NEURAL NETWORKS FOR ULTRASONIC GRAIN SIZE DISCRIMINATION

M. Unluturk and J. Saniie

Electrical and Computer Engineering Department
Illinois Institute of Technology
Chicago, IL 60616

ABSTRACT

In this study, we have developed the grain power spectrum neural network (GPSNN) to classify the ultrasonic backscattered grain signals for material characterization. The GPSNN has 32 input nodes, 13 hidden neurons determined adaptively, and one summing output node. A set of 4,490 training sequences is utilized to train the neural network. A new set of 12,572 testing sequences is used to test GPSNN performance. The samples tested for grain size discrimination are steel with grain sizes of 14 and 50 microns. GPSNN achieves an average recognition performance of over 98%. This high level of recognition suggests that the GPSNN is a promising method for ultrasonic nondestructive testing.

1. INTRODUCTION

The importance of evaluating the microstructure of materials ultrasonically has been long recognized. In particular, it is of high interest to estimate grain size or classify materials based on the scattering properties of their microstructure. Backscattered grain echoes are random signals that bear information related to both the grain size and frequency of sound. In ultrasonic grain size characterization a model for the grain signal consists of the convolution of components representing the contribution of the measuring system impulse response (i.e., the interrogating ultrasonic wavelet) and the grain scattering function. This function contains information related to many random physical parameters such as grain size, shape, orientation, boundary characteristics, and chemical constituents. Consequently, the grain scattering signal becomes random and exhibits a great deal of variability in the time domain. Therefore, spectral analysis is often adopted as an alternate method for signal characterization [1-4].

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 [5]. The attenuation coefficient for a given frequency, f, and at a distance, z, can be modeled as:

$$\alpha(z, f) = c_a(z)f + c_s(z)D^3 f^4 \qquad (1)$$

where $c_a(z)$ is the absorption constant and $c_s(z)$ is the scattering constant. Inspection of the above equation suggests that the high frequency component of the interrogating ultrasonic wavelet backscatters with higher intensity than the lower frequency components. This situation results in a higher expected frequency than that of the original interrogating wavelet.

In this study, we have developed the design procedure for a neural network to discriminate the frequency signatures inherent in ultrasonic grain scattering signals. This method, called the grain power spectrum neural network (GPSNN), offers practical advantages such as real-time processing, adaptability and training capability [6]. GPSNN deduces the relationship between the measurement power spectrum and classification output without knowing the scattering model, physical parameters, or the solution methodology. With the neural network, as each set of input vectors is applied to the neural network, the hidden layers configure themselves to recognize certain frequency features of the input vectors related to the scattering properties of the materials. After the GPSNN is fully trained, each hidden neuron will represent certain frequency characteristics of the total input space. Therefore, when the power spectrum of a new grain scattering signal is applied to GPSNN, each neuron is able to respond to the presence of a particular subset of frequency information which it was trained to recognize.

2. DESIGN OF GPSNN

To discriminate the frequency signatures inherent to grain signals, the backpropagation learning algorithm [6] is used to design the GPSNN. The block diagram of GPSNN is shown in Figure 1. The input data is normalized and segmented where it represents information pertaining to a predefined region of the materials. This data is used as the input to the power spectrum processor using the fast Fourier transform algorithm. Then, the power spectrum of segmented data is applied to a three

0-7803-3615-1/96/$5.00

layer fully interconnected neural network for classification. A set of desired output values (0 for grain Type-1 and 1 for grain Type-2) 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 backpropagating the gradient of the output error through the entire neural network. In this study, an adaptive hidden neuron algorithm is utilized in the design of the GPSNN. This adaptive hidden neuron algorithm is promising for determining the optimal number of hidden neurons.

The experimental data, used for both training and testing the GPSNN, is obtained using a broadband transducer with a 6.22 MHz center frequency and a 3 dB bandwidth of 2.75 MHz. A total of 38 experimental data sets were measured. Each experimental data set is composed of 512 points sampled at 25 MHz. This sampling frequency satisfies the Nyquist rate and reduces the correlation among the data points. Furthermore, the sparse sampling is also beneficial in reducing the neural network size.

The experimental data sets are normalized 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

$$x(nT) = \frac{r(nT) - \mu}{\sigma}, \quad n = 1, \cdots, N$$

$$\mu = \frac{1}{N}\sum_{n=1}^{N} r(nT), \qquad (2)$$

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{1}^{N}(r(nT) - \mu)^2},$$

where r(nT) is the digitized (sampling period is T) 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 block diagram of the ultrasonic grain power spectrum (GPSNN) is shown in Figure 1. An adaptive backpropagation algorithm is used for the optimal design of GPSNN. The input signal to the power spectrum block is created using a sliding window. The size of the sliding window is 64 samples, and the step between two successive windows is one sample. The first set is taken from the beginning of the experimental data. The second set is one sample to the right of the first set, and this is repeated until the window covers the entire 512 samples of the measured signal. The power spectrum, $X_p(k\Omega)$, of each input set is calculated by

$$X_p(k\Omega) = FFT\{x(nT)\} \cdot Conj\,[FFT\{x(nT)\}] \qquad (3)$$

where x(nT) is the normalized sampled value of the grain echoes, T is the time sampling interval, FFT is the Fast Fourier Transform, and Ω is the frequency sampling interval. The first 32 samples of $X_p(k\Omega)$ which span the entire grain frequency range are taken into consideration as an input to the neural network for signal classification. The output of this neural network, y, is given as

$$y = W^o \phi(W^h X) \qquad (4)$$

where the activation function for the hidden layer, $\phi(\ )$, is a tangent hyberbolic function. The term X is the input vector, W^h is the weight matrix for the hidden layer and W^o is weight vector for the output layer. Then, the output, y, is applied to the decision block in order to classify the grain size,

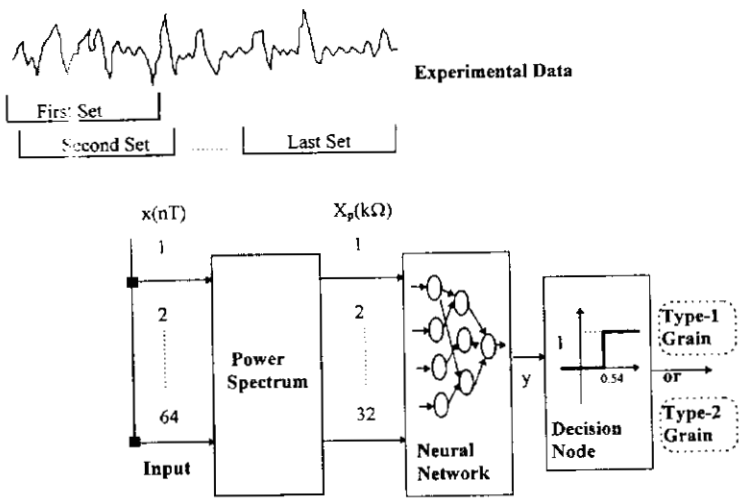

Figure 1. Block diagram of the ultrasonic grain power spectrum neural network (GPSNN).

$$y \le \eta \rightarrow \text{Type-1 Grain Signal} \qquad (5)$$
$$y > \eta \rightarrow \text{Type-2 Grain Signal}$$

A value of 0.54 is chosen for the threshold, η, to help decide whether the input grain signal is Type-1 or Type-2. This value is found using the output density functions (see Figure 2) of the training grain signals for Type-1 and Type-2. The output density functions are estimated using the Parzen method.

The key issue in the design of a neural network is determining the number of hidden neurons. The improper selection of hidden neurons may perform satisfactory for design data, but fails significantly for test data or causes unsatisfactory convergence (i.e., neural network is not fully trainable). To avoid these problems an adaptive algorithm for determining the number of neurons in the hidden layer is required. This adaptive technique starts with three hidden neurons and then adaptively increases the number of hidden neurons until convergence is guaranteed. Sum Square Error (SSE) is used as a measure of performance for the neural network. This error is used in updating the neural network weights using a backpropagation algorithm. When the SSE does not meet the appropriate criterion after 5000 epochs (an epoch is defined as one sweep through all the training samples), the number of hidden neurons is increased by one.

3. EXPERIMENTAL RESULTS

The experimental data, applied for both training and testing the GPSNN, is obtained using a broadband transducer with a 6.22 MHz center frequency and a 3 dB bandwidth of 2.75 MHz. A total of 38 experimental data sets was measured. The material applied for the microstructure is two steel blocks, type 1018, with two different grain sizes, 15 microns and 50 microns. Each experimental data set is composed of 512 points sampled at 25 MHz. This sparse sampling frequency satisfies the Nyquist rate and offers reduced correlation among the data points. Sparse sampling is also beneficial in reducing the size of the neural network and improving the overall efficiency of the grain size classification system.

From measured experimental data, a set of 4,490 training sequences was assembled to train the grain power spectrum neural network. A new set of 12,572 testing sequences was utilized to test the GPSNN performance.

Table 1 shows the training statistics of GPSNN. The number of inputs to the neural network is 32 which represents a power spectrum of grain signal spanning frequency 0-12.5 MHz. It should be noted that 4,490 training data sets were applied 52,225 times to estimate the optimal number of hidden neurons and their weights in order to satisfy the sum square error criterion. Table 2 presents testing results for the GPSNN.

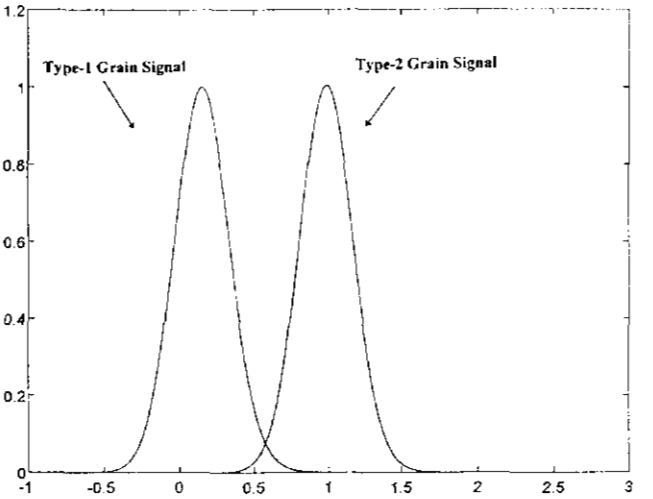

Figure 2. Density functions of the output of GPSNN for Type-1 and Type-2 grain signals.

Note that 28 additional experimental grain signals (14 measurements for Type-1: gr106-gr119; 14 measurements for Type-2: gr206-gr219) are used to test the trained neural network grain classifier. Since all these signals are segmented, a total of 12,572 testing sequences is used. As shown in the table, the GPSNN achieves an average recognition performance of 98%. This performance is impressive and statistically reliable since 17,062 data segments are used in training and testing the neural network. Furthermore, this high level recognition is desirable and practical since it is applied to a short data segment which represents information pertaining to a small depth of about 6.5 mm of steel samples.

Table 1. Training statistics for GPSNN using experimental data.

Number of Sample Vectors	**4490**
Number of Inputs	**32**
Number of Outputs	**1**
Number of Hidden Neurons	**13**
Epoch	**52225**

Table 2. Summary of the testing results for the GPSNN.

TYPE-1 Grain Signal	Percent Recognition	TYPE-2 Grain Signal	Percent Recognition
gr106	98.44%	gr206	98.21%
gr107	100%	gr207	93.98%
gr108	100%	gr208	95.99%
gr109	94.20%	gr209	100%
gr110	97.99%	gr210	95.99%
gr111	92.20%	gr211	100%
gr112	100%	gr212	93.98%
gr113	99.77%	gr213	98.66%
gr114	99.55%	gr214	100%
gr115	97.55%	gr215	98.21%
gr116	94.20%	gr216	100%
gr117	96.88%	gr217	100%
gr118	99.55%	gr218	100%
gr119	100%	gr219	100%

4. CONCLUSION

In this study we have developed a neural network that is designed to classify the power spectrum of the backscattered grain 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. In this study an adaptive method is used to determine the optimal number of neurons in the hidden layer. The optimal values for neural network weights are estimated using the backpropagation algorithm. Experimental measurements of steel grains are utilized to train and test the grain power spectrum neural network. This network shows a remarkable 98% classification performance.

5. REFERENCES

[1] J. Saniie and N. M. Bilgutay, "Quantitative Grain Size Evaluation Using Ultrasonic Backscattered Echoes," Journal of the Acoustical Society of America, Vol. 80, pp. 1816-1824, Dec. 1986.

[2] J. Saniie, Tao Wang, and N. M. Bilgutay, "Analysis of Homomorphic Processing for Ultrasonic Grain Signal Characterizations," IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, pp. 365-375, May 1989.

[3] T. Wang, J. Saniie and X. Jin, "Analysis of Low-order Autoregressive Models for Ultrasonic Grain Signal Characterization," IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, Vol. 38, No. 2, pp. 116-124, March 1991.

[4] J. Saniie and X. M. Jin, "Spectral Analysis for Ultrasonic NDE Applications Using AR, Prony and MUSIC Methods", Journal of the Acoustical Society of America, pp. tbd, October 1996.

[5] E. P. Papadakis, "Ultrasonic Attenuation Caused by Scattering in Polycrystalline Metals," Journal of the Acoustical Society of America, Vol. 37, pp. 703-710, 1965.

[6] J.A. Freeman and D. M. Skapura, Neural Networks: Algorithms, Applications and Programming Techniques, Addison Wesley Publishing Company, 1991.