI model

To compare the performance of the artificial intelligence model based on data augmentation, we utilized a classification model using ResNet18[3]. A total of 7 impact data points were classified into respective classes. The quantities of data for the baseline testing method (test-α) and the data augmentation method using the accelerometer array (test-β) are presented in Table 2. The results of train loss and validation loss for test-α and test-β are shown in Figure 2. The train loss for test-α and test-β at the last epoch were 0.122 and 0.178, respectively. The train error of test-β exhibited 0.056 lower than that of test-α. In test-α, as the epochs progressed, the loss fluctuation tended to increase and remain around 0.3. The validation loss for test-α and test-β at the last epoch were 0.012 and 0.003, respectively. The validation loss of test-β exhibited 0.011 lower than that of test-α and slight loss fluctuations were observed in test-α. Based on the test results, when applying the accelerometer array for testing and utilizing augmented data in the training of the artificial intelligence model, lower errors were observed in terms of both train loss and validation loss. Additionally, the model converged smoothly.

Table II: Applied data for train and validation of a classification model

Applied locations (classes)	Train dataset		Validation dataset	
	Test-α	Test-β	Test-α	Test-β
7	168	122,472	56	40,824

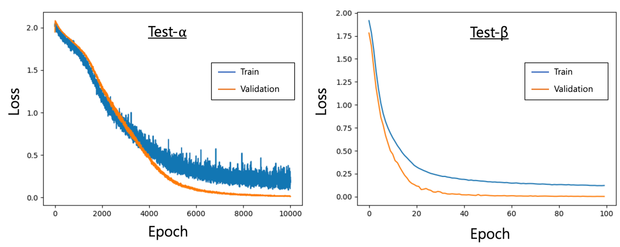

Fig. 2. Train and validation losses of a classification model (baseline data model : left, augmented data model : right)

3. Conclusions

By utilizing augmented artificial intelligence training data generated through the use of the accelerometer array, the errors of the AI classification model were compared. It was observed that the model utilizing augmented data outperformed from the perspectives of training and validation errors as well as convergence. It is anticipated that applying this data augmentation method will make it possible to generate ample data for the development and enhancement of fault diagnosis artificial intelligence models.

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