Performance Evaluation of Neural Network Based Ultrasonic Flaw Detection

Sungjoon Yoon, Erdal Oruklu and Jafar Saniie
Department of Electrical and Computer Engineering
Illinois Institute of Technology
Chicago, Illinois, 60616

***Abstract*—In this study, a robust flaw detection algorithm using Neural Networks (NN) is presented for NDE applications. A three-layer feedforward NN which can perform a complex nonlinear mapping process has been used as a detection processor following the subband decomposition of the measured signal. The neural network architecture is trained to suppress the clutter echoes while maintaining the integrity of flaw echoes. The training process allows the neural network to learn about the statistics and the variation of the clutter signal. The robustness of the NN method is examined through testing materials with different grain sizes and multiple flaws. It has been shown that NN can improve the flaw-to-clutter (FCR) ratio significantly when the input experimental signal has FCR equal to 0 or less. Experimental results show that a typical FCR improvement of 40dB can be achieved using NN post detectors as opposed to 15dB with the conventional techniques including minimum, median, average, geometric mean and polarity detectors. The experimental results also confirm that the NN detector is capable of distinguishing two adjacent flaw echoes whereas the conventional techniques detect the presence of a single anomaly only. Furthermore, due its trainability, NN performs robustly when some of the subband signals used for detection have little or no flaw information.**

I. Introduction

Ultrasonic target detection and classification in the presence of high grain scattering echoes is a significant NDE problem. In the ultrasonic testing of materials, it has been reported that the grain scattering echoes are randomly distributed across the entire frequency bands of the measured signal while the flaw signal is more visible in lower frequency bands [1]. Split spectrum processing (SSP) is an effective solution to decompose the broadband measured signal into several subbands [2]. The SSP combined with a post-detection processor can be used to enhance the flaw-to-clutter ratio (FCR). In this study, we evaluate the performance of several different processors including neural networks [3], median, minimum, average, polarity and geometric mean detectors. Neural networks provide superior FCR performance when compared to the other post-detection processors. Furthermore, realization of neural networks as an embedded processor is quite practical and the feasibility of a hardware/software realization of neural networks for real-time ultrasonic target detection systems has been reported in [4].

II. Split Spectrum Processing

The block diagram of an ultrasonic target detection system using SSP is shown in Fig. 1. The received ultrasonic signal, $r(n)$, is the input to SSP, $z_i(n)$ is the output of the ith bandpass filter, and α_i is the scaling factor to obtain the equally powered output signals of the SSP channels. Fig. 2 shows experimental data in the time domain (Fig. 2(a)) and frequency domain (Fig. 2(b)) as well as the frequency response diagram of the 8-channel SSP bandpass filters (Fig. 2(c) and Fig. 2(d)). Fig. 2(d) shows the frequency responses of the 8 subbands filters which cover the full frequency spectrum of the signal. In this case, some subband filter outputs may have zero or very low FCR and are considered to be null observations. Therefore, a robust flaw detection method which offers minimal sensitivity to the frequency coverage of filters is desirable. In this study, we evaluate the performance of different conventional detectors compared to neural networks applied to subbands spanning different spectrum ranges of the experimental signal.

III. Neural Networks

Neural networks are nonlinear mapping processes that allow training and adaptability for signal classification applications. The learning process enables neural networks to recognize the target patterns without mathematical models of the target signals. In this study, three-layer feedforward neural networks are used as the post-processor of the ultrasonic flaw detector. A diagram of a three-layer feedforward neural network with SSP is shown in Fig. 3. The neural nods in the second layer (which is called the hidden layer) receive the weighted inputs from the SSP outputs and then perform the activation function which is a non-linear mapping calculation. The mathematical equation for the neural nodes can be expressed by

$$y_j = \varphi(\sum_i w_{ji} x_i + b_j) \tag{1}$$

where x_i is a set of inputs of each neuron, y_j is a set of outputs of each neuron, and b_j is a set of bias of each neuron. Each input is multiplied by a weight coefficient w_{ji}. The subscript ji refers to the input i in neuron j. The term φ is an activation function. The activation function used in the hidden layer is the sigmoid function which can be expressed by

$$\varphi(x) = (1 + e^{-x})^{-1} \tag{2}$$

The output neural node sums up the weighted output of the hidden layer without an activation function. The learning process gives neural networks the ability to learn their environment and improve their performance. We adopt the backpropagation algorithm to train the neural network for the ultrasonic target detection system. The backpropagation

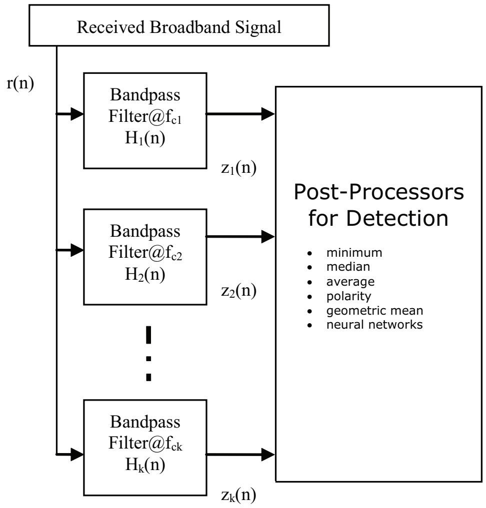


Fig. 1. Block diagram of split-spectrum processor

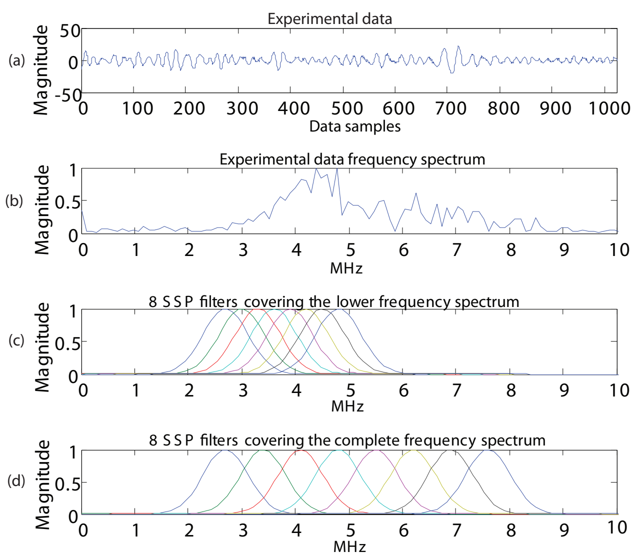


Fig. 2. Frequency spectrum of the experimental signal and bandpass filter locations

learning process is accomplished by adjusting the weights and bias values based on a set of input patterns and the corresponding set of desired output which is composed of an impulse for the flaw echo position and zeros for the microstructural scattering echoes. The neural networks have 8 input nodes and 5 hidden nodes.The number of input nodes is same as the number of SSP channels. The number of hidden nodes is chosen to achieve an acceptable detection performance by trial and error method.

IV. Performance Evaluation of Post-Processors

Neural networks results are compared with the other conventional post-processor such as minimum, median, averaging, geometric mean and polarity detectors [5], [6], [7].

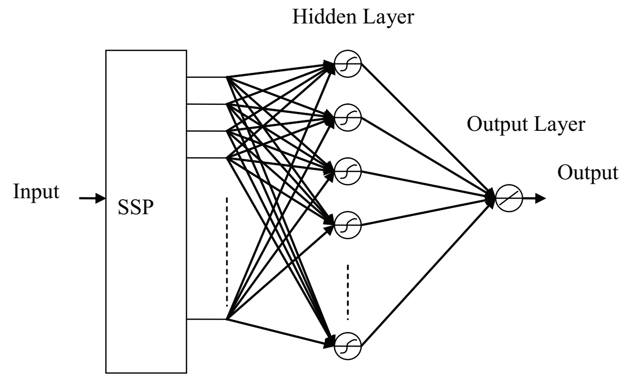


Fig. 3. A three-layer feed forward neural network with SSP

The equations of these techniques are as follows:
Averaging:

$$\phi_{av}(n) = \frac{1}{k}\sum_{j=1}^{k} |z_j(n)| \tag{3}$$

Median:

$$\phi_{med}(n) = median\left[|z_j(n)|\right],\ j = 1, 2, ..., k \tag{4}$$

Minimum:

$$\phi_{min}(n) = min\left[|z_j(n)|\right],\ j = 1, 2, ..., k \tag{5}$$

Geometric Mean:

$$\phi_{gm}(n) = \sqrt[k]{\prod_{j=1}^{k} |z_j(n)|} \tag{6}$$

Polarity Thresholding:

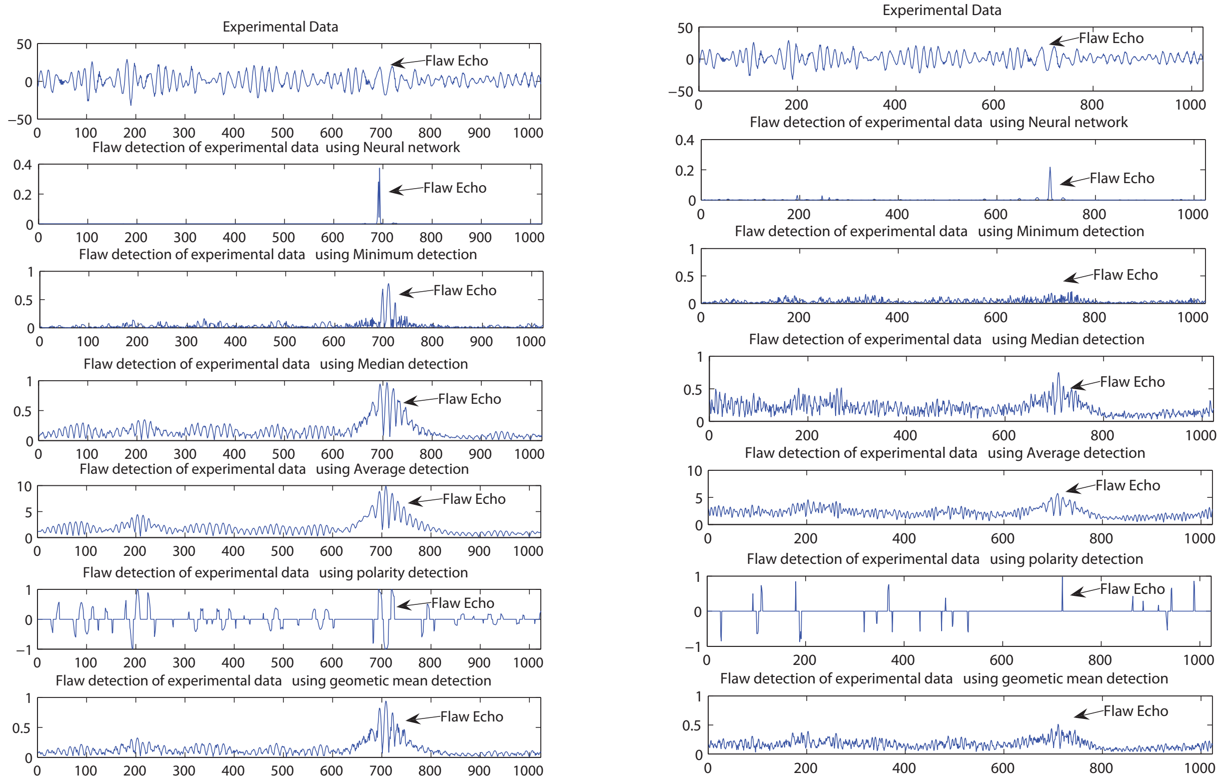
$$\phi_p(n) = \begin{cases} & if\ z_j(n) > 0\ or \\ z(n) & if\ z_j(n) < 0 \\ & for\ all\ j = 1, 2, ..., k \\ & \\ 0 & otherwise \end{cases} \tag{7}$$

where z_j is the SSP output on channel j, and k is the total number of the SSP channels.

For performance evaluation, the experimental A-scan data is acquired from a steel block (type 1018, grain size 50μm). The A-scan measurements were conducted using an ultrasonic transducer of 0.5 inch diameter with 5 MHz center frequency and 100 MHz sampling rate. Flaws are formed in the steel block by drilling several holes (1.5 mm diameter). For performance evaluation, flaw-to-clutter ratio (FCR) is calculated from the ratio of the maximum flaw echo amplitude and the largest amplitude of clutter echoes. Therefore, FCR can be defined as

$$FCR = 20 * log_{10}(F/C) \tag{8}$$

where F is the maximum flaw echo amplitude and C is the maximum clutter echo amplitude.



(a) FCR improvement results when SSP filters cover the low frequency region of the signal

(b) FCR improvement results when SSP filters cover the full frequency spectrum of the signal

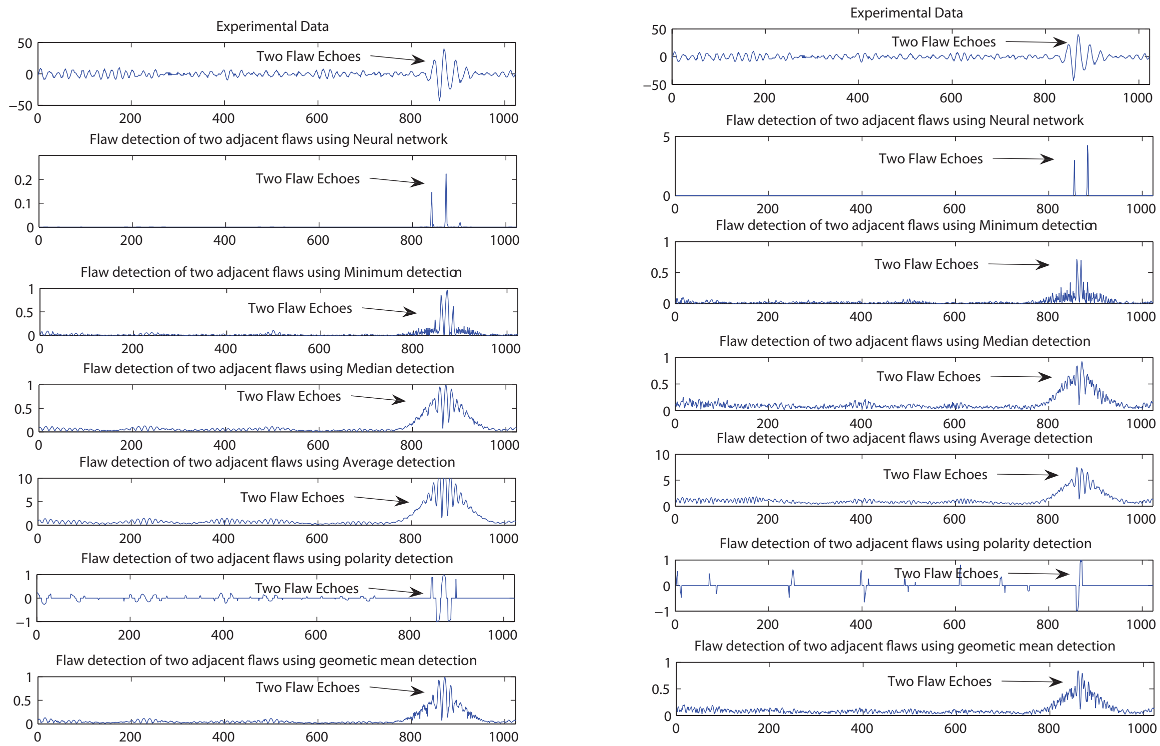
Fig. 4. Comparison of post-processing methods for experimental ultrasonic data with a single flaw

TABLE I
FLAW-TO-CLUTTER ENHANCEMENT OF VARIOUS FLAW DETECTORS USING EXPERIMENTAL DATA WHEN SSP FILTERS COVER THE LOW FREQUENCY REGION OF THE SIGNAL

Trial No	Input FCR	Neural Network detector	Minimum detector	Median detector	Average detector	Geometric Mean detector	Polarity Threshold detector
1	2.2dB	41.7dB	9.2dB	5.4dB	5.2dB	6.1dB	0.1dB
2	0.0dB	44.6dB	6.5dB	6.6dB	4.1dB	5.9dB	0dB
3	1.5dB	47.1dB	7.3dB	8.2dB	6.0dB	6.9dB	0dB
4	2.7dB	55.4dB	5.7dB	5.8dB	2.8dB	6.6dB	0dB
5	0.0dB	45.5dB	5.0dB	7.8dB	5.0dB	7.7dB	0dB
6	0.0dB	46.7dB	13.6dB	8.9dB	7.0dB	9.2dB	0dB
Mean	1.1dB	46.8dB	7.9dB	7.1dB	5.0dB	7.0dB	0dB
STD	1.2dB	4.6dB	3.1dB	1.4dB	1.5dB	1.2dB	0dB

TABLE II
FLAW-TO-CLUTTER ENHANCEMENT OF VARIOUS FLAW DETECTORS USING EXPERIMENTAL DATA WHEN SSP FILTERS COVER THE FULL FREQUENCY SPECTRUM OF THE SIGNAL

Trial No	Input FCR	Neural Network detector	Minimum detector	Median detector	Average detector	Geometric Mean detector	Polarity Threshold detector
1	2.2dB	26.3dB	0dB	0dB	1.7dB	0dB	1.1dB
2	0.0dB	44.6dB	4.7dB	0dB	0.8dB	1.6dB	0dB
3	1.5dB	22.5dB	0dB	2.6dB	2.5dB	2.3dB	0dB
4	2.7dB	22.2dB	2.8dB	0dB	1.5dB	2.5dB	0dB
5	0.0dB	13.6dB	0dB	0dB	0dB	0dB	0dB
6	0.0dB	16.9dB	2.4dB	3.3dB	2.0dB	2.4dB	1.0dB
Mean	1.1dB	23.7dB	1.7dB	1.0dB	1.4dB	1.5dB	0.3dB
STD	1.2dB	10.8dB	2.0dB	1.5dB	0.9dB	1.2dB	0.5dB



(a) FCR improvement results when SSP filters cover the low frequency region of the signal

(b) FCR improvement results when SSP filters cover the full frequency spectrum of the signal

Fig. 5. Comparison of post-processing methods for experimental ultrasonic data with two interfering flaw echoes

The comparison results of various detectors applied to SSP channels covering the low frequency region (ranging from 1.5 MHz to 6 MHz) are shown in Fig. 4(a). In this frequency region, there are no null observations. With the NN detector, the flaw echo is sharply detected without visible clutter. The other detectors improve the visibility of the flaw echo moderately. Fig. 4(b) shows the comparison results of various detectors applied to SSP channels covering the full frequency spectrum (ranging from 1.5 MHz to 9 MHz) of the ultrasonic data. It is important to point out that null observations exist in this frequency range. Neural networks can still detect the flaw signal; whereas the other detectors barely detect or fail to distinguish the presence of the flaw echo. Table I and Table II show the FCR results of the original input data and six different post-processors with two different subband filters coverage. These results confirm that the NN detector not only outperforms the conventional flaw detection methods but also shows less vulnerability to null observations.

The detection of two adjacent flaws is another challenging problem due to the interference between two flaw echoes. Fig. 5(a) and Fig. 5(b) show the comparison results of various ultrasonic target detectors for the detection of two adjacent flaw echoes with subbands spanning two different frequency ranges. These results show that neural networks can distinguish two adjacent flaw echoes whereas conventional post-detection processors fail to detect the presence of two flaws.

V. Conclusion

In this paper, we have presented a comparative study of neural network ultrasonic flaw detection techniques with respect to conventional post-processing methods including the minimum, median, average, geometric mean and polarity detectors in two different SSP conditions. The neural networks show superior results not only for single flaw echo but also for multiple flaw echoes even in the presence of null observations.

References

[1] J. Saniie, T. Wang, and N. M. Bilgutay, “Analysis of homomorphic processing for ultrasonic grain signal characterizations,” *IEEE Trans. Ultrason., Ferroelectr., Freq. Control*, vol. 36, pp. 365–375, May 1989.

[2] V. Newhouse, E. Ferguson, N. Bilgutay, and J. Saniie, “Flaw to grain echo enhancement,” in *Proc. of Ultrasound International Conference*, 1979, pp. 152–157.

[3] H. Sun and J. Saniie, “Nonlinear signal processing for ultrasonic target detection,” in *Proc. of the IEEE Ultrasonics Symposium*, vol. 1, Sendai, Japan, October 1998, pp. 855–858.

[4] S. Yoon, E. Oruklu, and J. Saniie, “Dynamically reconfigurable neural network architectures for ultrasonic flaw detection,” in *Proc. of the IEEE Ultrasonics Symposium*, Vancouver, Canada, October 2006, pp. 1377–1380.

[5] J. Saniie, K. Donohue, and N. Bilgutay, “Order statistic filters as postdetection processors,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 38, pp. 1722–1732, October 1990.

[6] N. Bilgutay, U. Bencharit, and J. Saniie, “Enhanced ultrasonic imaging with split-spectrum processing and polarity thresholding,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 38, pp. 1722–1732, October 1989.

[7] J. Xin, K. Donohue, N. Bilgutay, and X. Li, “Frequency-diverse geometric and arithmetic-mean filtering for ultrasonic flaw detection,” *Materials Evaluation*, pp. 987–992, August 1991.