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Detection of Ultrasonic closer flaws using Nonlinear signal processing

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The ultrasonic flaw detection is an important problem in the nondestructive evaluation (NDE) of materials. In order to successfully detect and classify flaw echoes from high scattering grain echoes, an efficient and robust method is required. In this paper, a method using split-spectrum processing (SSP) combined with a neural network (NN) has been developed and applied on the ultrasonic signals to perform the detection of closer echoes. SSP can display signal diversity and is therefore able to provide the signal feature vectors for signal classification. The neural network (NN) performs highly complex nonlinear mapping by which signals can be classified according to their feature vectors. Therefore, the combination of SSP and NN (SSP-NN) presents a powerful technique for ultrasonic NDE. The SSP is achieved by using Gaussian bandpass filters. Then, an adaptive three layer neural network using a backpropagation learning process is applied to perform the classification processing of frequency diverse data. The SSP-NN method has been tested using both simulated and experimental ultrasonic signals, and the results show that SSP-NN has good sensitivity in the detection of ultrasonic closer flaws echoes drowned in the noise.
Key word : Ultrasonic NDE, Nonlinear signal processing, SSP, Neural networks

1 Introduction

In ultrasonic nondestructive evaluation (NDE), a broadband acoustic pulse is transmitted into a specimen, and then targets (i.e., crack, flaw, delamination...) as well as microstructure (i.e., grains) will reflect this pulse. The reflected signal is highly complex due to the interference of multiple echoes with random amplitude and phase. Furthermore, the frequency-dependent absorption and scattering property of the specimen will also cause the energy attenuation of the signal. Therefore, the success of ultrasonic target detection depends on the effectiveness of the signal processing algorithm and the development of a robust classification technique. In this study, SSP is used to display the diversity of ultrasonic signals on the time-frequency plane. Then, the nonlinear classifiers are applied to detect targets according to the signal features obtained on that plane. The SSP is implemented by using Gaussian bandpass filters. The parameters of the Gaussian filters include the number of filters, the bandwidth, and their center frequencies. These parameters and signal characteristics govern the signal correlation among the SSP channels. The nonlinear classifier studied in this work is a neural networks (NN).

Neural networks (NN), due to their trainability and adaptability, are powerful tools for signal classification. Without solution methodology or mathematical models of the target signals, NN can recognize the target patterns alter a training process. In NDE applications the important issue in the design of the NN is the selection of the training strategy and training data such that a target echo embedded in a scattering noise can be recognized.

In this paper, we focus on SSP followed by a three-layer feed forward neural network for ultrasonic flaw detection. The design and performance of SSP-NN is examined using both simulated and experimental data.

2 The system structure of SSP-NN

The purpose of the SSP is to enhance the signal SNR ratio by splitting signal spectrum into smaller frequency bands or channels. This method is very helpful if the spectrum of background noise is randomly distributed in the frequency domain and the spectrum of target signals is concentrated in the frequency domain. This is because that since the target signals appeared concentrically in the frequency domain, the correlation among the SSP channels could be used to enhance the SNR ratio. On the contrary, if the noise is randomly distributed on the SSP channels then the correlation will be small.

Due to this reason, in the design of the SSP, the selection of the SSP filter should be based on extracting the target signal by using their correlation on the SSP channels, which is decided by the parameters of the SSP filters, and the signal spectrum property [1]. The implementation of the SSP algorithm is shown in Figure.1.

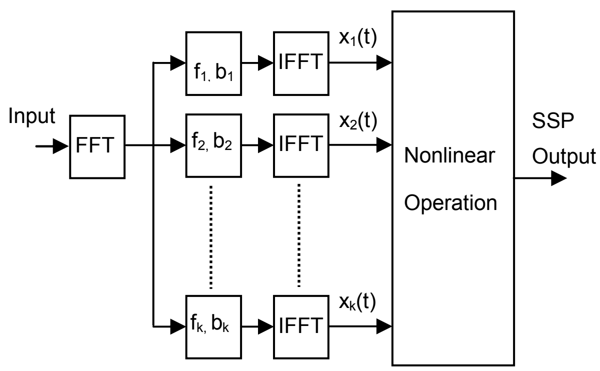

Fig.1 The structure of SSP for generation of k narrowband.

The SSP described above presents only signal features and can be viewed as an initial stage of signal processing. However, we still need another processor which can classify flaw and grain echoes by using the signal feature vectors. As shown in Figure 2, a three-layer feedforward neural network is used for this purpose.

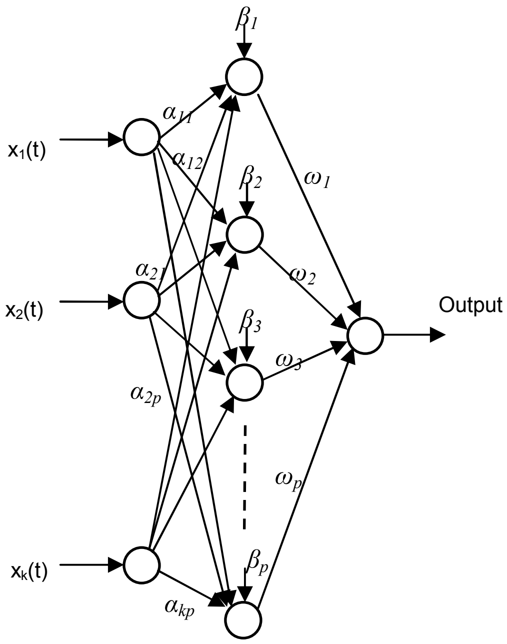

Fig.2 Three-layer Neural network.

The neural nodes in the first layer do not perform any computation but feed signals to the second layer. The neural nodes in the second layer receive the weighted inputs from the first layer and then perform a large mapping calculation by using the activation function to yield the output of the second layer.

Then, the output neural to produce the net output. The neural node model in the nodes in the third layer sum up the output of the second layer connecting weights α_{ij}, and the output connecting weights ω_j second layer consists of connection and activation. The input node and the effect of j-th hidden node on the output node indicate the effect of the i-th input node on the j-th hidden respectively. The cell body is represented by an activation function, sigmoid function, and can be written as:

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

The overall operation of the three-layer neural network can be described by the following equation:

$$f(\bar{x}) = \sum_{i=1}^{p} \omega_i \varphi\Big(\sum_{j=1}^{k} \alpha_{ij} x_j - \beta_i\Big) \tag{2}$$

The importance of the above equation has been examined by many researchers including Kolmogorov [2] in 1957, Lorentz [3] in 1962, Sprecher [4] in 1965, and Cybenko [5] in 1989. Equation (2) approximates any continuous function of k real variables. Therefore, if we can find the parameters ω_j , α_{ij} and β_j to perform a particular mapping function, we can then establish a neural network which can classify flaw and grain echoes. To reach this goal, a training process for neural networks is required. This learning process gives neural networks the ability to learn their environment, improve their performance and ultimately obtain the parameters of ω_j , α_{ij} and β_j for a particular application.

3 Numerical simulation

In order to apply the proposed algorithm, we have set up a numerical experiment simulating a material with two defects very close in time with 100% of noise, as illustrated by the A-scan signal in figures 3, 4 and 5.

The transducer is supposed to be centered at *10MHz*, and the time lag between both defects is variable for the three figures.

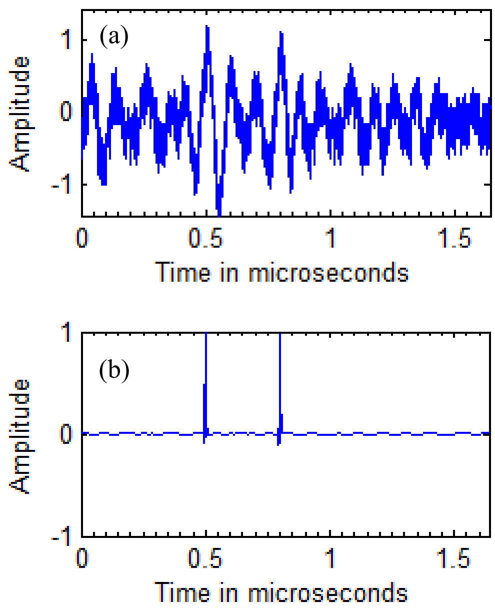

Fig.3 (a) Signal with two echoes drowned in noise separated by $\Delta\tau$*=0.3µs* (equivalent to *0.87mm*), (b) Results obtained by SSP-NN.

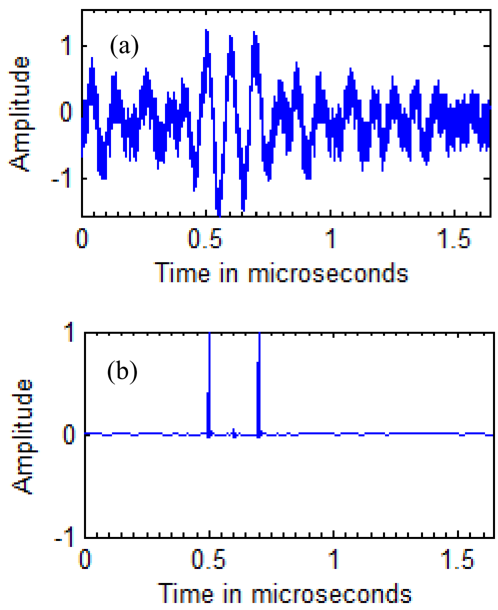

Fig.4 (a) Signal with two echoes drowned in noise separated by $\Delta\tau$*=0.2µs* (equivalent to *0.58mm*), (b) Results obtained by SSP-NN.

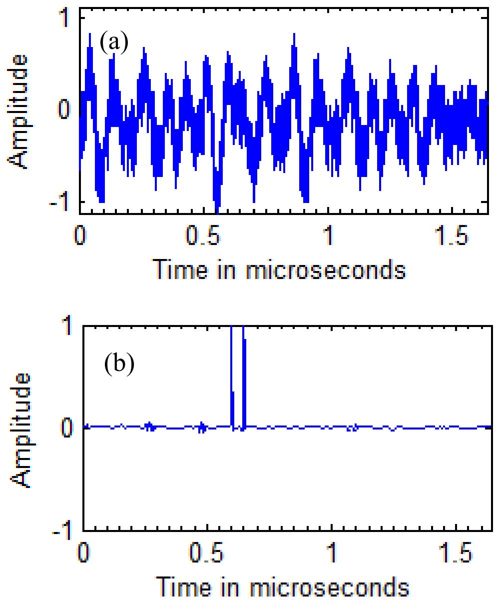

Fig.5 (a) Signal with two echoes drowned in noise separated by *Δτ=0.05μs* (equivalent to *0.14mm*), (b) Results obtained by SSP-NN.

4 Experiments

The experiment undertaken in this work is illustrated in Figure 3.This case is often encountered in industry. Two defects are present in the same zone with distance of some *mm* and having almost equal depths. This geometry gives ultrasonic signals where two echoes are very closer in time and superimposed. This problem of resolution can induce the expert controller in error who could pose a bad diagnosis by affirming the presence of only one defect instead of two defects. So the aim of this experiment is to show the utility of this type of treatment to the users of the NDT by ultrasounds. The parts to be controlled are 3, they are in steel with a thickness equal to 10 mm containing two distant holes of 1, 2 and 3mm respectively and with diameters of 2 mm. The depths of the holes are between 4 and 5 mm. The centre frequency of ultrasonic transducer used in this experiment is 10MHz. Figure 6 shows the layout of a signal obtained on one of the parts where we observe two reflected echoes (echo A and echo B) by the two holes. The objective is to detect the two echoes and to estimate the time which separates them.

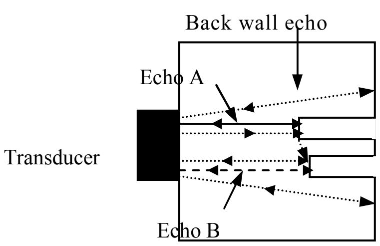

Fig.6 Steel part with two holes leading to the back face.

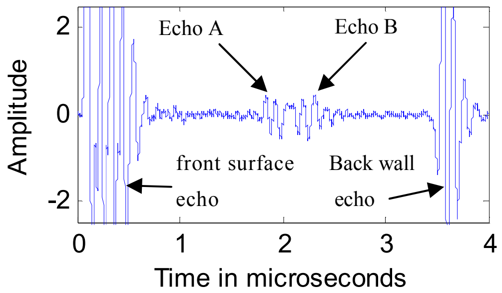

Fig.7 A-scan signal of the part with two echoes.

The experimental signals obtained are illustrated by the figures 8a, 9a and 10a. The results of SSP-NN, they are illustrated by the figures 8b, 9b and 10b.

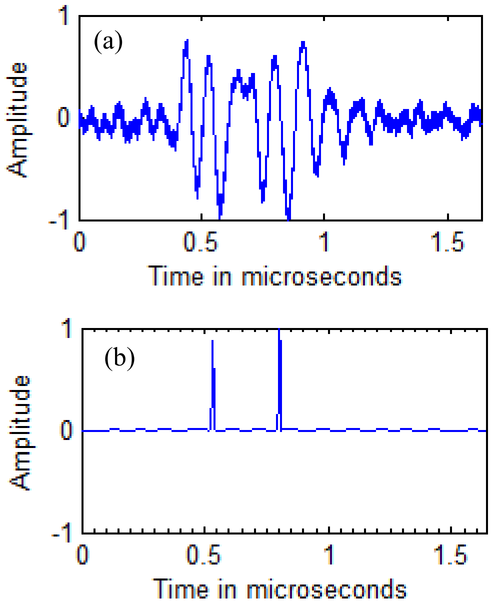

Fig.8 (a) A-scan signal of the part with two distant holes of 3*mm*, Output of SSP-NN (τ_A=0.53μs, τ_B=0.8μs and $\Delta\tau$=0.27μs).

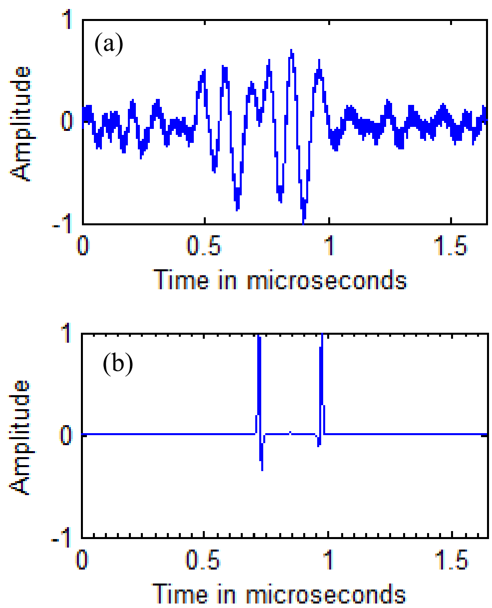

Fig.9 (a) A-scan signal of the part with two distant holes of 2*mm*, Output of SSP-NN (τ_A=0.71μs, τ_B=0.97μs and $\Delta\tau$=0.26μs).

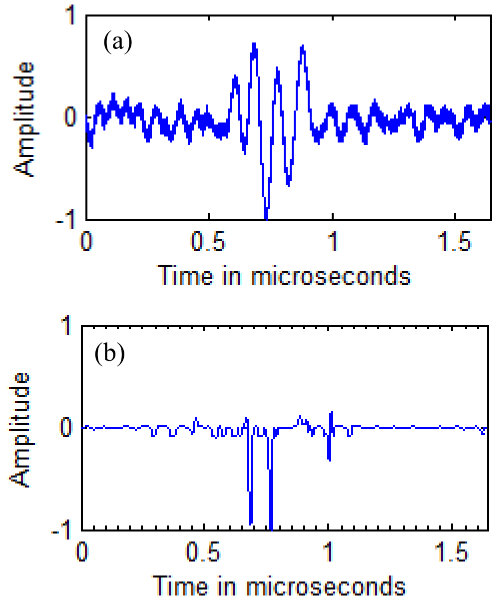

Fig.10 (a) A-scan signal of the part with two distant holes of 1*mm*, Output of SSP-NN (τ_A=0.7µs, τ_B=0.76µs and $\Delta\tau$=0.06µs).

5 Conclusion

In this work, we have applied the SSP algorithm combined with neural network for the ultrasonic flaw detection application. The SSP algorithm utilizes the inherent property of ultrasonic signals on the frequency domain to enhance the SNR of flaw echoes. This algorithm also provides the signal features on the joint time-frequency plane, which are used by the nonlinear classifiers for detection purpose. In the implementation of the SSP filters, the affecting factors include the number, the bandwidth, and the center frequencies of the SSP channels. In addition, the overlap among the SSP channels decides the correlation of the SSP charnels. These parameters are very sensitive to affect the result of the SSP algorithm. In our design, the number and the bandwidth of the SSP channels are selected to cover the entire frequency bands of the transmitted broadband ultrasonic echoes. The signal correlation on the SSP channels is obtained by carefully adjusting the filters' parameters as well as inspecting the frequency property of the grain and flaw echoes, and filters are selected to optimize the system performance.

We have shown that SSP-NN can he used for ultrasonic flaw detection in a situation where the flaw echo is highly masked by grain scattering echoes. The SSP algorithm creates signal features, which can be applied to the NN for the purpose of pattern of the target signal should he emphasized over the signal recognition. In the training of the neural network, the pattern of grain scattering. This study has demonstrated that a three-layer feedforward neural network, when properly trained, is able to perform highly complex signal recognition. The experimental part which validated these results enabled us to determine with precision the position of the various echoes and consequently the differences in depths between the defects.

Like prospect with this work, generalization with more than two echoes on the same signal remains to be developed.

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