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Deep Convolutional Neural Networks Applied to Ultrasonic Images for Material Texture Recognition

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***Abstract*—Texture recognition nondestructively by estimating the grain size has been widely used for the characterization of the physical and structural integrity of materials. As the ultrasonic signal passes through the materials, signal energy attenuates due to scattering and absorption, which are functions of the frequency and grain size distribution. Thus, the scattering and attenuation of ultrasonic echoes can be utilized for grain size evaluation and microscopic texture analysis. In this paper, we propose to investigate the performance of using deep convolutional neural networks (CNNs) to learn grain scattering features and classify materials. An ultrasonic testbed platform is assembled to obtain 3D ultrasonic data from heat-treated steel blocks with different grain sizes. The 3D acquired data are utilized to construct 2D images (B-Scans and C-Scans) to train the proposed deep CNNs classifiers for texture analysis. Several state-of-the-art deep CNNs are trained and compared to classify the grain scattering textures of three heat-treated steel blocks. These deep CNN classifiers are pre-trained on large datasets (ImageNet) followed by further training with transfer learning (TL) using experimental ultrasonic images. A lightweight TL based deep CNN classifier known as LightWeightTextureNet (LWTNet) was utilized to classify material textures with high validation accuracy of 99.58%.**

Keywords — *Material Texture Recognition, Deep CNN, Transfer Learning, Grain Size Estimation*

I. INTRODUCTION

Material texture recognition nondestructively by estimating the grain size using ultrasonic microstructure scattering signals and signal attenuation is a promising method for the characterization of the physical and structural integrity of materials [1] [2]. However, it is difficult to measure the signal attenuation which shows local grain size variations along the entire propagation path. Thus, the scattering signal is characterized to estimate the grain size distribution using the statistical variation in the scattered energy as a function of depth [3][4]. The intensity of the backscattered signal is the non-explicit function of average grain size, ultrasonic frequency, and random distribution of grains.

To better characterize scattering signals for texture recognition, the Rayleigh scattering region where the ultrasonic wavelength is larger than the average grain diameter is used for testing [5]. Rayleigh scattering region exhibits the most sensitivity to frequency and grain size distribution. Traditional characterization of the materials process is often complex and requires manual monitoring. For system automation, machine learning methods [6-8] are more reliable and practical. Neural network methods have been used to characterize grain size backscattered signals [9][10][11][12]. In recent years, convolutional neural networks (CNN) [13] are emerging and exploit convolutional layers to learn image features automatically, then recognizes visual objects with high accuracy. Among them, deep convolutional neural networks (deep CNN) have been proven with powerful learning ability due to the use of multiple feature extraction stages [8]. In this study, we propose to investigate the performance of using deep CNN to learn grain scattering features and classify material textures. Ultrasonic C-scan images are constructed from acquired backscattered signals from three heat-treated steel blocks, then used to train deep CNNs. And a lightweight deep CNN model called LightWeightTextureNet (LWTNet) is introduced to recognize material textures with high accuracy for fast automatic ultrasonic NDE applications.

Section II of this paper presents the ultrasonic NDE system implementation to acquire backscattered signals. Section III presents four different architectures of deep CNNs for texture recognition. Performance of these deep CNNs are analyzed and compared. Section IV concludes this paper.

II. SYSTEM AND EXPERIMENT SETUP

In this study, an ultrasonic NDE system, as shown in Figure 1, is built to obtain backscattered signals from three steel blocks with different grain sizes. An ultrasonic pulser/receiver, Panametrics Model 5052PR, is used as the signal generator and echo receiver. An oscilloscope, Keysight MSOX2024A, is used as high-frequency digitizer to synchronize digital signal from the pulser/receiver with the oscilloscope. A water tank is built for ultrasonic testing. The water tank is mounted with two stepper motors, thus allows us to move the ultrasonic transducer precisely along x and y axes. A good ultrasonic energy propagation is guaranteed by submerging the test specimen under the water. The ultrasonic NDE system is fully automated by using Python scripts controlled by a desktop computer.

Figure 2 shows the ultrasonic NDE experimental setup to implement the C-scan testing and to acquire backscattered signals (3D data cube). A C-scan was created with 200x200 measurements and each measurement is the backscattered grain signal which consists of 7680 samples. The 3D acquired data are utilized to construct C-scan images with the size of 200x200 pixels to train deep CNNs. The red dashed line cube in Figure 2 indicates the volumetric C-scan area. C-scans at four depths for steel blocks of 14, 24, and 50 microns are shown to indicate the statistical variance of microstructure scattering signals. Measurements are acquired using a broadband piezoelectric transducer centered at 5 MHz. In this study, three types of heat-treated 1018 steel blocks with different grain sizes were used to acquire ultrasonic grain scattering data. These steel blocks have grain sizes of 14, 24 and 50 microns respectively, and they will be referred to as *Grain14, Grain24* and *Grain50* in this paper. We collected 4800 C-scans for each of *Grain14, Grain24, Grain50* steel blocks to train the deep CNNs.

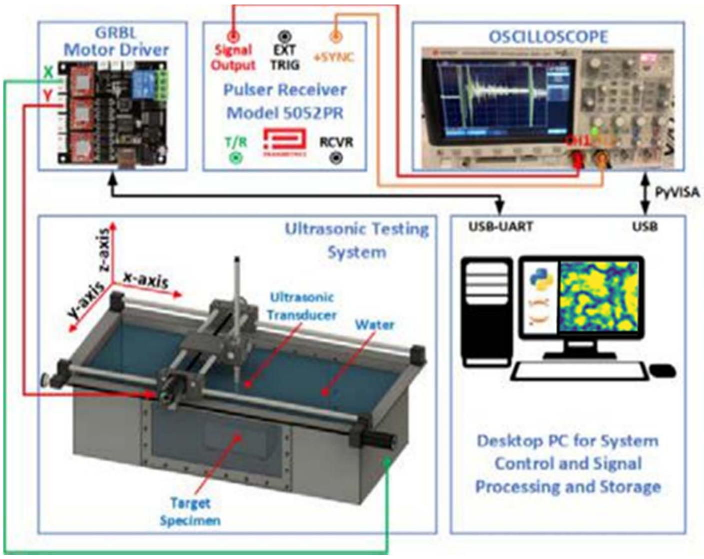

Figure 1. Ultrasonic NDE System Block Diagram

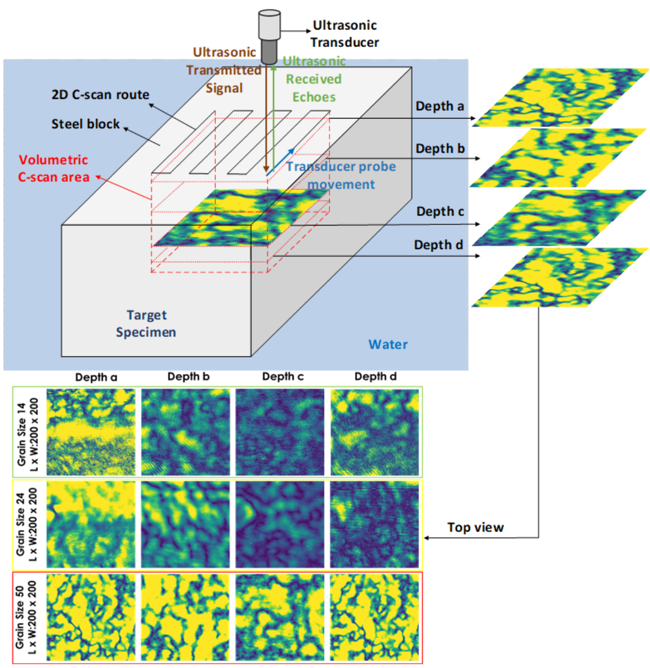

Figure 2. Ultrasonic C-scan Testing to Acquire Backscattered Signals and 2D Scattering Images

III. Material Texture Recognition

Material microscopic texture recognition is used to characterize backscattered signals of these three types of heat-treated steel blocks. To evaluate the performance using deep CNN to recognize material textures, C-scan images are used for training deep CNNs. These C-scan images for *Grain14, Grain24, Grain50* steel blocks were constructed from acquired 3D data cubes, then been labeled. In the following three subsections, a light-weight deep CNN: LWTNet, is introduced to classify three types of steel textures using ultrasonic C-scan images. And four different architectures of deep CNNs with three size levels are trained to investigate the performance applying deep CNN for textures recognition. To compare different deep CNN architectures in parallel, the convolutional bases were trained with the same 3 dense layers using the same training configuration. The deep CNNs were pre-trained on large datasets (ImageNet) followed by further training with transfer learning (TL) [14] with experimental ultrasonic images. The transfer learning enhances the classification accuracy while reducing the computational cost. The dense layers consist of an input layer, a hidden layer of 256 neurons, and an output layer of 3 neurons. To further improve the training performance, 'relu', 'softmax' activations are used with 0.5 dropouts [13]. The deep CNNs were trained with 50 epochs on the Intel (R) Core (TM) i7-8750H, CPU@2.20GHz 2.21GHz computer with GTX 1070 GPU. Among all the training data, we used 20 percent for the neural networks' validation.

A. Texture Recognition using the Light-Weight Deep CNN

The LWTNet is using EfficientNet [15] as the convolutional base with the 3 dense layers as the classifier. The EfficientNet is 8.4x smaller and 6.1x faster than the best existing Deep CNN bases [15]. Figure 3 shows the architecture of LWTNet. LWTNet architecture contains the convolutional layer with 32 filters using kernel size 3x3. This convolutional layer is followed by 3 types of mobile inverted bottleneck layers known as MBConv-A, MBConv-B, MBConv-C [15] as shown in Figure 3. These bottleneck layers have different expansion rates and kernel sizes. The acquired C-scans are fed as inputs to train the neural network. Each 3D block shows one type of building layers. The bottleneck layers work as normal convolutional layers but have much fewer parameters, which is less prone to overfitting and reduces computation cost. Meanwhile, LWTNet uses the residual connection, pointwise convolution, and depthwise separable convolution [15] in bottleneck layers to enhance the recognition performance. In this study, LWTNet was trained using TL to recognize material textures using C-scans and achieves 100% training accuracy and 99.58% testing accuracy to characterize *Grain14, Grain24, Grain50* steel blocks.

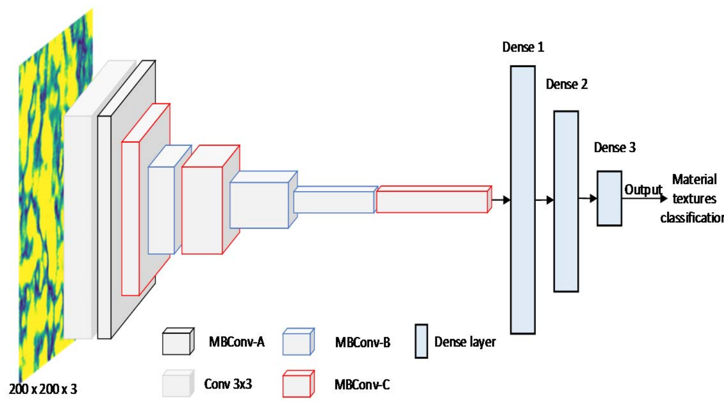

Figure 3. LWTNet Architecture

B. Texture Recognition using the Large Size Deep CNN

VGG16 (VGGNet) achieves 92.7% top-5 test accuracy on the ImageNet dataset which contains 14 million images belonging to 1000 classes in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [8]. It has 16 weight layers and follows the architecture pattern of convolutional layers with 3x3 kernel and 2x2 max pooling. In this study, VGG16 was trained using TL with the same 3 dense layers as shown in Figure 3 to recognize material textures using C-scans and achieves 100% training accuracy and 92.98% testing accuracy to characterize *Grain14, Grain24, Grain50* steel blocks.

C. Texture Recognition using the Middle Size Deep CNN

Inception V1 was the state-of-the-art deep CNN architecture at ILSRVRC 2014 [8]. It has produced the record lowest error at the ImageNet classification dataset. Inception V3 further improves accuracy based on Inception V1. InceptionV3 has 42 layers deep, but computation cost is much more efficient than that of VGGNet by using pointwise convolution, batch normalization, convolution factorization [8].

ResNet, which was proposed in 2015 by researchers at Microsoft Research introduced a new architecture called Residual Network [8]. ResNet50V2 has 50 layers deep while achieving good performance with less computation cost than that of VGGNet by using residual blocks.

In this study, InceptionV3 and ResNet50V2 were trained using TL with the same 3 dense layers as shown in Figure 3 to recognize material textures using C-scan images. These two middle sizes deep CNNs achieve 100% training accuracy and 96.34%, 92.59% testing accuracy separately to characterize *Grain14, Grain24, Grain50* steel blocks.

Table 1. Performance Comparison for Material Textures Classification using Deep CNNs

Model	Training Accuracy	Validation Accuracy	CNN Base Parameters	CNN Base Size
LWTNet	100%	99.58%	5,330,571	29 MB
InceptionV3	100%	96.34%	23,851,784	92 MB
ResNet50V2	100%	92.59%	25,636,712	98 MB
VGG16	100%	92.98%	138,357,544	528 MB

Table 1 shows material textures classification results to characterize *Grain14, Grain24, Grain50* steel blocks using deep CNNs. Our trained deep CNNs achieve 100% training accuracy and average 95.37% validation accuracy. And the LWTNet outperforms other deep CNNs and achieves 100% training accuracy, 99.58% validation accuracy. Meanwhile, LWTNet uses much fewer parameters with smaller storage size for fast interference in low latency automatic applications.

IV. CONCLUSION

Deep CNNs have a powerful learning ability to automatically classify visible objects in images due to the use of multiple feature extraction stages. In this study, state-of-art deep CNNs, such as VGG16, InceptionV3, EfficientNet, and ResNet50V2 with different architectures indicating three size levels were trained to accurately estimate grain sizes of three heat-treated steel blocks. These deep CNN classifiers were pre-trained on large datasets followed by further training with transfer learning (TL) with experimental ultrasonic images. A lightweight TL based deep CNN classifier known as LightWeightTextureNet (LWTNet), was proposed to classify material textures with a validation accuracy of 99.58%. To examine and classify experimental results, an ultrasonic testbed platform is assembled, and a C-scan is created to obtain 3D ultrasonic data from steel blocks with different grain sizes. The 3D acquired data are utilized to construct 2D images (C-scan) for training purposes. A series of experiments are conducted to collect ultrasonic images to train the deep CNNs, then results are compared for texture recognition performance analysis. Our results show that deep CNNs can recognize material textures using ultrasonic C-scan images with high accuracy. And the LWTNet outperforms other deep CNNs and achieves 99.58% validation accuracy while using much fewer parameters with smaller size. The LWTNet can be used for low latency automatic embedded ultrasonic NDE applications.

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