Frequency Discrimination Using Neural Networks with Applications in Ultrasonics Microstructure Characterization

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ABSTRACT

The ultrasonic echoes backscattered from the microstructure of materials often display a random pattern. Both the scattering and attenuation of echoes depends on the frequency of sound and the grain size distribution. These effects are inherent to measured random signals and can lead to characterizing the microstructure of materials. In this study, neural networks, based on the backpropagation algorithm, have been used to discriminate time and frequency signatures inherent to grain signals. The samples of grain signals are applied directly or preprocessed for feature selection before being applied to the neural network. The methods of feature selection are signal power spectrum, autocorrelation, and autoregressive coefficients. These methods have been applied to both simulated and experimental data. Overall recognition performance as high as 100% for simulated data and 87% for experimental data has been obtained, although this high performance has not occurred for some feature selection methods.

INTRODUCTION

Ultrasonic echoes backscattered from the microstructure of large grained materials often exhibit a random pattern which is dependent upon both the frequency of the sound and the grain size distribution. Characteristics of the backscattered signals can therefore be used to discriminate between certain materials based on their scattering properties [1-3]. In this study, neural networks are utilized to characterize and discriminate different ultrasonic backscattered signals. Neural networks have been used extensively in many applications (speech recognition, image recognition, character recognition, echo cancellation, data compression,... [4]), and more recently in the field of ultrasound for both medical and industrial applications [5-8]. Neural networks are, in their most general sense, a collection of various layers of nodes which can be connected in a variety of configurations. We have designed three and four layer fully interconnected neural networks, utilizing the backpropagation algorithm. Each node consists of the weighted sum of the nodes in the preceding layer passed through the sigmoid threshold function [4]. A set of desired output values is then compared to the actual output of the neural network for every set of input values. The weights are then appropriately updated using the gradient of the output error with respect to the weight value being updated. Tolerances of 0.1 have been used to train the neural networks and testing was performed using 0.1 and 0.4 tolerances.

The inspiration for using the neural network has been based on the structure of the neural network itself. If one views the backscattered signal of two different materials, one will not find any apparent difference between the two signals. With the neural network, as each set of input vectors is applied to the neural network, the hidden layers configure themselves to recognize certain features of the input vectors related to the scattering properties of materials. After the network has been fully trained, the hidden layer neurons will each represent some characteristic or feature of the total input space. Thereafter, when new scattering signals are applied to the network each internal neuron will be able to recognize the presence of that particular feature which it was trained to recognize.

The training process involves providing the input features and adapting the network to a series of scattering patterns in order to generate the desired output signals. These patterns are used as inputs and sent through the network, the output is then compared to the desired output in which an error signal is generated. This error signal is backpropagated to previous layer neurons where it is used to adjust the weights on the neurons to reduce the output error signal. The backpropagation neural network will eventually adjust its internal weights such that all the training patterns will generate the desired output signal. The internal hidden layer neurons are now configured to recognize specific features of an ultrasonic input signal.

In this study, we have used both simulation and experimental scattering data to evaluate the recognition performance of neural networks. In addition, several feature selection methods have been examined in order to enhance the recognition of

1051-0117/92/0000-1195 $1.00 © 1992 IEEE

neural networks.

SIMULATION OF THE GRAIN SIGNAL

Two different signal structures have been used in the simulation of ultrasonic scattering signals in order to incorporate time and frequency signatures. The first method is shown in Figure 1. In this method two random signature functions are generated which are associated with the scattering characteristics of two specimen having different grain sizes. These two signature functions are used for a Type-1 and Type-2 class of signals. A random noise is added to the signature functions in order to corrupt their apparent recognition. Bandpass filtering, representing the characteristics of the ultrasonic transducer, is then performed to obtain a scattering signal similar to the random pattern of the actual experimental ultrasonic signal. This data is suitable to test the performance of neural networks for discriminating grain signature functions.

In the second method of signal simulation, a random impulse generator is used to generate pulses of random amplitudes and delays. In this method, we assume the signature function is inherent to the frequency spectrum associated with scattering and attenuation. Therefore, bandpass filtering (representing the composite frequency characteristics of the ultrasonic transducer and grain signature function) of these random pulses is performed. This data is then used to evaluate the performance of neural networks for discriminating random patterns associated with different frequency components. The block diagram of this simulation method is shown in Figure 2.

Two sets of microstructure signals (Type-1 and Type-2), based on method 1 and method 2 signal simulations, are shown in Figures 3 and 4 respectively. Figure 3 is simulated using 100

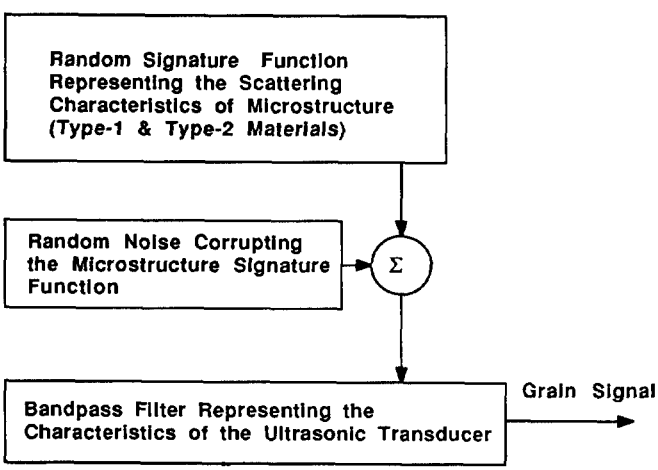

Figure 1. Block diagram of grain signal simulation incorporating time signature function (method1).

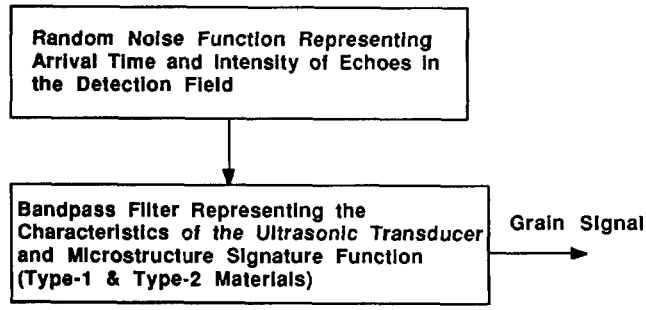

Figure 2. Block diagram of grain signal simulation incorporating frequency signature function (method 2).

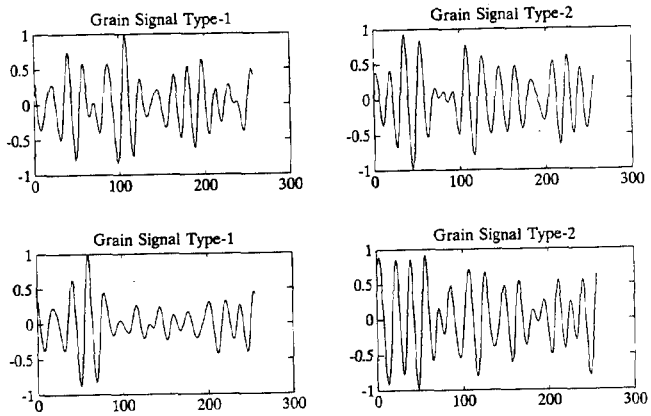

Figure 3. Simulation of ultrasonic grain scattering signals using method 1 simulation (including time signature).

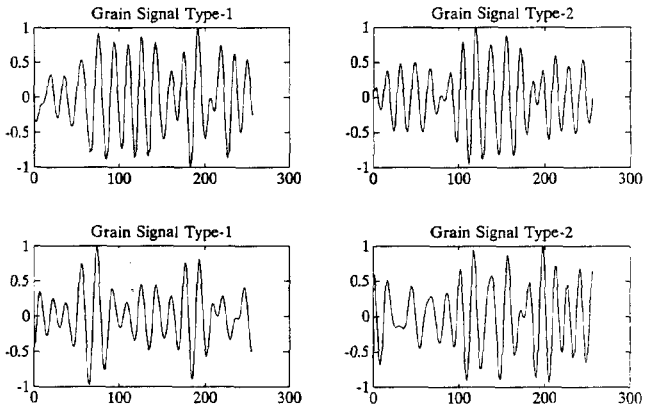

Figure 4. Simulation of ultrasonic grain scattring signals using method 2 simulation (including frequency signature).

random impulses (grain signature functions) distributed randomly over 256 data points. The noise signal consists of 256 random numbers which are superimposed on the grain signature function. Both the grain signature and random noise have uniform density functions and the signal-to-noise ratio is zero dB for both Type-1 and Type-2 microstructure signals. The bandpass filter is Gaussian with a center frequency of 5.86 MHz and 3dB bandwidth of 2.1 MHz. Figure 4 is simulated using 128 random impulses distributed randomly over 256 data points. This random signal is bandpass filtered (Gaussian shape) with 3 dB bandwidth of 2.1 MHz and center frequencies of 5.86 MHz (representing Type-1), 6.25 MHz (representing Type-2). Note that the signals presented in Figures 3 and 4 are very similar to random patterns of ultrasonic backscattered grain signals. All these random signals have different inherent time or frequency signatures which are not readily recognizable. Therefore, it is the goal of this investigation to utilize neural networks for ultrasonic backscattered signal classification.

FEATURE SELECTION METHODS

Signal Conditioning and proper feature selection methods are always desirable in order to increase the sensitivity of neural networks for a higher degree of pattern recognition. In this study, we normalized the microstructure signals to be bounded between +1 and -1. These samples of the normalized signal are applied to neural networks directly (Direct Method) or preprocessed for feature selection before being applied to the neural network. The methods of feature selection are signal power spectrum (PS Method), autocorrelation (AC Method), and autoregressive (AR Method) coefficients. The mathematical relationship for these methods are:

Direct Method:

$$Input\ Signal = \hat{r}\ (\ nT\ )\ ;$$

PS Method:

$$Input\ Signal = PS\ (\ k\omega\ )$$

$$= FFT(\hat{r}\ (\ nT\ ))\ *\ Conj\ (FFT\ (\hat{r}\ (\ nT\ )))\ ;$$

AC Method:

$$Input\ Signal = IFFT\ (PS(k\omega))\ ;$$

AR Method:

$$\hat{r}(nT\ ) = \sum_{i=1}^{N} a_i\ \hat{r}(nT-iT\ )\ ;$$

$$Input\ Signal = a_i$$

Where

$\hat{r}(nT)$: Normalized sampled values of the backscattered signal
T: Time sampling interval
FFT: Fast Fourier transform
IFFT: Inverse FFT
a_i: AR coefficients estimated using the Burg algorithm
ω: Frequency sampling interval

A block diagram of neural network signal recognition using the above feature selection methods is shown in Figure 5.

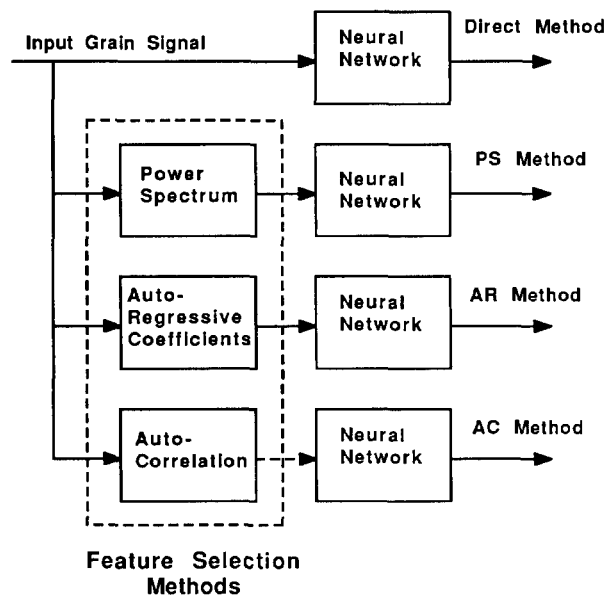

Figure 5. Block digram of neural network signal recognition using different feature selection methods.

DESIGN OF NEURAL NETWORKS

In this study, both three and four layer neural networks have been used. The three layer neural network consists of 256 input nodes, 127 hidden layer nodes, and 1 output node. The four layer neural network consists of 256 input nodes, 2 hidden layers of 127 and 255 nodes, and one output node. These neural networks have been evaluated for both time and frequency signature functions of grain scattering. The training set consisted of two sets of data (50 sets Type-1 and 50 sets Type-2). Each type of data contained its own unique grain signature function. A new set of 100 testing sequences (50 set Type-1 and 50 set Type-2) was used to evaluate the performance of the trained network. Training tolerances of 0.1 and testing tolerances of .1 and .4 were both used.

Time Signature Recognition

Simulation method 1 (see Figure 1) is used to simulate the grain signal with a time signature function. Data was obtained using a 100 MHz sampling rate. The two bandpass filtered signals are Gaussian centered at 5.86 MHz and 6.25 MHz with a 3dB bandwidth of 2.1 MHz. There is a 0 dB signal-to-noise ratio between the imbedded grain signature function and the random noise signal. The results of training the neural network with the Direct Method (no preprocessing except data normalization, see Figure 5), indicates an ability to discriminate between the two training sets with a 100% performance. Subsequent training and testing with two sets of data (Type-1 and Type-2), both centered at 5.86 MHz also results in a 100% recognition. This suggests that the neural network for the Direct Method is trained to recognize the time signature function rather than frequency signature. Note that the PS Method, AR Method and AC Method perform poorly when the signal contains only time signature. Incorporated frequency signature in data resulted in improved recognition performance for these methods.

Frequency Signature Recognition

To study the frequency recognition of neural network, grain signals are generated using simulation method 2 (see Figure 2). The frequency signature for Type-1 and Type-2 signals are Gaussian, centered at 5.86 MHz and 6.25 MHz. The bandwidth of these two signals is 2.1 MHz. Note there is a 6% frequency difference between the two signals. The results for training the neural network with the Direct Method (see Figure 5, normalized time domain samples) show that the neural network is unable to perform frequency discrimination in the time domain. Subsequent testing for signals centered at 5.86 MHz and 6.64MHz show an increase to 66% frequency recognition. There is a 9% frequency difference in this case. These results imply that if the two frequencies are significantly separated, the frequency differentiability of the neural network improves.

Frequency signature discrimination has also been investigated with autoregressive (AR Method) coefficients which are estimated using the Burg Algorithm. The rationale for using the AR Method is that it is an all-pole model that will give good peak frequency discrimination. The 10th order model was chosen as being a reasonably accurate estimate of the frequency spectrum. The neural network frequency discrimination of Type-1 and Type-2 data is improved to 100% when the PS method (see Figure 5) was used for feature selection. With this method the neural network was able to perform frequency discrimination above 80%. Subsequent testing using 10th order AR coefficients on signals with frequency separation of 9% showed a 98% performance result. The AR coefficients are only an approximation of the frequency spectrum, however, they are particularly good at estimating peak frequency which is of particular interest in this study.

Autocorrelation of the input sequences is also used to train the neural network. The Autocorrelation (AC Method) is applied to signals at 5.86 MHz and 6.25 Mhz (6% frequency separation). The results show that training the neural network with autocorrelated data produces an impressive 100% performance rate. This indicates that the AC-Method can effectively be used as a means of frequency discrimination. This high performance can be attributed to the property of autocorrelation which emphasizes the frequency component with highest energy. Similar 100% recognition performance is obtained using the PS Method.

EXPERIMENTAL RESULTS

The main objective for using neural networks is to classify materials experimentally according to their ultrasonic scattering characteristics. The experimental data is obtained with a Panametric broadband transducer with a 6.22 MHz center frequency and a 3 dB bandwidth of 2.75 MHz. Two types of data are generated from a steel block type 1018. Type-1 represents signals backscattered from the specimen with an average grain size of 14 um. Type-2 is the signal from the sample with an average grain size of 50 um. Two sets of experimental results for both Type-1 and Type-2 are shown in Figure 6. The grain size of the two samples has been analyzed by the intercept method that correlates to the average grain boundary spacing. Using a 100 MHz sampling rate, 20 observations were obtained for each material at different locations. This has been done in order to minimize correlation between the backscattered data. The resulting data consisted of 20 observations of each sample with an array length of 2048 points. Both 3 and 4 layer neural networks have been used to classify the scattering signal with training tolerances set at .1 and testing tolerances set at .4. The neural network has been trained using different segments of the 2048 length data set. In this case the segments of data used were either 1-256, 1000-1255, or 1793-2048. As in the simulated data case, the experimental data has been preprocessed for feature selection in one of 4 different ways (see Figure 5).

The results show that training the neural network directly with the raw experimental data produces a 81%-87% recognition accuracy. This indicates that the neural network is an effective means for providing discrimination of ultrasonic backscattered signals. Training the neural network with power spectrum coefficients provides a 56%-84% recognition performance. However, using power spectrum coefficients seems to be dependent on the location of the training/testing data segments. Training the neural network with the autocorrelation of the experimental data shows an 81%-87% recognition performance. Tests using the 10th order AR coefficients for training the neural network provides a 62%- 72% accuracy. The lower performance of the AR coefficients could be due to

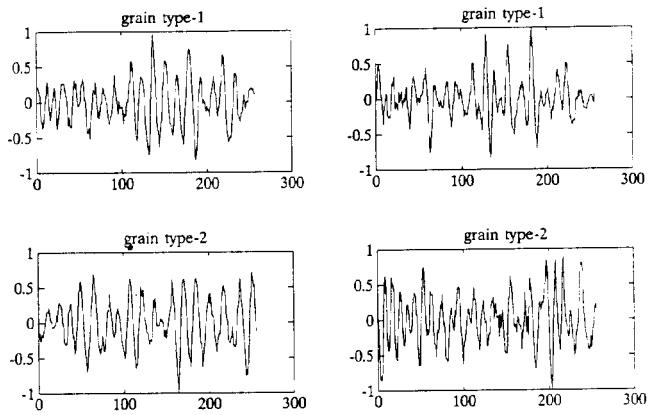

Figure 6. Ultrasonic grain signals backscattered from steel samples (Type-1 grain size is 15 micrometers and Type-2 grain size is 50 micrometers).

the low order of AR coefficients and small frequency differences between Type-1 and Type-2 experimental data.

CONCLUSION

This study has shown that neural networks can be used as an effective means for ultrasonic grain signal discrimination. The inherent time and frequency signatures associated with grain scattering adjusts the neural network weights resulting in the desired output for recognition. It has also been shown that by preprocessing the raw data for feature selection, the frequency discrimination ability of the neural networks is enhanced.

ACKNOWLEDGEMENT

This work is supported in part by the office of Naval Research, Contract/Grant # N00014-92-J-1735.

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