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Eddy Current Testing for Research Reactor Fuel Rods via Deep Learning

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1. Introduction

Nuclear fuel rods for research reactors used in HANARO require a cladding layer surrounding the nuclear fuel core to effectively transfer heat generated during operation and smooth coolant flow. During cladding the fuel core, defects such as surface scratches, pinholes, blisters, and dents or a gap between the fuel core and the coating layer may occur. The flaws present in the coating layer lead to the leakage of the fissile material. The leaked fissile material can migrate into the cooling water in research furnace, which causes safety problem. Eddy current testing (ECT) should be performed to inspect the coating layer defects.

ECT has been studied and used in the non-destructive testing field for defect detection [1-2]. ECT can detect various defects that occur in fuel rods as well as clads by using multiple frequencies. However, the reliability of ECT signal analysis is highly dependent on the operator, thus proper signal analysis method is needed to secure the high reliability of the test result.

In this study, deep learning technique is applied to improve the reliability of defect inspection results by ECT. There is a successful case to introduce deep neural networks in pipe wall-thinning measurement by ECT [3]. In this study, the depth of defects in an Al1060 rod was estimated by ResNet18-1D, a variant of ResNet18 for time-series data. The average performance was compared according to input channel (1, 2, 3, 4, 5, 6, 7, 8, and 1~8) and batch size (32, 64, 128, 256, 512, and 1024). The result shows that favorable inspection frequency exists for defect depth estimation by ResNet18-1D and it is crucial to choose the proper batch size when training small datasets.

2. Experiment

2.1. Specimen

For the standard rod, an AL1060 dummy concentrically extruded rod was used. The standard rod has artificial defects that enable to calibration of an eddy current system [4]. Seven types of notch defects were fabricated by electro-discharge machining as shown in Fig. 1. The depths of the notches were 100%, 80%, 60% 40%, 20%, 17%, and 13% of the cladding thickness (0.79 mm).

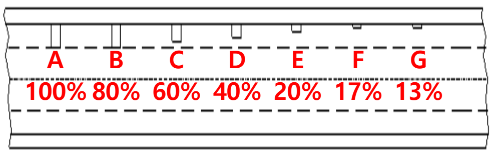

Fig. 1 Dimension of the standard defects

2.2. Eddy Current Inspection

Zetec MIZ-27ET and the probe designed for reactor fuel rod inspection [1] were used to eddy current inspection for the artificial defects. The inspection frequencies were 30 kHz, 15 kHz, 6 kHz, and 3 kHz. For each frequency, the two-channel signals were collected at a rate of 12 inches per second with an excitation voltage of 16 V and a sampling rate of 400 samples per second. The phase angle was set to 40 degrees at the 100% notch defect signal for each channel. The measurement was conducted 98 times.

3. Data Labelling

There are eight types of labels: intact case and seven defect cases. Each signal obtained from single measurement includes intact parts and seven defect parts. A human expert about eddy current signals labeled each segment of 150 samples with its corresponding defect depth as shown in Fig. 2.

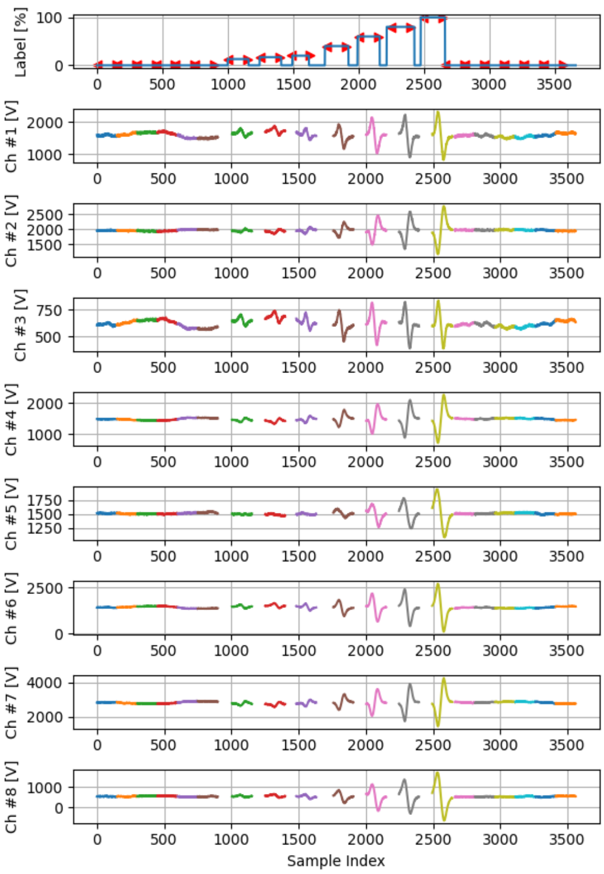

Fig. 2 Labels and 8-channel Signals

Of the total 1862 segments, 1176 were the intact cases and 686 were the defect cases. In the defect cases, there were 98 segments of each defect depth. For deep learning, the segments were divided into three datasets: train, validation, and test (60%, 20%, and 20% respectively). Using stratified shuffle split, the proportions of labels the same between the datasets.

4. Deep Learning

4.1. Neural Network: ResNet18-1D

The residual network (ResNet) is architecture for convolutional neural networks with skip connections. The input to a layer is added to the output of the layer with the skip connection, which helps to avoid banishing gradient problem as well as to train deeper networks. That is the reason why ResNet has achieved excellent performance on image classification. Since the original ResNet18 is designed for image data, two-dimensional operations of ResNet18 should be replaced with one-dimensional operations for signal data as shown in Table 1. This variant is called ResNet18-1D in this study. Multi-channel signals can be input to ResNet18-1D like image data if the signals between each channel have a high correlation between channels like the red, green, blue channels in the image. In this study, the inputs were signals with a length of 150 and the output was a floating value for the defect depth.

4.2. Training and Testing

To train ResNet18-1D, mean absolute error was adopted as the loss function and Adam optimizer was used to minimize the loss.

Table 1 Architecture of ResNet18-1D

Layer Name	Output Shape	ResNet18-1D
	B x C x 150	input
conv1	B x 64 x 75	[1 x 7 conv, 64, stride 2]
max pooling	B x 64 x 38	[1 x 3 max pool, stride 2], skip connection
conv2_x	B x 64 x 38	[1 x 3 conv, 64, stride 1] x 2, skip connection, [1 x 3 conv, 64, stride 1] x 2
conv3_x	B x 128 x 19	[1 x 3 conv, 128, stride 2], [1 x 3 conv, 128, stride 1], skip connection, [1 x 3 conv, 128, stride 1] x 2
conv4_x	B x 256 x 10	[1 x 3 conv, 256, stride 2], [1 x 3 conv, 256, stride 1], skip connection, [1 x 3 conv, 256, stride 1] x 2
conv5_x	B x 512 x 5	[1 x 3 conv, 512, stride 2] x 2, skip connection, [1 x 3 conv, 512, stride 1] x 2
average pooling	B x 512 x 1	skip connection, [1 x 1 avg pool]
fully connected	B x 1	[512 x 1 fully connections]
		ouput

※ B: batch size, C: the number of channels

In the training step, ResNet18-1D was fitted with train dataset and evaluated with validation datasets for each epoch. The initial learning rate was 0.001 and it became halved when the validation loss was not updated for more than 5 times. The training was stopped when the validation loss was not updated for more than 10 times. For a case, the loss and the comparison of truth and prediction is shown Fig. 3.

4.3. Results

To compare the performance according to input channel (1, 2, 3, 4, 5, 6, 7, 8, and 1~8) and batch size (32, 64, 128, 256, 512, and 1024), training and testing were conducted 10 times per case. Average performance is shown in Fig. 4. Using channels 5 (6 kHz), 7 (3 kHz), and 8 (3 kHz), the averaged losses were lower than the others. Using channel 7 (3 kHz) with a batch size of 32, the error was the lowest. In terms of batch size, the performance degraded by batch size, especially 256 or higher.

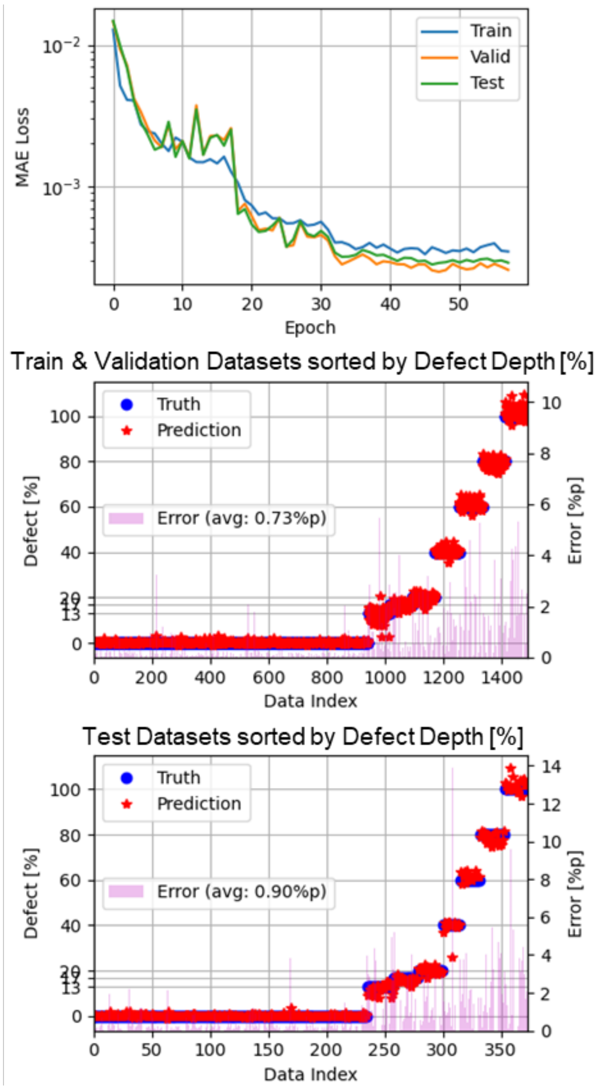

Fig. 3 Loss and the comparison of truth and prediction

Input Channel	Batch Size 32	64	128	256	512	1024	Average
1	1.07	1.17	1.32	1.65	2.42	3.56	1.86
2	1.05	1.01	1.13	1.29	2.05	3.03	1.59
3	1.02	1.02	1.15	1.47	2.40	4.24	1.88
4	1.61	1.80	1.86	2.08	2.71	4.03	2.35
5	0.67	0.75	0.88	1.11	1.90	2.43	1.29
6	2.20	2.56	3.00	3.36	4.16	5.26	3.42
7	0.59	0.61	0.70	1.05	1.81	2.07	1.14
8	0.70	0.76	0.80	1.03	2.13	2.94	1.39
All	1.02	1.20	1.35	2.02	2.54	5.59	2.29
Average	1.10	1.21	1.35	1.67	2.46	3.68	

Fig. 4 Errors according to batch size and input channel

5. Conclusions

The depth of artificial notches in an Al1060 rod was estimated by ResNet18-1D, a variant of ResNet18 for time-series data. The depths of the notches were 100%, 80%, 60% 40%, 20%, 17%, and 13% of the cladding thickness (0.79 mm). Using Zetec MIZ-27ET and the probe designed for reactor fuel rod inspection, the raw signals were acquired 98 times. A human expert labeled each segment of 150 samples with its corresponding defect depth. The labeled segments consist of 1176 intact segments and 98 segments for each defect depth. Using stratified shuffle split, the segments were divided into three datasets: train, validation, and test (60%, 20%, and 20% respectively). Loss function and optimizer were mean absolute error Adam, respectively. Learning rate decay and early stopping were also adopted. Average performance was compared according to input channel (1, 2, 3, 4, 5, 6, 7, 8, and 1~8) and batch size (32, 64, 128, 256, 512, and 1024). Using the favorable channels shows higher performance than that using all channels. Using channel 7 (3 kHz) with a batch size of 32, the error was the lowest. This result shows that favorable inspection frequency exists for defect depth estimation by ResNet18-1D. The performance degraded by batch size, especially 256 or higher. Therefore, it is important to choose the proper batch size, especially when training small datasets.

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