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Multilayer Perceptron Neural Networks for Grain Size Estimation and Classification

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***Abstract* – Grain size estimation nondestructively as a method for characterizing the mechanical and structural integrity of materials has been long recognized. The scattering and attenuation of ultrasonic echoes depend on the frequency of the sound and grain size distribution. It is of high interest to estimate grain size and classify materials based on the scattering properties of the specimen microstructure. In this study, an ultrasonic NDE system is used for acquiring ultrasonic scattering signals. Backscattered signals collected from three steel blocks with different grain sizes are used to train the neural network for material classification and quality control. Scattering signals in time domain, frequency domain, and time-frequency distribution are applied to the neural network for grain size characterization and classification. The validation accuracy of the trained network is as high as 99% for grain size classification.**

Keywords – Grain Size Estimation, Neural Network, Ultrasound NDE, Backscattered Signal, Time-frequency Distribution

I. INTRODUCTION

Grain size characterization using ultrasonic microstructure scattering signals and signal attenuation is a promising method but somewhat limited for structural health monitoring [1] [2]. Signal attenuation measurements represent values within the entire propagation path and local grain size variations are difficult, if not, impossible to assess. The direct characterization of the scattering signal can be utilized to acquire information related to statistical variation in the scattered energy as a function of depth which is correlated to the grain size distribution [3] [4]. The intensity of the backscattered signal is a nonexplicit function of the average grain size, ultrasonic frequency, and random distribution of individual grains.

In the Rayleigh scattering region, where the sound wavelength is larger than the grain size, the scattering coefficient is proportional to the average grain volume and the fourth power of the ultrasonic wavelet center frequency [5]. This is the most sensitive region for the grain size characterization, although, the signal is complex and cannot be readily characterized by conventional signal processing techniques. Therefore, a Multilayer Perceptron Neural Network (MLPNN) is designed and trained to characterize different grain sizes of heat-treated steel blocks [6] [7] [8] [9].

Section II of this paper presents the ultrasonic NDE system implementation with the laboratory equipment and experimental setup for acquiring backscattered signals. The acquired backscattered signal will be used as the input of the neural network for the grain size estimation. Section III presents ultrasonic grain size estimation algorithms based on MLPNN. Three different types of signal processing algorithms namely time domain segmentation, Power Spectrum Density (PSD) estimate and Split Spectrum Processing (SSP) technique are applied to the signal before passing the signal to the neural network for classification. Performance of these algorithms are analyzed and compared. Section IV concludes this paper.

II. SYSTEM AND EXPERIMENT SETUP

For this study, a testbed system is designed and implemented to obtain ultrasonic backscattered signals from steel blocks that have different grain sizes. Figure 1 is the system block diagram of the ultrasonic NDE system designed for this study. A Panametrics Model 5052PR ultrasonic pulser receiver is used in the system as the signal generator and echo receiver. It includes ultrasonic high voltage pulser, Transmit/Receive switch, filters and amplifiers in the system. An oscilloscope, Keysight MSOX2024A, is used as high frequency digitizer in the system. Digital synchronization signal is provided by the pulser receiver to synchronize with the oscilloscope. A water tank for ultrasonic testing with two stepper motors mounted allows us to move the ultrasonic transducer along x and y axes. The stepper motors are directly driven by an Arduino based stepper motor controller board. The ultrasonic NDE system is controlled by a desktop computer through USB ports. Customized Python libraries are implemented for controlling the stepper motor controller board using GRBL library and communicate with the oscilloscope using PyVISA library [10] [11]. The signal acquisition process is fully automated by using Python scripts.

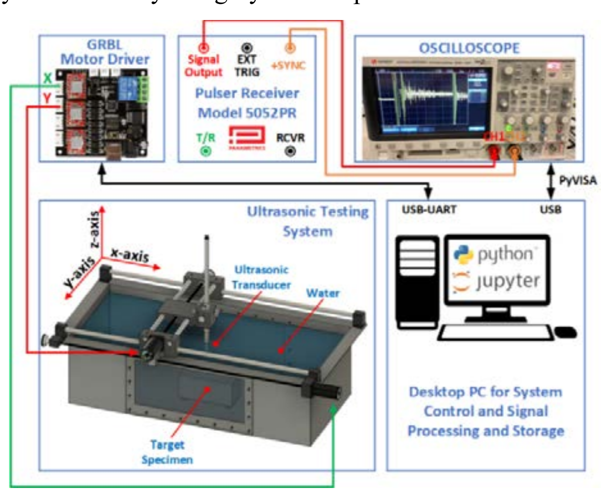


Figure 1. Ultrasonic NDE System Block Diagram

Figure 2 shows the ultrasonic NDE experimental setup to acquire backscattered signals for grain size estimation. A broadband immersive type of piezoelectric transducer centered at 5 MHz is used to acquire raw data in this study. A pulse echo type of system described in Figure 1 is used for the backscattered signal acquisition. The backscattered signal is generated by microstructure (i.e., grains) scattering. To make the backscattered signal cleaner, a designed delay path from the transducer and the upper surface of the specimen is created.

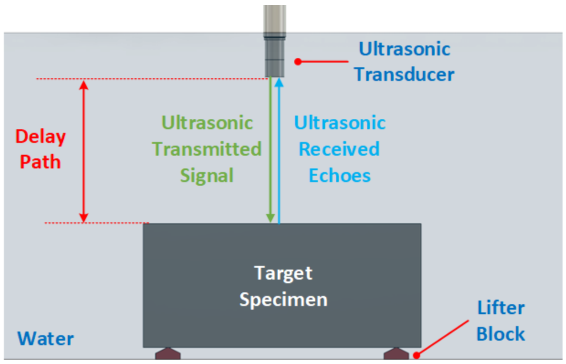


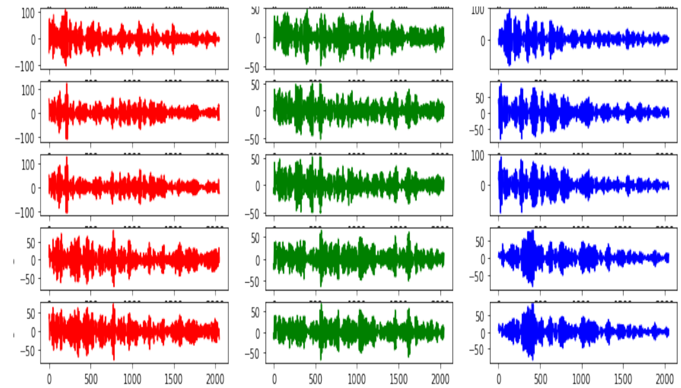
Figure 2. Ultrasonic Testing Arrangement to Acquire Backscattered Signal

The ultrasonic grain scattering signal is sampled at 1 GSPS with 8-bits resolution and resampled (or downsampled) to 100 MSPS. In this study, three types of 1018 steel blocks with different grain size were used. Among these three type 1080 steel blocks, two blocks were heat-treated at 1600- and 2000-degree Fahrenheit. Each block has the grain size of 14, 24 and 50 microns and they will be referred to as *Grain14*, *Grain24* and *Grain50* throughout this paper. The backscattered signals acquired from these blocks with different grain sizes will later be used for training MLPNN

Figure 3 shows five plots of randomly selected backscattered signal raw data acquired for each test specimens. Signal displayed in Figure 3 are preprocessed by using down sampling, filtering, time synchronization, etc. These experimental grain signals measurements were made in Rayleigh scattering region which means the diameter *d* of the scattering center is very small compared with the ultrasonic wavelength [12]. The signal displayed in red, green and blue separately represent the backscattered signal obtained from the steel block with grain size of 14, 24 and 50 microns. We collected 40 backscattered signals for each specimen with different grain sizes for training the neural network.

III. MLPNN BASED GRAIN SIZE ESTIMATION ALGORITHM

To characterize the backscattered signal with different grain size using neural network, the raw backscattered data must be prepared and labeled for training. In the following three subsections, three different data preparation methods are introduced for training the MLPNN. To compare different data preparation methods in parallel, the pre-processed data will be passed to the neural network with the same hyper parameter and training for the same amount of iterations. The neural network has two hidden layers of 512 and 256 neurons and will be trained with training data prepared in different methods for 50 epochs. Among all the training data, we will use 20 percent for neural network validation. For each grain size characterization algorithm, the signal will be segmented into different length of 256 samples which cover around 7.6 mm distance in the specimen if we assume the sound velocity in steel is 5920 m/s.

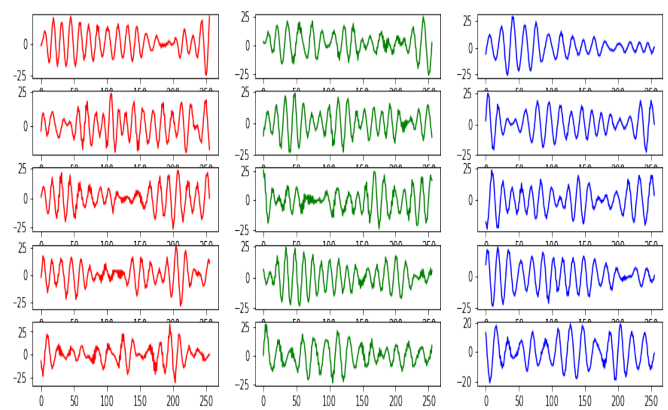


(a) Grain14 (b) Grain24 (c) Grain50

Figure 3. Time Domain Raw Data

A. *Classification using Time Domain Signal*

In this method, MLPNN is modeled and trained in TensorFlow using short segments with 256 samples of the backscattered signal in time domain. The sampled backscattered signal is sliced into time segments as shown in Figure 4, five randomly selected time segments from each specimen labeled in different colors were plotted.



(a) Grain14 (b) Grain24 (c) Grain50

Figure 4. Normalized Time Domain Segments of Backscattered Signals

After training the neural network for 50 epochs, the training validate accuracy converge. The neural network has the training accuracy of almost 100%. The testing accuracy of *Grain14* vs *Grain24* signals, *Grain14* vs *Grain50* signals, and *Grain24* vs *Grain50* signals were 83.33%, 94.72% and 93.68% respectively. Results show that using time domain segments as training input can recognize different grain sizes using backscattered signals with an average testing accuracy of 90.57%. The trained neural network performed marginal in classifying *Grain14* and *Grain24*. The network can recognize *Grain50* from *Grain14* and *Grain24* successfully.

B. Classification using PSD of Signal

Figure 5 is the Power Spectrum Density (PSD) estimate of the normalized time segments displayed in Figure 4 using Welch averaged modified periodogram method [13]. The PSD estimation of the backscattered signal acquired from steel blocks with grain size of 14, 24 and 50 microns are marked with different colors in the figure. The PSD signal will be used as the training input of the MLPNN.

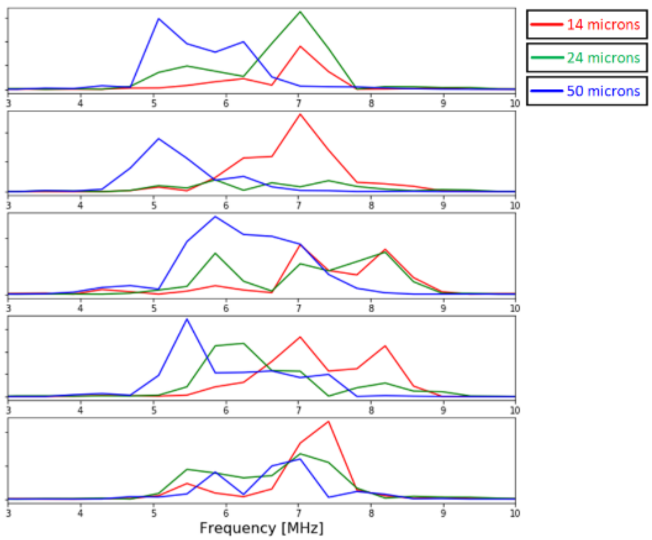


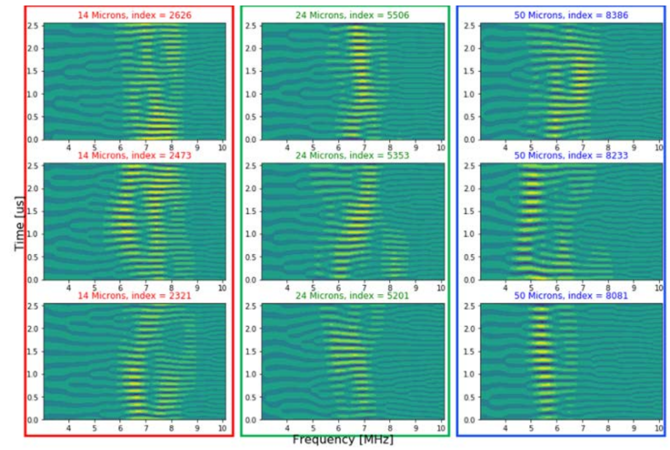
Figure 5. Power Spectrum Density Estimate

After training the neural network for 50 epochs using the PSD estimation of the normalized backscattered signal segments, the testing accuracy for grain signal classification accuracy of 98.82% (*Grain14* from *Grain24*), 99.51% (*Grain24* from *Grain50*) and 99.93% (*Grain14* from *Grain50*) when we use the neural network to separate The average testing accuracy is 99.42%. Results indicates that the PSD of the time segments gives the most accurate testing accuracy.

C. Grain Signal Classification using SSP

SSP is an algorithm that performs time-frequency analysis [14] [15]. In SSP, the time domain signal is first transformed into frequency domain using discrete Fourier transform (DFT). In frequency domain, multiple Gaussian frequency bands are generated to split the spectrum into multiple frequency components. These components are separately recovered into time domain and finally concatenated as the time-frequency distribution for signal analysis. Before passing the SSP representation of the backscattered signal into MLPNN as training input, the SSP representation of the signal will be segmented in time axis. Figure 6 shows the segmented SSP results for 256 samples in time axis. Three randomly selected segments from each specimen are plotted.

After training the MLPNN for 50 epochs, the testing accuracy of using SSP were 85.14%, 94.17% and 94.58% when we characterize *Grain14* vs *Grain24*, *Grain14* vs *Grain50* and *Grain24* vs *Grain50*. These results are slightly better than using time domain signal segments for training the neural network. However, SSP based MLPNN demands higher computing power to dissect and digest the sampled data. Also, adding frequency dimension to the training data will increase the input size which may need a neural network with higher capacities in terms of more neurons, layers, and consequently more coefficients.



(a) Grain14 (b) Grain24 (c) Grain50

Figure 6. Time-Frequency Domain

TABLE I. TESTING ACCURACY OF THE NEURAL NETWORK

	Time (%)	SSP (%)	PSD (%)	Average
Grain14 against Grain24	83.33	85.14	98.82	89.10
Grain14 against Grain50	94.72	94.17	99.51	96.13
Grain24 against Grain50	93.68	94.58	99.93	96.06
Average	90.57	91.30	99.42	93.76

IV. CONCLUSION

For this study, a testbed system is designed and implemented to acquire ultrasonic NDE signals from steel blocks that have different grain sizes (14, 24 and 50 microns). A 5 MHz ultrasonic piezoelectric transducer is used to test the steel block with different grain sizes. The ultrasonic grain scattering signal is sampled at 100 MHz with 8-bits resolution. The received signal is sliced into time segments with the length of 256 samples which represent the distance of roughly 7.6 mm in the target specimen. Table I shows the summation of the testing accuracy of different algorithms. The training accuracy was almost 100% and the testing results classified grain signals with as high as 99.93% accuracy.

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