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Application of Machine Learning for Model-Assisted Probability of Detection in Eddy Current Non-destructive Testing Systems

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ABSTRACT

This paper presents a novel application of machine learning for the model-assisted probability of detection (MAPoD) study of non-destructive testing (NDT) systems. Machine learning has been widely used for regression tasks. Model-assisted probability of detection (MAPoD) is an important method for quantifying the detection capability of non-destructive testing systems. However, for the study of the probability of detection, to propagate the uncertainty of random inputs into the model response, a large amount of model evaluation is required, which leads to extremely high computational costs. This makes it impossible to complete the probability of detection study of non-destructive testing systems within the specified time. In this work, a supervised convolutional neural network method is applied to accelerate MAPoD study of eddy current NDT systems by partially replacing the accurate physical-based model. The accuracy and efficiency of the proposed method are compared with those of the pure physical model method using a specific numerical example which considers an ECNDT system with placing a circular coil probe above a flat plate with a rectangular surface flaw. We use two metrics to evaluate the accuracy of the MAPoD study: the normalized root-mean-square error (NRMSE) between the validated and predicted responses and the probability of detection (PoD) parameters at a given flaw length. The results show that the proposed method can achieve the required accuracy level of 5% for NRMSE and 1% for PoD metrics, while only requiring 30 evaluations of the physical model per flaw length. Compared with the pure physical model, which requires 1000 evaluations of the physical model per flaw length, the proposed method can save 97% of the computational effort. This demonstrates the feasibility and superiority of the proposed method for the MAPoD study of ECNDT systems.

Keywords: machine learning, convolutional neural network (CNN), model-assisted probability of detection (MAPoD), eddy current nondestructive testing (ECNDT)

INTRODUCTION

Within artificial intelligence (AI), machine learning has emerged as the method of choice for developing practical software for computer vision, speech recognition, natural language processing, robot control, and other applications [1]. In the past few decades, machine learning has also driven the development of electromagnetic computation [2]. Convolutional Neural Network (CNN) [3] is a famous machine learning architecture inspired by biological organisms' natural visual perception mechanism. Traditional convolutional neural network consists of a series of layers connected sequentially. In addition to convolutional layers, pooling layers, and fully connected layers are also added to achieve better performance. Figure 1 shows a typical structure of a convolutional neural network. The first layer in this example is a convolutional layer, made up of convolutional kernels that act on the input. The output of this layer is referred to as feature maps. Often, convolutional layers are followed by max-pooling layers to reduce the dimensionality of the maps. The conv-maxpool structure repeats for a while, ending with one or more fully connected layers. The feature maps obtained from conv-maxpool operations are flattened into a vector, which is then fed into the fully connected layer and each neuron corresponds to a specific feature.

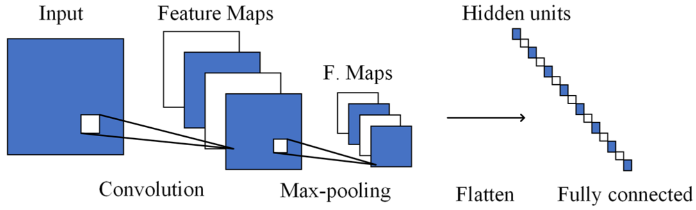


Figure 1: A simple CNN structure made of convolutional, subsampling, and fully connected layers.

Eddy current non-destructive testing detects the test piece without any direct physical contact and can detect cracks or flaws in most conductive materials. The PoD calculation for eddy currents was initially developed and obtained only through experiments. However, experiments are time-consuming and expensive. To reduce the cost, various physics-based simulation models have been developed [4]. However, in considering of large amount of uncertainties propagated in MAPoD analysis, physics-based simulation models face many challenges, such as (1) the high computational cost of solving each physics-based model; (2) there may be many variability parameters in non-destructive testing systems; (3) the study of probability of detection requires multiple repeated physical based model evaluations.

To reduce the computational cost, various metamodeling methods have since been developed [4-6]. The metamodeling method is a very effective method that treats the relationship between random input and response in eddy current non-destructive testing as an uncertain "black box". It establishes a surrogate model based on training data. Many metamodeling methods have accelerated the study of MAPoD, to name a few, the polynomial chaos expansion (PCE) method [4], Kriging [5], support vector machine (SVM) [6], and neural network (NN) [7]. This article proposes a supervised CNN whose hyperparameters are optimized by the Hyperband algorithm, and it replaces the physical eddy current non-destructive testing model partially in the analysis of MAPoD study.

MACHINE LEARNING-BASED PORTABILITY OF DETECTION

Workflow

In the MAPoD analysis, the first step is to sample from the input parameter space. The uncertainty parameters of random sampling satisfy different probability distributions. The Monte Carlo Sampling (MCS) strategy generates verification and prediction points, while the Latin Hypercube Sampling (LHS) strategy generates training points. Training data are used to build the convolutional neural network, and testing data are used to test the accuracy of it. If the accuracy does not satisfy the requirement, new training datasets with more sample points are required. Once the convolutional neural network-based model is accurate enough, a probability of detection analysis will be conducted.

Convolutional Neural Networks

Convolutional neural networks are widely used for their excellent performance in various machine learning tasks, such as computer vision, speech recognition, and health care. As shown in Figure 1, the output of a convolutional operation is given by [3]

$$c_{i,j}^{(L_c)} = a\left[\sum_{m=1}^{N_{c,v}}\sum_{n=1}^{N_{c,h}} f_{m,n} c_{i+m-1,j+n-1}^{(L_c-1)} + b^{(L_c-1)}\right] \qquad \textbf{(Eq. 1)}$$

where a is the activation function, $N_{c,h}$ and $N_{c,v}$ refer to the number of grids in the convolutional kernel in the horizontal and vertical directions, respectively, $f_{m,n}$ is the weight of the kernel at the m'th row and n'th column of the grid in the kernel, $c^{(L_c)}$ is the output of the convolution in the L_c'th convolutional layer, and $c^{(L_c-1)}$ is the input into the L_c'th convolutional layer. The value of $c^{(L_c-1)}$ is from either a max-pooling layer or a convolutional layer. The output of a max-pooling layer is given by [3]

$$p_{i,j}^{(L_p)} = \max_{1\le m\le N_{p,v},\; 1\le n\le N_{p,h}} p_{i+m-1,\,j+n-1}^{(L_p-1)} \qquad \textbf{(Eq. 2)}$$

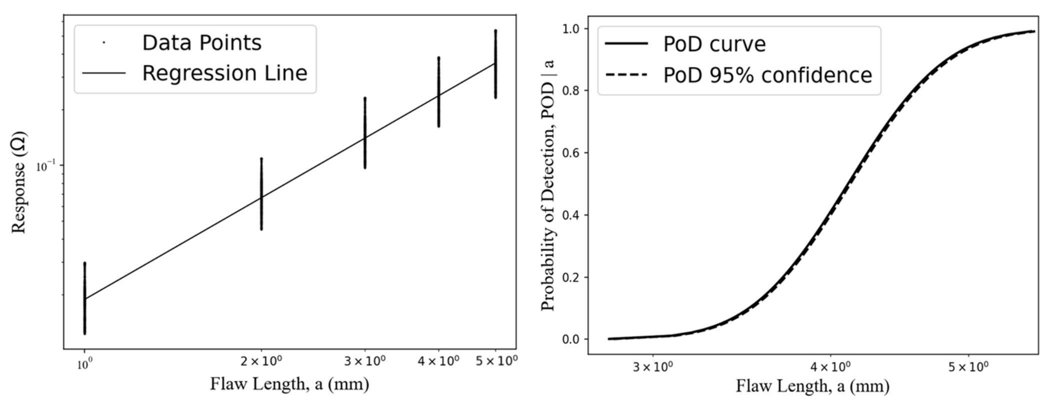
where $N_{p,h}$ and $N_{p,v}$ refer to the number of grids in the max-pooling kernel in the horizontal and vertical directions, respectively, $p^{(L_p)}$ is the output of the L_p'th max-pooling layer, and $p^{(L_p-1)}$ is the input into the L_p'th max-pooling layer. Unlike the convolutional kernel, the max-pooling kernel has no parameters, it selects the maximum pixel value. Max-pooling is performed to reduce the number of parameters in a CNN [2].

The feature maps obtained through conv-maxpool operations are flattened in terms of spatial dimensions. In other words, each feature map is represented as a two-dimensional matrix. To prepare these feature maps for further processing, we flatten them into a one-dimensional vector. This flattened vector is then fed into a fully connected layer, which allows us to perform regression analysis for MAPoD study.

The hyperparameters used in the CNN are the number of convolutional and max-pooling layers and the convolutional and max-pooling kernel size. The number of filters of each convolutional kernel and the stride of each kernel are considered as well. Other hyperparameters include the number of neurons in fully connected layers, the maximum number of epochs, the learning rate, and the activation function. This study applies the Hyperband algorithm to select the number of convolutional and max-pooling layers, and the number of neurons in fully connected layers. The size of the convolutional and max-pooling kernels both are 1 × 1 and have a stride. The cost function used is the mean square error [7]. The activation function selected for the study is the hyperbolic tangent function, with a maximum number of epochs set to 15000 and an optimizer of Adamax [8].

NUMERICAL EXAMPLES

In the numerical testing, an eddy current non-destructive problem, which uses a coil with a finite cross-section to detect surface cracks on a metal plate, is analyzed by COMSOL simulation software. The flaw lengths range from 1 - 5 mm. The selected uncertainty variables are with normal distribution of N (2, 0.7) mm in the x position, a uniform distribution of U (12.5, 14.5) mm in the y position, and U (-1.5, 1.5) mm in the z position, respectively, of the probe. In MAPoD analysis, 1000 physical model-based evaluations are required for each flaw length, and a total of 5000 evaluations are needed. To achieve the required accuracy level of 5% for NRMSE values and PoD metrics, the convolutional neural network model requires only 30 evaluations of the physical model per flaw length and saves 97 percent of the computational effort compared with the pure physical model.



(a) (b)

Figure 2: (a)The Logarithmic linear regression curve. (b)The PoD curve.

The regression analysis and PoD curves predicted by the convolutional neural network are shown in Figure 2 (a) and (b), respectively, which are consistent with the evaluations of pure physical model. The PoD metrics predicted by the convolutional neural network model and calculated by physical models are shown in Figure 3. It can be observed that the relative differences between the predictions by the convolutional neural network model and the pure physical model calculation are within 1%. Therefore, accurate and efficient convolutional neural network models can replace pure physical models partially for MAPoD analysis.

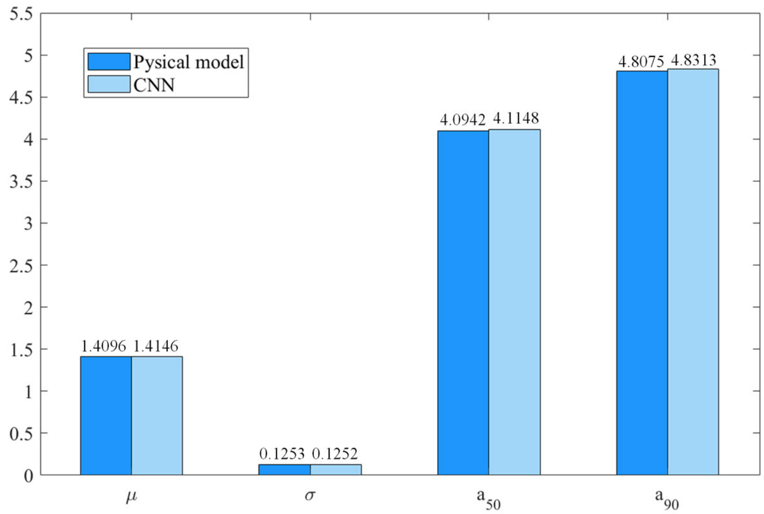


Figure 3: PoD Metrics.

CONCLUSION

In this article, the MAPoD analysis of eddy current non-destructive testing based on a convolutional neural network model is investigated. To achieve the required accuracy level of 5% for NRMSE values and 1% for PoD metrics, the convolutional neural network model requires only 30 evaluations of the physical model per flaw length, instead of 1000 evaluations of the pure physical model. These results show that compared with pure physical-based simulation models, the proposed model improves the efficiency of MAPoD analysis while maintaining good accuracy.

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