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Development of a Deep-Learning-Based Flaw Detection Algorithm for Analysis of Pulsed Eddy Current Nondestructive Test Data

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1. Introduction

In this study it is attempted to develop Artificial Intelligence (AI) in nondestructive evaluation that estimates the degree of flaw from unknown Pulsed Eddy Current (PEC) signals using deep learning of PEC test [1,2] data. The PEC is effective tool for the detection of wall thinned defects such as Corrosion Under Insulation (CUI) and Flow Accelerated Corrosion (FAC) occurred in insulated pipes. However, it is very difficult to correlate with measured signals and wall thinning effectively. In order to overcome this weakness we applied machine learning techniques such as Support Vector Machine (SVM) [3] and Convolutional Neural Network (CNN) [4] based deep learning. To facilitate deep learning, we developed deep learning model by performing pre-processing (normalization and denoising) of signal data to select pre-processing conditions that can improve estimation accuracy.

2. Methods and Results

In order to discriminate the step difference in Mock-up sample more clearly, we applied signal pre-processing technique based on machine learning. SVM is effective to separate the signal reflected by different plane, but the separation was not clear in the thinner part of the pipe. In order to eliminate the ambiguity at thin region of pipe, the CNN based deep learning model was applied. Table I shows the operation environment for deep learning models.

Table I: Operation Environment for Deep Learning

Operating System	Programing language	Deep Learing Library	Input Data	Output Data
Windows 10 (64 bit)	Python 3	Tensor Flow 2	*.csv	*.csv

2.1 Production of Insulation Piping Test Specimen for Deep Learning

The ISI 106 steel pipe with schedule 60, size 10 was machined with 5 step evenly of total length 1,500 mm, and the maximum thickness of the piping is 12.7 mm. The thickness was 12.68 mm, 10.78 mm, 8.88 mm, 6.98 mm, and 5.08 mm at every 300 mm interval, creating stair-shaped defects. There are four points at which the thickness changes and the thickness difference of each end is 1.9 mm.

The thickness of the insulation material surrounding the pipe is made of 65mm plastic covered with 0.5 mm thickness stainless cladding. At one end of the pipe surrounded by insulating material, measurement points of 1 to 9 were determined at intervals of 150 mm, and the lines connecting these points are called side lines. A total of eight side lines were set to A to H at 45° intervals along the circumference of pipes stacked with insulating materials. At this time, the total measurement points from A1 to H9 are 72.

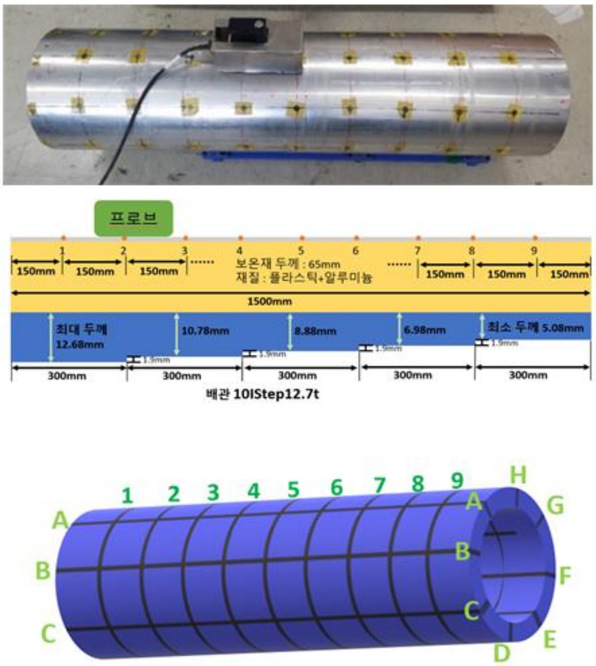

Fig. 1. Production of Insulation Piping Test Specimen of 10IStep12.7t.

2.2 Signal Pre-processing and Characterization

- Raw signal amplification and moving average.

The analog signal induced from pipe was amplified before converting to digital signal (Fig. 2). Moving averaging (Fig. 3) was applied to alleviate the discrete characteristics of the digital converted data.

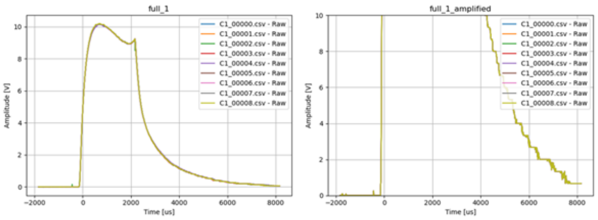

Fig. 2. Example of Raw Data (left: before, right: after amplification).

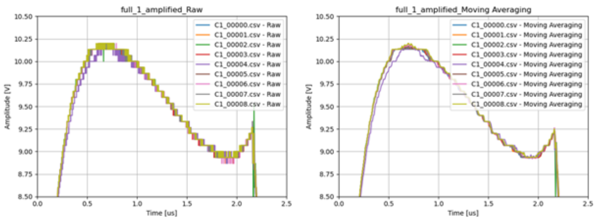

Fig. 3. Example of Moving Average (left: before, right: after application of moving average).

- Estimation of piping wall-thinning conditions by conventional signal processing techniques for raw signals (Fig. 4)

When the conventional signal processing technique is used, it is confirmed that the amplitude is reduced and the delay is delayed in the time region according to the step and inflection. There is also an error in the data itself measured 10 times at the same point, and in particular, the error in time delay characteristics was greatly affected by the operation of the test device. It was verified that the time delay seems to be different at points with different thicknesses, but the time delay value deviates in areas with the same thickness (Fig. 5).

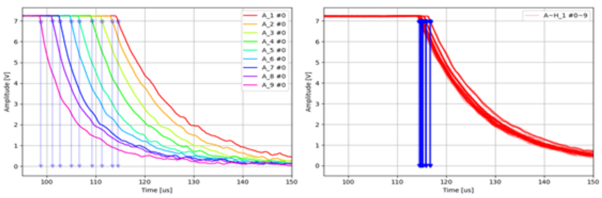

Fig. 4. Conventional Time Extraction Method of a Specific Voltage (voltage vs. time).

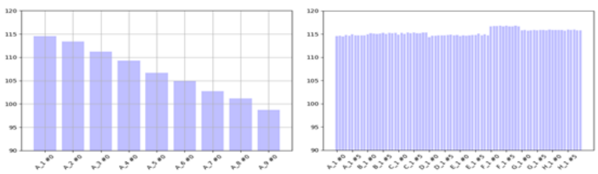

Fig. 5. Time Delay Characteristics for Different or Same Wall-Thinning Position (left: different, right: same wall-thinning).

- Diagnostic performance comparison for arbitrary data

Of the total 720 data, 80 data for each 9 different wall-thinning states were present, and the diagnostic performance for arbitrary data (Figs. 6-7) was compared by randomly dividing them into Fitting: New = 9:1 (72:8) and calculating Mean Square Error (MSE) for 72 data after Fitting with 648 data. As a result of diagnosing arbitrary data not utilized for Fitting through time delay-based extraction, it was difficult to clearly specify a single wall-thinning state as the predicted degree of wall-thinning appeared in both close states. As a result of diagnosing arbitrary data that were not used for fitting through the average voltage extraction method, the predicted degree of wall-thinning was clearly classified as a single wall-thinning state at points 1 to 6, but it was difficult to specify a single wall-thinning state at points 7 to 9. To overcome the limitation that the fitting for the mean voltage extraction method in the form of A*exp (-x/beta) does not sufficiently reflect the characteristics of the data, nonlinear characteristics were applied to the data using the Support Vector Machine (SVM) [3] and Convolutional Neural Network (CNN) [4] models

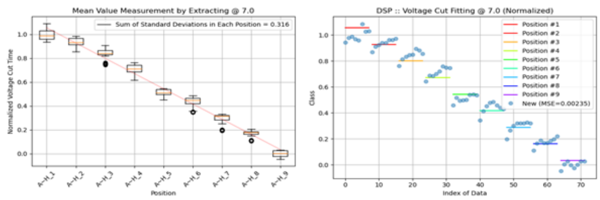

Fig. 6. Diagnosis of Arbitrary Data by Conventional Time Extraction Method of a Specific Voltage.

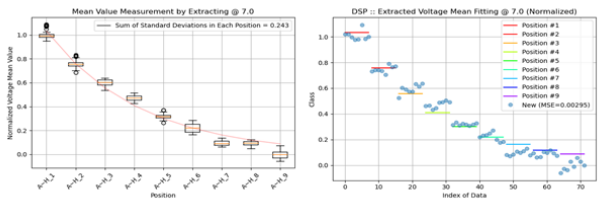

Fig. 7. Diagnosis of Arbitrary Data by Extracted Voltage Mean Method.

2.3 Development of Deep Learning Model

- Using Support Vector Machine (SVM) model

As one of the machine learning, it is a supervised learning model for pattern recognition and data analysis, and is mainly used for classification and regression analysis. Given a set of data belonging to either category, the SVM creates a non-probabilistic binary linear classification model that determines which category the new data will belong to based on the given set of data. The created classification model is represented by data as boundaries in the ideological space, and SVM is an algorithm that finds the boundary with the largest width among them. SVMs can be used in nonlinear classification as well as linear. This development introduced a kernel technique that maps a low-dimensional space to a high-dimensional space for nonlinear classification of pulsed eddy current signals.

According to the SVM model, the larger C, the less likely it is to exist in the measurement data, and when the gamma sees the same first column as 10, it recognizes two outliers and finds a decision boundary easily, but when C=100, it is classified a little unreasonably. This time, let's look at the effects of gamma. If you look at the first row with C set to 1 from left to right (Fig. 8), you can see that the gamma is getting larger and larger, as the decision boundary is greatly affected by the data samples near the decision boundary. In other words, it may be said that the gamma parameter adjusts the curvature of the decision boundary. As the value of gamma increases, the blue space becomes smaller and smaller (see Fig. 8), as mentioned above, because the distance at which each data point exerts its influence has become shorter. As with parameter C, too low is likely to be under-fitting, and too high is likely to be overfitting. Therefore, through the repetition of Trial & Error, an appropriate value satisfying both parameters was found, but satisfactory results were not obtained.

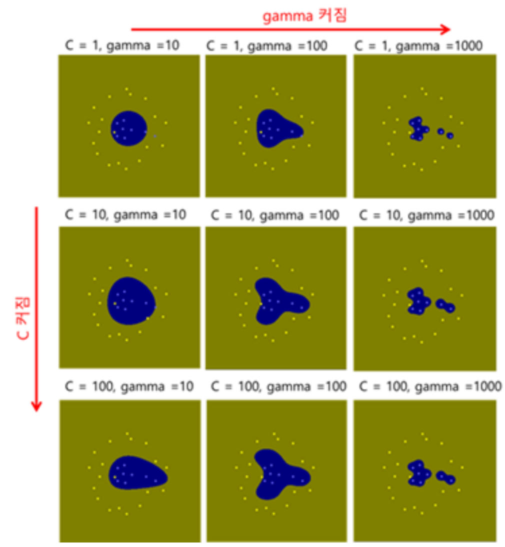

Fig. 8. Analysis by SVM model.

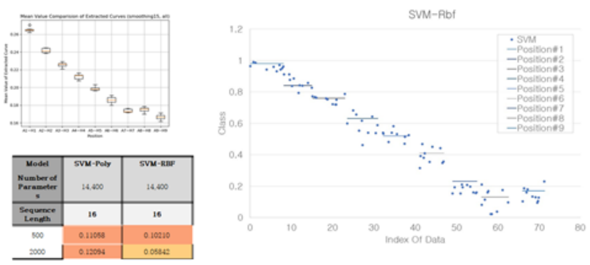

Fig. 9. Classification by SVM model.

- Using Convolutional Neural Network (CNN) model

After learning the degree of flaw determined by an eddy current detection expert through deep learning, it attempted to develop a non-destructive evaluation AI model that estimates the degree of flaw from an unknown eddy current signal. To facilitate deep learning, we developed a time series deep learning model by performing pre-processing (normalization and denoising) of signal data to select pre-processing conditions that can improve estimation accuracy.

Considering the effectiveness of Pulsed Eddy Current signal collection environment and practicality, we developed signal pre-processing and deep learning algorithms using compatible Open Source in desktop PC environments where eddy current signal collection is mainly performed.

The deep learning model was performed in the order of performance optimization through characteristic analysis by single channel time series data pre-processing conditions, selection of a deep learning model for a single channel time series data, and hyperparameter adjustment of deep learning model

2.4 Data Learning and Diagnosis Using Deep Learning Models

In order to utilize the three deep learning models (VGG19, Xception, and Inception) used for image classification for learning and diagnosis, all two-dimensional operations were converted to one-dimensional operations to suit time-series data. The Fitting: New = 9:1 (72:8) dataset used in the signal processing technique was used as the train test dataset, and the diagnostic performance was compared with MSE, but the learning stop point was selected when the Mean Absolute Error (MAE) of the test dataset did not decrease by more than 10 times. All three deep learning models (VGG19, Xception, and Inception) set the initial Learning Rate (LR) of 0.0001, and reduced LR by 0.5 times, if MAE did not decrease in more than five learning courses (Epoch).

For the test data, the difference in performance between Batch Size (8, 16, 32) and samples (500, 1000, 1500, 2000) is shown in Table II. Compared to the conventional time extraction method of a specific voltage, the MSE was decreased by 58.3% from 0.00235 to 0.00098 from Inception (Batch Size: 8) at the same Sequence Length = 1000. When Inception (Batch Size: 8) was used, MSE was the lowest at Sequence Length = 2000, which was decreased by 65.1% compared to the conventional time extraction method of a specific voltage.

Table II: MSE According to Model and Learning Conditions

Model	**VGG19**			**Xception**			**Inception**		
Number of Parameters	88,479,297			20,657,657			16,913,121		
Sequence Length	**8**	**16**	**32**	**8**	**16**	**32**	**8**	**16**	**32**
500	0.00151	0.00151	0.00173	0.00160	0.00131	0.00190	0.00224	0.00411	0.079
1000	0.00211	0.00178	0.00205	0.00134	0.34174	0.00182	0.00098	0.00173	0.001
1500	0.00225	0.00207	0.00231	0.00123	0.34642	0.00152	0.00106	0.00102	0.20
2000	0.00217	0.00172	0.00416	0.00149	0.34915	0.34437	0.00082	0.00114	0.002

3. Conclusions

Considering the effectiveness of PEC signal collection environment and practicality, we developed signal pre-processing and deep learning algorithms using compatible Open Source in desktop PC environments where eddy current signal collection is mainly performed. It is verified that the time delay seems to be different at points with different thicknesses, but the time delay value deviates in areas with the same thickness.

From this study, it is confirmed that the amplitude is reduced and the delay is decreased with decreasing wall thickness of surrogated sample machined with stepped configurations in the inner side of pipe, but the difference was not clear in the last two thinned stepped region of pipe. The SVM and CNN algorithms were applied to separate the signal effectively with wall thickness. The CNN can separate the thickness difference more effectively than SVM in the thin thickness region.

Compared to the conventional time extraction method of a specific voltage, the MSE was decreased by 58.3% from 0.00235 to 0.00098 from Inception (Batch Size: 8) at the same Sequence Length = 1000. When Inception (Batch Size: 8) was used, MSE was the lowest at Sequence Length = 2000, which was decreased by 65.1% compared to the conventional time extraction method of a specific voltage.

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