Intelligent Ultrasonic Systems for Material Texture Recognition using Data-Efficient Neural Networks

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***Abstract*— Material texture recognition nondestructively by estimating the grain size using ultrasonic inspection has been extensively used for the characterization of material microstructures. Artificial intelligence, such as neural networks, can automate and recognize material textures accurately. However, training and deploying neural networks with high recognition accuracy is time-consuming. This limits the performance of ultrasonic applications. In this study, we investigate using several data-efficient neural networks to classify material textures using ultrasonic images. An ultrasonic testbed platform is assembled to acquire 3D ultrasonic data to train the neural networks for texture analysis. The DEUTR (Data-Efficient Ultrasonic Texture Recognition) Transformer Neural Network (TNN), is proposed to recognize material textures with high accuracy and data efficiency. The TNN utilizes a simple network architecture that replaces the convolutions and recurrence entirely with the attention mechanism resulting in reducing training and execution time. For performance comparison, several data-efficient Convolutional Neural Networks (CNN): NasNetMobile, MobileNet, Xception, were trained with Transfer Learning (TL) to learn grain scattering features using ultrasonic images. By training these neural networks, we obtained the average training and testing accuracy of 99.47% and 98.04% to recognize material textures and the highest image throughput of 148 images/seconds using the DEUTR transformer neural network on testing. We aim to build an intelligent ultrasonic system to recognize material textures with high accuracy at the microstructural level for data-efficient NDE applications.**

Keywords*— *Intelligent Ultrasonic NDE System, Data-Efficient Neural Networks, Transformer Neural Networks, Convolutional Neural Networks, Texture Analysis, Grain Size Estimation

I. Introduction

Ultrasonic testing for nondestructive evaluation (NDE) of materials has been widely used because it has high inspection accuracy and penetration depth, and is inexpensive compared with other NDE methods [1]. Meanwhile to characterize the microstructure of materials is challenging but can be achieved by estimating the grain size using ultrasonic testing [2]. To approximate the grain size, the ultrasonic backscattered signals are characterized since the signal intensity is the non-explicit function of the average grain size and random distribution of grains [3]. In addition, for better characterization of the backscattered signals, the Rayleigh scattering region [4] is utilized for acquiring the ultrasonic signals as the Rayleigh region is very sensitive to frequency and grain size distribution [4]. Recently, machine learning is emerging in various industries [5] and has been utilized in NDE [6][7][8] to enhance performance evaluation. In ultrasonic NDE, neural networks have been used for grain size estimation by characterizing the backscattered signals [9][10]. And the deep Convolutional Neural Network (deep-CNN) [11] can learn ultrasonic backscattering features accurately [12] but requires substantial computational resources and time for training and execution. In addition, the Transformer Neural Network (TNN) uses the attention mechanism which replaces the convolutions and recurrence entirely resulting in reducing the demand for computational resources and time in training [13]. And the TNN outperforms the state-of-the-art deep-CNNs in image recognition while using less computation time to train [14]. Therefore, for data-efficient ultrasonic NDE applications, specifically in the computational constraint or real-time evaluation environment, fast training and deploying the neural networks with high accuracy are significant. In the previous research, we have utilized the TNN to learn ultrasonic backscattering features for material textures recognition with high accuracy [15]. In this study, we further optimized the TNN, and proposed the DEUTR transformer neural network to classify material textures accurately with high data efficiency. Meanwhile, for performance comparison, we also trained several data-efficient deep-CNNs using backscattering images followed by further training using Transfer Learning (TL) [16]. These deep-CNNs are highly optimized to recognize images accurately with high data efficiency. To examine experimental results, an ultrasonic testbed system was assembled to acquire the backscattered signals, and the 3D C-scanning was created to acquire backscattering images. These images are from three heat-treated 1018 steel blocks with different grain sizes to train these data-efficient neural networks. We aim to build an intelligent ultrasonic NDE system to recognize material textures with high accuracy at the microstructural level for data-efficient applications.

In this paper, Section II presents the intelligent ultrasonic NDE system set up in the laboratory and the 3D signal acquisition for extracting C-scan images for machine learning. Section III presents the data-efficient neural networks for material textures recognition. The performance of using these neural networks is analyzed and compared. Section IV concludes this paper.

II. Experimental Setup

Figure 1 shows the experimental setup and 3D C-scan to acquire the ultrasonic backscattering images. The experimental setup includes a water tank mounted with two stepper motors to automatically move the transducer for signal acquisition. And the Panametrics Model 5052PR, pulser/receiver, and the Keysight MSOX2024A oscilloscope are used to acquire and display the received backscattered signals. Then the acquired 3D data cube which consists of a sequence of backscattering images is processed by the intelligent image recognition unit to train and deploy the neural networks to classify material scattering textures. The C-scan was created with 200 × 200 measurements and each measurement has 7680 backscattered signals. The acquired backscattering images at four depths for three steel blocks with grain sizes of 14 (Grain14), 24 (Grain24), and 50 (Grain50) microns are shown in Figure 1. In this study, we used 4800 backscattering images for each steel block specimen to train these data-efficient neural networks.

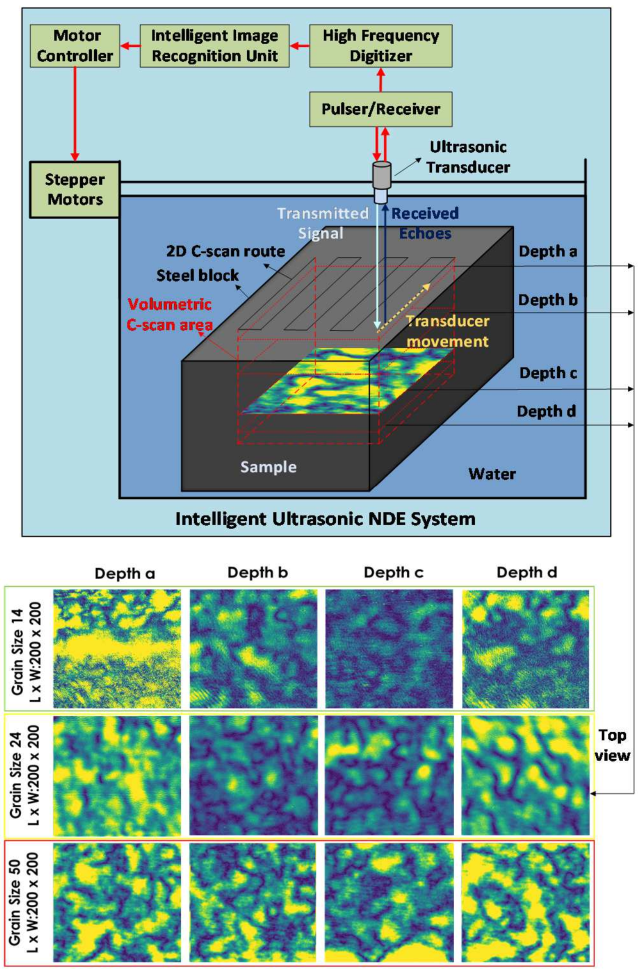

Figure 1. Intelligent Ultrasonic NDE System and 3D Testing Arrangement to Acquire Backscattering Images

III. Material Texture Recognition Using Data-Efficient Neural Networks

In the following three subsections, we introduce using the data-efficient neural networks to classify material textures for Grain14, Grain24, and Grain50 steel blocks. The acquired backscattering images are labeled, then used to train the neural networks. In addition, the texture recognition performance is analyzed, compared based on the training accuracy, testing accuracy, and data efficiency. The data efficiency is measured by the image processed throughput on testing. The image processed throughput is the number of backscattering images evaluated per second. To improve the training performance, these data-efficient deep-CNNs were pre-trained on large image datasets (ImageNet) using transfer learning (TL) [16] followed by further training with acquired backscattering images. In addition, the neural networks were trained with 30 epochs using 80%, and 20% of experimental backscattering images for training and testing respectively. The training was conducted on the Intel (R) Core (TM) i7-8750H, CPU@2.20GHz computer with NVIDIA GTX 1070 GPU 16GB RAM.

A. *Material Texture Recognition using DEUTR Transformer*

The Transformer Neural Network (TNN) utilizes the multi-head attention mechanism [13] which replaces the convolution and recurrence operations for image recognition. This attention mechanism reduces the computational cost to train and deploy the neural network while outperforms the state-of-art CNN, such as the deep-CNN, in large-scale image recognition [14]. In training, each backscattering image is divided into image patches and linearly encoded into lower dimensions into the DEUTR transformer encoders for further training. In each transformer encoder block, the multi-head attention optimizes the training process and parallelizes the learning. Thus, the attention mechanism improves the recognition performance by reducing the complexity per layer and sequential operations to enhance data efficiency [13]. Next, layer normalization and the residual connection are used to reduce the training time and improve the recognition accuracy [14].

B. *Material Texture Recognition using MobileNet*

The MobileNet is a lightweight deep-CNN and utilizes the depthwise separable convolution architecture to enhance data efficiency. In the large-scale image recognition dataset (ImageNet), the MobileNet achieves the same recognition accuracy as the deep-CNN: VGG16 while reducing the size to be 32 times smaller and being 27 times less computationally intensive [17].

C. *Material Texture Recognition using NasNetMobile*

The NasNetMobile is a small version of the NasNet [18] and is designed for data-efficient applications on the resource-constrained embedded system. The NasNet is a convolutional neural network built by utilizing the reinforcement learning based on Neural Architecture Search (NAS) framework [18] to optimize the architecture configurations. Compared with the previous state-of-the-art model on image recognition, the NasNet has a reduction of 28% in computational demand while is 1.2% better in top-1 accuracy than the best human-invented neural network in ImageNet [18].

Table 1 below shows the results using the data-efficient neural networks to classify material textures of Grain14, Grain24, and Grain50 steel blocks. For performance comparison, the Xception [11] deep-CNN was also trained because this neural network improves the depthwise separable convolution and achieves higher accuracy than state-of-the-art deep CNNs: VGG-16, ResNet-152, InceptionV3 on ImageNet [11].

TABLE 1. PERFORMANCE COMPARISON USING DATA EFFICIENT NEURAL NETWORKS FOR MATERIALS TEXTURE RECOGNITION

Model	Training Accuracy	Testing Accuracy	Image Processed Throughput
DEUTR Transformer	99.26%	97.31%	148 images/second
NasNetMobile	99.29%	97.59%	28 images/second
MobileNet	99.87%	99.21%	64 images/second
Xception	99.54%	96.66%	12 images/second

In Table 1, as we can see that these neural networks can estimate grain size using experimental backscattering images with high recognition accuracy and high image classification throughput. And we obtained the average training accuracy of 99.47%, the average testing accuracy of 98.04%, and the highest image processed throughput of 148 images/second on testing the DEUTR Transformer. Although the NastNetMobile, MobileNet slightly outperforms the DEUTR Transformer on testing accuracy, these data-efficient deep-CNNs were pre-trained on ImageNet using the transfer learning which enhances the recognition accuracy.

IV. CONCLUSION

In this study, we investigated the performance of using the data-efficient neural networks to nondestructively recognize textures of three steel blocks with different grain sizes by using ultrasonic backscattering images. An ultrasonic NDE testbed system was built, and 3D scanning was created to acquire the backscattering images to examine the results. In these data-efficient neural networks, the DEUTR transformer neural network was proposed to classify material textures with high data efficiency and accuracy. This neural network uses the multi-head attention mechanism to parallelize the training using image patches sequentially, which greatly enhances the data efficacy and recognition accuracy. In addition, the MobileNet utilizes the depthwise separable convolution to enhance the data efficiency by reducing the convolutional multiplications significantly. Next, the NasNetMobile uses reinforcement learning based on Neural Architecture Search to find the best convolutional architecture to enhance the recognition performance regarding accuracy and data efficiency. Therefore, by using these neural networks, we obtained the average training accuracy of 99.47%, the average testing accuracy of 98.04%, and the highest image processed throughput of 148 images/second on testing the DEUTR Transformer. Future work is to further enhance the recognition accuracy and data efficiency, such as shrinking or factorizing the neural networks.

REFERENCES

[1] S.K. Dwivedi, M. Vishwakarma, A. Soni, "Advances and Researches on Non Destructive Testing: A Review," *Journal of Materials Today: Proceedings*, 2018.

[2] J. Saniie and N. M. Bilgutay, "Quantitative grain size evaluation using ultrasonic backscattered echoes," *The Journal of the Acoustical Society of America*, 1986.

[3] J. Saniie, T. Wang and N. M. Bilgutay, "Analysis of homomorphic processing for ultrasonic grain signal characterization," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, 1989.

[4] J. Saniie and N. M. Bilgutay, "Grain Size Evaluation Through Segmentation and Digital Processing of Ultrasonic Backscattered Echoes*," IEEE International Ultrasonics Symposium*, 1984.

[5] L.B. Meng, B. Mcwilliams, W. Jarosinski, H.Y. Park, Y.G. Jung, J. Lee, J. Zhang, " Machine Learning in Additive Manufacturing: A Review," *Journal of The Minerals, Metals & Materials*, 2020.

[6] C.Q. Hu, Y.X. Duan, S.C. Liu, Y.Q. Yan, N. Tao, A. Osman, C. Ibarra-Castanedo, S. Sfarra, D.P. Chen, C.L. Zhang, " LSTM-RNN-based defect classification in honeycomb structures using infrared thermography," *Journal of Infrared Physics & Technology*, 2019.

[7] X. Zhang, J. Saniie, A. Heifetz, "Neural Learning Based Blind Source Separation for Detection of Material Defects in Pulsed Thermography Images," *IEEE International Conference on Electro Information Technology (EIT)*, 2020.

[8] X. Zhang, J. Saniie, W. Cleary, A. Heifetz, "Quality Control of Additively Manufactured Metallic Structures with Machine Learning of Thermography Images," *Journal of The Minerals, Metals & Materials*, 2020.

[9] J. Saniie, M. Unluturk, T. Chu, "Frequency discrimination using neural networks with applications in ultrasonics microstructure characterization," *IEEE Ultrasonics Symposium Proceedings*, 1992.

[10] M. S, Unluturk and J. Saniie, "Neural Network Based Order Statistic Processing Engines," *Journal of Signal and Information Processing*, 2012.

[11] W. Rawat and Z. Wang. "Deep Convolutional Neural Networks for Classification: A Comprehensive Review," *Neural Computation*, 2017.

[12] X. Zhang, B. Wang, J. Saniie, "Deep Convolutional Neural Networks Applied to Ultrasonic Images for Material Texture Recognition," *IEEE International Ultrasonics Symposium*, 2020.

[13] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. "Attention is all you need," *In NIPS*, 2017.

[14] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, N.Houlsby. "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale," *ICLR* 2021.

[15] X. Zhang, J. Saniie, " Material Texture Recognition using Ultrasonic Images with Transformer Neural Networks," *IEEE International Conference on Electro Information Technology (EIT)*, 2021.

[16] PM. Cheng, HS. Malhi, "Transfer Learning with Convolutional Neural Networks for Classification of Abdominal Ultrasound Images," *Journal of Digital Imaging*, 2017.

[17] A.G. Howard, M.L. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, H. Adam, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv:1704.04861*, 2017.

[18] B. Zoph, V. Vasudevan, J. Shlens, Q.V. Le, "Learning Transferable Architectures for Scalable Image Recognition," *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018.