Frequency discrimination of ultrasonic signal using neural networks for grain size estimation

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Abstract— **A neural network model has been developed to discriminate the frequency signatures inherent to ultrasonic microstructure scattering signals consisting of multiple irresolvable echoes of random amplitude and arrival time. A practical method which is called the grain power spectrum neural network (GPSNN) has been studied. This model is also compared with two other neural network models, called grain autocorrelation neural network (GACNN) and the grain amplitude neural network (GANN). The materials tested for grain size discrimination were three steel blocks type 1018 (two blocks were heat-treated at 1600 and 2000 degrees Fahrenheit for 4 hours) with grain sizes of 14 microns (ASTM No. 9), 24 microns (ASTM No. 7) and 50 microns (ASTM No. 5). Experimental grain signals were obtained using a broadband transducer with a 5 MHz center frequency and the measurements were made in the Rayleigh scattering region. A set of 2565 training sequences was utilized to train the neural network. A new set of 855 testing sequences was acquired to test the GPSNN, GACNN and GANN performance. Overall, GPSNN and GACNN achieved an average recognition performance of 94% and 90% respectively. This high level of recognition suggests that the GPSNN is a promising method for ultrasonic nondestructive testing and grain size estimation. In contrast, GANN failed to sort the grain scattering signals and was able to correctly classify the signal only 50% of the time.**

Keywords- Ultrasound; Grain size estimation; Neural network

I. INTRODUCTION

There are two major ultrasonic grain size estimation techniques. Those techniques are based on attenuation and scattering measurements [1-3]. Attenuation measurements have been the most accepted technique and scattering measurements needed substantial amounts of signal processing. Similarly, in medical imaging there are ongoing efforts to explore methods that lead to the ultrasonic characterization of tissues for diagnostic purposes.

Scattering by grains contributes to a large portion of ultrasonic attenuation, with the remaining attenuation dependent on absorption which is a linear function of frequency. The intensity of scattering is a nonexplicit function of individual grain diameters, the ultrasonic wavelength, the inherent anisotropic character of the individual grains, and the random orientation of the crystallites. In the Rayleigh scattering region (the wavelength,λ is larger than the average grain diameter, D) the scattering coefficients vary with the third power of the grain diameter and the fourth power of the frequency, while the absorption coefficient increases linearly with frequency. The attenuation coefficient for a given frequency, f , and at a distance, z can be modeled as:

$$\alpha(f) = c_a f + c_s D^3 f^4 \tag{1}$$

where c_a is the absorption constant, and c_s is the scattering constant. In pulse-echo testing of grains is solid materials, the power spectrum of the backscattered grain signals can be modeled as:

$$R(f) = A(f)S(f)U(f)H(f) \tag{2}$$

where $A(f)$ is the power function corresponding to the attenuation characteristics of the signal propagation path in the material, $S(f)$ is the frequency-dependent power scattering function proportional to the scattering coefficients, $U(f)$ is the power spectrum of the ultrasonic transducer, including both transmit and receive characteristics, and is often represented as a broadband Gaussian shape echo, and $H(f)$ is a frequency modulation power spectrum due to random sums of small scatterers (i.e., grains) with random amplitudes (i.e., sizes) and phases (i.e., positions) within the detection range cell (see Figure 1). Inspection of the above equations suggests that due to microstructure scattering, high frequency components of the interrogating ultrasonic wavelet backscatter with higher intensity than the lower frequency components. This situation results in a higher expected frequency than that of the original interrogating wavelet. We have developed a neural network procedure to distinguish the frequency components that exist in grain signals. This procedure is called the grain power spectrum neural network (GPSNN).

II. GPSNN DESIGN

The back propagation learning algorithm [4] is used to train the grain power spectrum neural network (GPSNN). The block diagram of GPSNN is shown in Figure 2. The ultrasonic measured data is segmented where it represents information pertaining to a predefined region of materials. This segmented data is applied to the input of the power spectrum processor utilizing the fast Fourier transform algorithm. The output of it is normalized and is presented to a three layer, fully

interconnected neural network for classification. The output layer of the neural network is inputted by the weighted sum of outputs of the hidden and bias nodes in the hidden layer. These weighted inputs are processed by a hyperbolic tangent function. A set of desired output values is then compared to the estimated outputs of the neural network for every set of input values of the power spectrum of the backscattered grain echoes. The weights are appropriately updated by back propagating the gradient of the output error through the entire neural network. In this study, an adaptive learning rate algorithm [4] is used. This adaptive learning rate algorithm is promising for reaching the optimal solution faster.

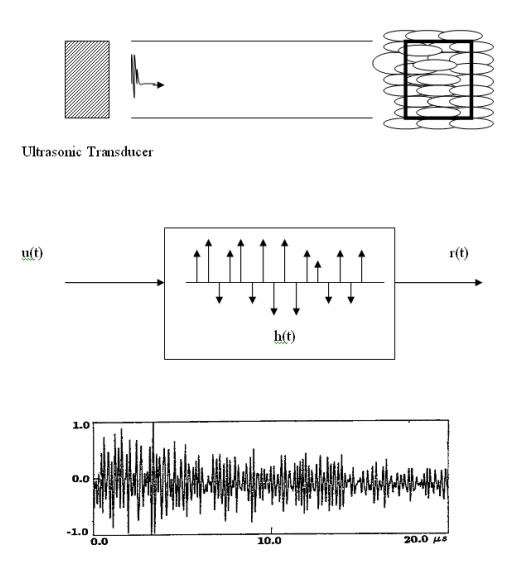

Figure 1. Ultrasonic Backscattered Signals

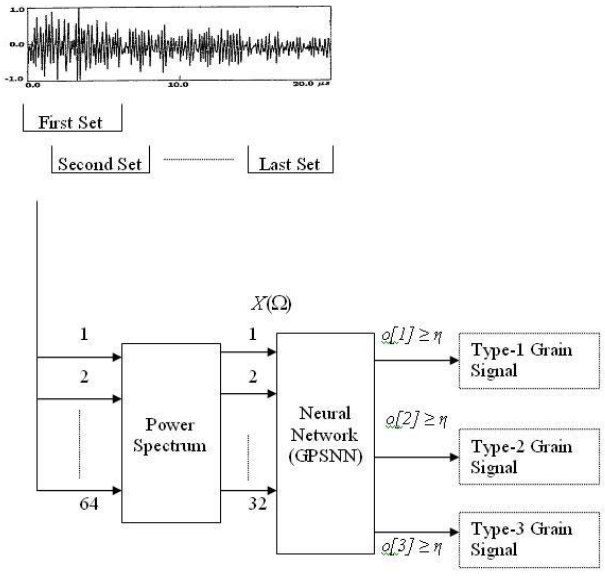

Figure 2. Block diagram of the ultrasonic grain power spectrum neural network (GPSNN) system. Only one output neuron at a time is expected to be turned on and all the rest of the neurons are turned off to indicate which type of grain signal is present at the input.

We normalize the segmented power spectrum data by removing the mean and dividing it with the standard deviation. This normalization is highly desirable because it desensitizes the neural network to the signal offset and/or signal gain. Normalization is given as

$$X(k\Omega) = \frac{R(k\Omega) - \mu}{\sigma}, \quad k = 1, \cdots, N$$
$$\mu = \frac{1}{N} \sum_{k=1}^{N} R(k\Omega), \tag{3}$$
$$\sigma = \sqrt{\frac{1}{N-1} \sum_{k=1}^{N} (R(k\Omega) - \mu)^2},$$

where $f = k\Omega$, and $R(k\Omega)$ is the segmented power spectrum of the experimental grain signal, μ and σ are the estimated mean (i.e., signal offset) and the estimated standard deviation (i.e., measurement scale) respectively.

The input signal to the power spectrum block (see Figure 2) is created using a sliding window. The size of the sliding window is 64 samples, and the step between two successive windows is 8 samples. The first set is taken from the beginning of the experimental data. The second set is 8 samples to the right of the first set, and this is repeated until the window covers the entire 512 samples of the measured signal. The first 32 samples which span the entire frequency range are taken into consideration as an input to the neural network for signal classification. Hence, the neural network needs 32 inputs and 3 neurons in its output layer to classify the grain signals. The hidden layer has 20 neurons. This number was picked through experimentation and experience. During testing, GPSNN accomplished a recognition performance of 94% with that many hidden neurons. And also, if the network has trouble classifying, then neurons can be added to the hidden layer. Figure 3 shows a three layer neural network that is designed to classify the grain signal power spectrum. The hidden neuron's output of this neural network, y_j , is given as

$$y_j = \phi\left(\sum_{i=1}^{N} X_i w_{ji}^{h} + \theta^{j}\right) \tag{4}$$

where $j = 1, \cdots, L$ and the activation function for the hidden and output layer, $\phi()$, is a tangent hyperbolic function defined as

$$\phi(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{5}$$

The term X_i is the normalized input vector, w_{ji}^{h} is the weight from i^{th} input neuron to the j^{th} hidden neuron.

$$X = [X(\Omega), \cdots, X(i\Omega), \cdots, X(N\Omega)] \qquad (6)$$

The output neuron's output of GPSNN, $o[j]$, is given as

$$o[j] = \phi\left(\sum_{k=1}^{L} y_k w_{jk}^{\ o} + \beta^j\right) \qquad (7)$$

where $j = 1, 2, 3$. The term $w_{jk}^{\ o}$ is the weight from j^{th} output neuron to the k^{th} hidden neuron.

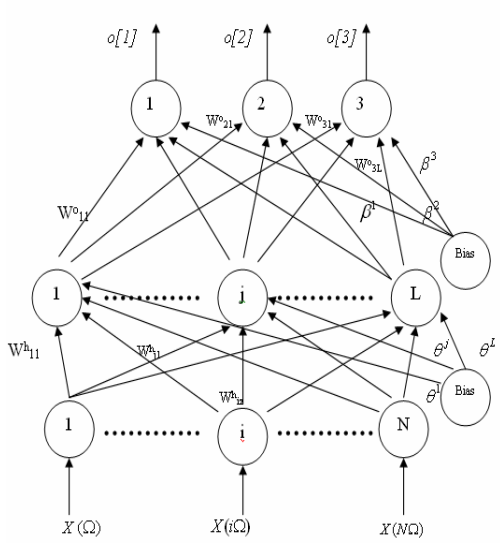

Figure 3. A three-layer model of grain power spectrum neural network (N=32 and L=20)

Back propagation with an adaptive learning rate algorithm is used to estimate the hidden layer and output layer weights and biases for the optimal design of GPSNN. Then, the output vector *o*, is applied to the decision block in order to classify the grain size,

$$\begin{aligned} &o[1] \geq \eta \ \ and \ \ \ o[2], o[3] < \eta \longrightarrow Type\text{-}1 \\ &o[2] \geq \eta \ \ and \ \ \ o[1], o[3] < \eta \longrightarrow Type\text{-}2 \\ &o[3] \geq \eta \ \ and \ \ \ o[1], o[2] < \eta \longrightarrow Type\text{-}3 \end{aligned} \qquad (8)$$

where Type-1 represents 14 micron grain size signal, Type-2 represents 24 micron grain size signal and Type-3 represents 50 micron grain size signal. If the input signal is Type-1, then the first output neuron is expected to be turned on and the rest of the outputs are expected to be turned off (see Figure 2). A value of 0 is chosen for the threshold, η , to help decide whether the input grain signal is Type-1, Type-2 or Type-3. This threshold value is found using the probability density functions of the training grain signals for Type-1, Type-2 and Type-3. The probability density functions are estimated using the Parzen method. Hence, an estimate of the density function from samples can be obtained as:

$$f_j(y) = \frac{1}{n\sigma_j} \sum_i \Phi\left(\frac{y - y_i}{\sigma_j}\right), \qquad (9)$$

where n is 855, $y_i \{i = 1, 2, \cdots, n\}$ is the neural network output for Type-1, Type-2 or Type-3, $\Phi(\ )$ is the Gaussian density function (i.e., $\Phi(y) = e^{-y^2}$) and constant σ_j is chosen to be 0.25 for the experimental data ($j = 1$ for Type-1, $j = 2$ for Type-2 and $j = 3$ for Type-3). If the same penalty or cost is assumed with the miss-detection and false alarm rate, the value η is at point of intersection of Type-1, Type-2 and Type-3 pdf's as shown in Figure 4.

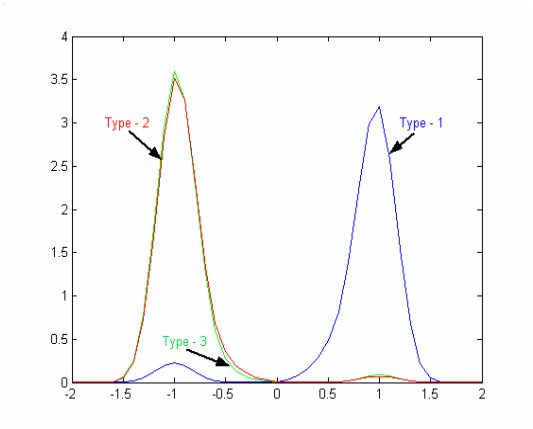

Figure 4. Probability Density Functions of the Output of GPSNN.

III. RESULTS AND DISCUSSION

To reach the performance goal, a sliding window is used to segment the data in order to arrange as many sets of data as possible for training and testing the neural network. From experimental measurements, a set of 2565 training sequences, 32 samples each, was assembled to train the grain power spectrum neural network. A new set of 855 testing sequences was utilized to test the GPSNN performance. Figure 5 shows a sample of 4 A-scans (i.e., amplitude scan) of Type-1, 4 A-scans of Type-2 and 4 A-scans of Type-3 measured grain signals. The corresponding power spectra of these A-scans are shown in Figure 6. Both the A-scans (Figure 5) and their power spectra (Figure 6) exhibit random pattern and a set of features that can be used for classification is not recognizable. However, due to the scattering theory of the microstructure, the grain signal backscattered from larger grains is expected to display lower frequency content than the grain signal backscattered from smaller grains. But this trend in frequency content is not readily quantifiable due to random peaks and dips in the power spectra. Therefore, a trained neural network is conceivable to recognize the microstructure signals backscattered from materials with different grain sizes.

GPSNN achieves an average recognition performance of 94%. This performance is impressive and statistically reliable because 2565 data segments are used in training and testing the neural network. Furthermore, this high level of recognition is desirable and practical since it is applied to a short data

segment that represents information pertaining to a small depth of about 6.5 mm of steel samples.

An alternative to using the GPSNN for grain signal classification is to train the neural network directly using A-scan data. In this study we have repeated training the neural network by applying the A-scan (64 samples) to the neural network directly.

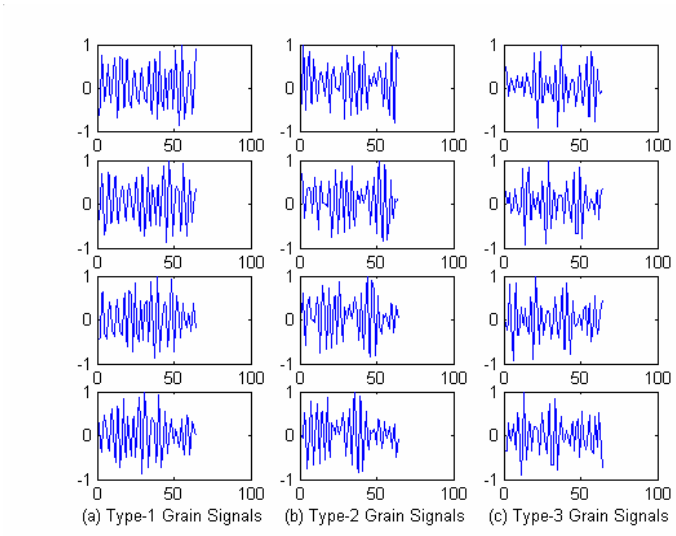

Figure 5. Examples of backscattered grain signals.

This method is called the grain amplitude neural network (GANN). As discussed earlier, no notable feature can be recognized in A-scan signals due to the random amplitude and phase of the backscattered echoes. In spite of randomness, it is desirable to probe A-scans using GANN in order to detect any unforeseeable grain scattering characteristics that may exist in the time domain.

Similar to the training technique GPSNN, a total of 2565 training sequences are assembled to train the GANN. A new set of 855 testing sequences is utilized to test the GANN performance. The pdf's of GANN output for Type-1, Type-2 and Type-3 signals significantly overlap. Consequently, a major difficulty is encountered using GANN for classifying grain A-scans. The testing results offer a far from desirable 50% correct classification. This would indicate that there is no significant manifestation of an underlying pattern in the grain A-scan that can be detected by GANN for classification. The superb performance for GPSNN can be attributed to adequate differences in the power spectrum of the signal, governed by frequency dependent attenuation and scattering (see Equation 1) that allows the neural network to adapt for recognition. On the contrary, the A-scan contains and displays information related not only to the power spectrum but also to the random phase spectrum. This random phase interferes with and obscures the inherent frequency characteristics of grain A-scans needed for properly training GANN.

IV. Conclusion

In this study we have developed a neural network that is designed to classify the power spectrum of the grain backscattered signals (i.e., the A-scan) using ultrasound. The backscattered grain echoes are random signals that bear information related to both the grain size and frequency of sound. However, this information is not readily quantifiable and lacks uniquely recognizable features. Therefore, the neural network becomes appealing for classifying these signals because they are trainable. The optimal values for neural network weights are estimated using the back propagation algorithm. Experimental measurements of steel grains are utilized to train and test the grain power spectrum neural network. This network shows a remarkable 94% classification performance. Parallel classification performance is also achieved when training the neural network using the autocorrelation of grain signals. These results are encouraging and suggest that neural networks are potentially useful for nondestructive testing and quality control. Furthermore, the grain power spectrum neural network renders practical advantages such as real-time processing, adaptability and training capability. It is important to point out that similar neural network designs can be used in medical ultrasonic imaging for tissue characterization and diagnosis.

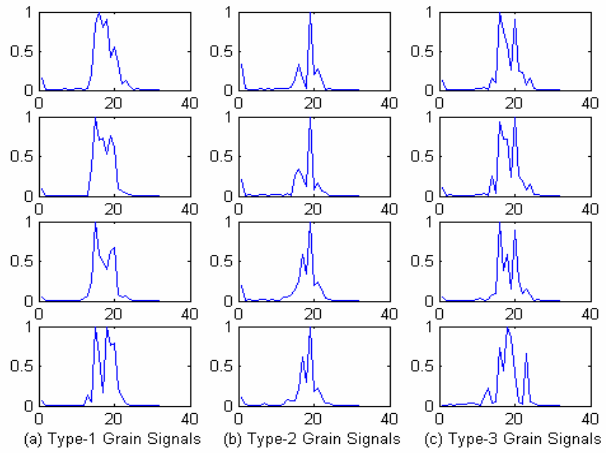

Figure 6. Power spectrum of grain signals shown in Figure 5.

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