Ultrasonic Imaging and Flaw Detection with Optimized Convolutional Transformer Neural Networks

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Abstract*— Flaw detection using the ultrasonic imaging technique has been widely used for Structural Health Monitoring (SHM). Ultrasonic testing has the advantages of one-sided measurement, high penetration depth, and inspection accuracy. Artificial intelligence (AI) such as Deep Learning (DL) methods can automate the inspection process with high reliability for imaging and SHM. Neural Networks (NNs) and DL methods can detect flaws using ultrasonic images with high accuracy but suffer extensive computational costs for training and deployment. In this study, we propose a lightweight transformer NN, UFDCTNet: Ultrasonic Flaw Detection Convolutional Transformer Neural Network (TNN), optimized with data-efficient Convolutional NN (CNN) for flaw detection using ultrasonic imaging. TNN utilizes the self-attention network architecture that learns global representations and allows high parallelism in computation resulting in reduced training time. CNNs learn local representations with fewer parameters because of inherent spatial inductive bias. This UFDCTNet utilizes the advantages of CNNs to learn spatially local representations resulting in fewer model parameters for fast training. For performance analysis, we trained data-efficient TNN and CNN using ultrasonic images to detect flaws. To examine training results, NNs are trained with the USimgAIST dataset consisting of 7000 experimental B-scan images representing without-flaw and with-flaw cases. A pulsed laser ultrasonic scanning system was used to collect these B-scan images from 17 stainless steel specimen plates with various types of flaws and some plates without any damage.

Keywords*— *Flaw Detection, Convolutional Optimization, Lightweight Transformer Neural Networks, Data-Efficient Neural Networks, Ultrasonic Imaging, In-situation SHM

I. Introduction

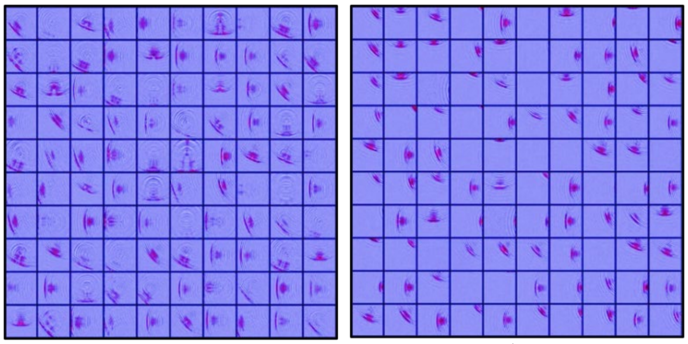
Ultrasonic imaging for flaw detection has been extensively used for the Non-destructive Evaluation (NDE) of materials [1]. However, the high interfering noise associated with the flaw's environment hampers the flaw detection performance [2]. Advanced ultrasonic signal processing methods have been applied to improve the flaw-to-clutter ratio [3][4]. Artificial intelligence (AI) such as DL methods are emerging in various industrial NDE applications and can automate the inspection process with high reliability for imaging and SHM [5]-[8].

In DL methods, NNs have been applied for ultrasonic NDE applications, such as material microstructure characterization, data compression, and flaw detection [9]-[12]. However, training and deploying NNs, such as deep-CNNs, with high accuracy require extensive computational resources and efforts to obtain efficient NN architecture [13]. Therefore, in this study, we introduce the utilization of data-efficient convolutional architectures, such as depthwise separable convolution, pointwise group convolution, and inverted residuals, to optimize this TNN training to find the optimal solution [13]. TNN utilizes the self-attention network architecture that learns global representations and allows high parallelism in computation resulting in reduced training time [14][15]. CNNs learn local representations with fewer parameters because of inherent spatial inductive bias [13]. Hence, we propose a lightweight TNN: UFDCTNet, which utilizes the advantages of CNNs to learn spatially local representations using ultrasonic images resulting in fewer model parameters for fast training. For performance analysis, we introduced the UFDTNet: Ultrasonic Flaw Detection TNN and the UFDCNN: Ultrasonic Flaw Detection CNN. The flaw detection performance is compared by training the UFDCTNet, UFDTNet, and UFDCNN for a similar number of model parameters to detect flaws using ultrasonic images. To examine training results, we trained NNs using the USimgAIST dataset [16] which includes 7000 experimental ultrasonic images of with-flaw and without-flaw cases. A pulsed laser ultrasonic scanning system was used to collect these ultrasonic images from 17 stainless steel specimen plates with various types of flaws and some plates without any damage.

In this paper, Section II includes the USimgAIST dataset for training NNs to detect flaws. Section III includes the UFDCTNet, UFDTNet, and UFDCNN for flaw detection. The flaw detection performance is analyzed by training the NNs for a similar number of model parameters using ultrasonic images. Section IV concludes this paper.

II. Ultrasonic USimgAIST Dataset

Figure 1 presents the USimgAIST dataset which includes 7000 experimental ultrasonic images (B-scan) of with-flaw and without-flaw cases [16]. A pulsed laser ultrasonic scanning system was used to collect these ultrasonic images from 17 stainless steel specimen plates with various types of flaws and some plates without any damage. These stainless-steel plates are 3mm thick and include two types of defects. The slit defects have lengths l = 3mm, 5mm, and 10mm. The drill hole defects have diameters ϕ = 1mm, 3mm, and 5mm. In data acquisition, a pulsed laser is applied to the specimens from the ultrasonic NDE scanning system to generate ultrasonic signals, and a contact transducer is attached to the specimens to acquire data for flaw detection [16]. A central area with the size of 100mm-by-100mm was created on the front/back sides of specimen plates for ultrasonic laser scanning. Ultrasonic B-scan images were collected in laser scanning and used to train NNs to learn features in ultrasonic signals to detect flaws. To enhance training performance, the acquired ultrasonic images were normalized with an image resolution of 224 by 224 to train NNs.



a b

Figure 1. USimgAIST Ultrasonic Images (a) Defective Cases, (b) Non-defective Cases

III. FLAW DETECTION USING NEURAL NETWORKS

The following sections introduce the NNs: UFDCTNet, UFDTNet, and UFDCNN for flaw detection using ultrasonic B-scan images from the USimgAIST dataset. The ultrasonic images were labeled as defective cases and non-defective cases to train NNs and we used 20 percent for the NNs' testing. The flaw detection performance is compared by training the NNs for a similar number of model parameters based on training accuracy and testing accuracy. The NNs were trained with 100 epochs without any pre-training. The training was experimented on Google Colab 26GB RAM Tesla T4 GPU.

A. Flaw Detection using UFDCTNet

In this study, we introduce a lightweight transformer NN, UFDCTNet, optimized with data-efficient convolutional NN for flaw detection using ultrasonic imaging. TNN utilizes the self-attention network architecture that learns global representations and allows high parallelism in computation resulting in reduced training time. CNNs learn local representations with fewer parameters because of inherent spatial inductive bias. This UFDCTNet utilizes the advantages of CNNs to learn spatially local representations resulting in fewer model parameters for fast training. In addition, various data-efficient convolutional architectures, such as depthwise separable convolution, pointwise group convolution, and inverted residuals, were trained to optimize this lightweight TNN to find the optimal solution.

The architecture of the UFDCTNet is shown in Figure 2. This NN consists of optimized combinations of spatial convolution, inverted residual bottleneck, and convolutional transformer encoder to learn features in ultrasonic images followed by pointwise convolution and global average pooling [17] to detect flaws. The pointwise convolution uses the 1x1 convolution to reduce computational cost and the global average pooling to reduce feature dimensions to enhance training performance.

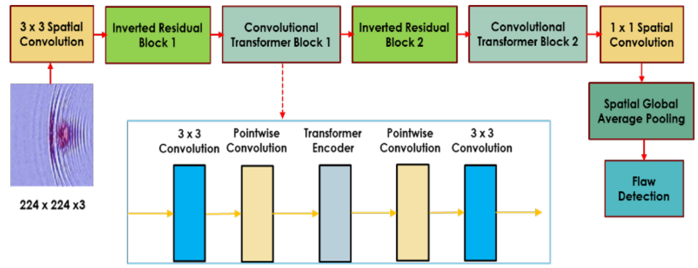


Figure 2. UFDCTNet Architecture

The convolutional transformer layers were built using the transformer encoders [14] optimized with 3x3 spatial and pointwise convolutional layers to enhance training performance. In addition, the inverted residual blocks work as normal convolutional layers but include much fewer parameters [17]. Thus, this reduces the computational cost and the proneness of overfitting. In this study, this optimized convolutional TNN: UFDCTNet, was trained using ultrasonic images and achieved 98.96% training accuracy and 97.27% testing accuracy to detect flaws.

B. Flaw Detection using UFDTNet

The TNN utilizes the self-attention network architecture that learns global representations and allows high parallelism in computation resulting in reduced training time. The UFDTNet consists of patch and position embeddings and five transformer encoder blocks to extract features in ultrasonic images. Next, the features are processed by pointwise convolution and global average pooling to detect flaws. In each transformer encoder, the multi-head attention mechanism is used to reduce the computational cost to train NN in a data-efficient method. By applying this attention mechanism, the sequential operations and complexity per layer are reduced. In addition, the transformer encoder is optimized with layer normalization and position-wise fully connected feed-forward network to enhance training performance [14]. In this study, we trained the UFDTNet using ultrasonic images and achieved 94.26% training accuracy and 93.14% testing accuracy to detect flaws.

C. Flaw Detection using UFDCNN

CNN can learn local representations with fewer parameters because of inherent spatial inductive bias. The UFDCNN is optimized with inverted residual blocks which use the depthwise separable convolution architecture as the MobileNet [18]. The depthwise separable convolution largely reduces the computational cost by minimizing the multiplication operations. And this data-efficient architecture is achieved by dividing one full convolution into depthwise convolution and pointwise convolution [18]. In this study, the UFDCNN consists of four inverted residual blocks to extract features in ultrasonic images, then the features are processed by pointwise convolution and global average pooling to detect flaws. By training the UFDCNN, we achieved 95.82% training accuracy and 94.27% testing accuracy to detect flaws.

TABLE 1. NNS PERFORMANCE COMPARISON USING ULTRASONIC USIMGAIST DATASET FOR FLAW DETECTION

Model	Training Accuracy	Testing Accuracy
UFDTNet	94.26%	93.14%
UFDCNN	95.82%	94.27%
UFDCTNet	98.96%	97.27%

Table 1 shows the performance analysis of using NNs to detect flaws with ultrasonic images from the USimgAIST dataset. By training NNs, we obtained the average accuracy of 96.35% and 94.89% for training and testing respectively, to detect flaws using experimental B-scan images. We achieved the highest detection accuracy of 98.96% and 97.27% for training and testing using this convolutional optimized UFDCTNet to detect flaws. These NNs can be fast-trained and deployed with high accuracy for low latency and high-performance ultrasonic flaw detection imaging applications.

IV. CONCLUSION

In this study, we developed convolutional optimized TNN for high-performance flaw detection using ultrasonic NDE imaging. TNN utilizes the self-attention network architecture that learns global representations and allows high parallelism in computation resulting in reduced training and execution time. CNNs learn local representations with fewer parameters because of inherent spatial inductive bias. This optimized TNN: UFDCTNet, utilizes the advantages of CNNs to learn spatially local representations resulting in fewer model parameters for fast training and deployment. In addition, data-efficient convolutional architectures, such as depthwise separable convolution, pointwise group convolution, and inverted residuals, are trained to optimize this lightweight TNN to find the optimal solution. For performance comparison, several data-efficient NNs, UFDTNet and UFDCNN, are trained for a similar number of model parameters to detect flaws using ultrasonic images. To validate results, NNs are trained with the USimgAIST dataset consisting of 7000 real B-scan images representing without-flaw and with-flaw cases. By training these NNs, we obtained the average flaws detection accuracy of 96.35% and 94.89% for training and testing respectively, and the highest detection accuracy of 98.96% and 97.27% for training and testing using this convolutional optimized UFDCTNet to detect flaws. Future works involve further optimizing this convolutional TNN to enhance the overall NDE performance.

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