SPLIT SPECTRUM TECHNIQUE AS A PREPROCESSOR FOR ULTRASONIC NONDESTRUCTIVE EVALUATION

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INTRODUCTION

Nondestructive evaluation (NDE) is the process of detecting, locating, characterizing and sizing of an anomaly in an engineering material. There are many methods of performing NDE of which ultrasound is a widely used technique. Ultrasound has been used for several decades as a tool for nondestructive evaluation and material characterization and has emerged as a powerful method of analysis with the on going computer revolution. Many powerful and computationally intensive methods and algorithms have become feasible with the availability of very fast and not-too-expensive computers. Analog-to-digital conversion and digital signal processing have become common in ultrasonic signal analysis for both nondestructive evaluation and noninvasive diagnosis. Some of the signal analysis techniques in use today are (1) deconvolutions [1], (2) Homomorphic signal processing techniques such as cepstrum analysis [1], (3) feature extraction and feature classification techniques [2] and (4) artificial neural networks [3, 4]. These signal analysis techniques have been shown to be very effective for all the phases of NDE ranging from detection to characterization and sizing.

Deconvolutions and homomorphic analysis [1] are effective methods of improving the detection and, to a certain extent, characterization of the anomalies. Feature extraction and classification as well as artificial neural networks are effective tools for the characterization and sizing of previously detected anomalies. The techniques are very effective in analyzing ultrasonic signals which are not corrupted by a high degree of material noise (interference noise produced due to ultrasonic scattering by material texture). However, when the signals being processed have a low signal-to-noise ratio (SNR) due to the presence of ultrasonic material noise, the performance of all the techniques will be adversely affected which might result in unreliable detection and/or characterization of the anomalies. As a result, it would be necessary to first enhance the SNR of the input signals by using some method of signal processing.

There are several methods of SNR enhancement when the ultrasonic signals are corrupted by noise due to scattering of ultrasound by the texture of the material being inspected. This paper deals with the effectiveness of split spectrum processing (SSP) [4-8] in improving the performance and reliability of signal analysis techniques such as deconvolutions and neural networks when used in tandem with such techniques.

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BACKGROUND INFORMATION AND MOTIVATION

Split spectrum processing (SSP) is the process of reducing material noise through decorrelation of ultrasonic signals by virtue of frequency diversity obtained by multiple bandpass filtering of the received ultrasonic signals. The methodology has been well documented in literature [4-8]. However, for the sake of completeness, a brief description of the technique follows.

Split spectrum processing is implemented by using many equally spaced overlapping Gaussian bandpass filters to 'split' the spectrum. The center frequencies of the first and the last filters are determined by the half-power bandwidth of the received signal. The bank of filters, when applied in frequency domain (software implementation) to the complex spectrum of the signal received from the test material, split the spectrum into 'N' narrow banded frequency spectra. Each one of the 'N' narrow banded spectra yields one time domain signal when the inverse FFT is taken. The resultant 'N' time domain signals (called split time domain signals or the spectral decomposition components) are normalized. The 'N' frequency diverse signals so obtained are further processed using one of the algorithms of SSP. Further details of the method can be found in the literature [4, 5].

There are two important algorithms that could be applied to the frequency diverse signals obtained by splitting the spectrum. They are minimization [7] and polarity thresholding [4]. Minimization and polarity thresholding algorithms are based on the physics of wave-grain interaction. The fact that the interference pattern changes when the frequency of interrogation is changed is utilized by the algorithms of SSP. Further details of the algorithms can be found in the literature [4].

It has been shown in the past [4] that performance of SSP is substantially improved when the algorithms are used in tandem. It was shown that when two algorithms are applied by selecting the minimum amplitude (absolute minimum with its algebraic sign restored - see reference [4] for details) only when there is no polarity reversal, SNR enhancement increases several folds. Hence, the algorithms have been used together for this paper, first minimization and then polarity thresholding.

Split spectrum processing has been traditionally used only to improve SNR of the ultrasonic signals which in turn improves the detectability of anomalies [4-8]. The technique has not played a significant role in the characterization and sizing of anomalies. The reason for this was that the original implementation of SSP [7] did not retain the phase information necessary for many of the characterization methods. However, the modified implementation of SSP [4, 5] has eliminated the problem and has rendered the SSP technique useful for characterization and sizing applications as well.

It was shown recently [9] that SSP does indeed retain size information to be able to size the detected anomalies using amplitude information. The purpose of this paper is to demonstrate that the phase information, although altered nonlinearly by the recently modified [4] SSP process, can still be used for characterization applications because the nonlinearities introduced are consistent for all the input signals thereby transforming the input signals into a new 'domain'. As a result, as long as a similarly modified point spread function (PSF) is used, deconvolutions can be still performed, and, as long as the artificial neural network (ANN) is retrained with the processed training signals, the ANN can still be used for characterizing the reflections from the anomalies.

RESULTS

Results from three different samples will be presented to demonstrate three different aspects of NDE. First, signals from EPRI ultrasonic database [10] (obtained from centrifugally cast stainless steel) will be presented before and after SSP processing to demonstrate the improvement of location information. Second, results of processing signals obtained from a wing spar made of a thick (0.75") composite will be presented to demonstrate the improvement in system identification and deconvolution. Third, results of impact damage characterization using ANN will be presented both before SSP and after SSP to demonstrate the improvement of reliability of ANN processing due to improved input SNR (after input signals are processed by SSP technique). Yet another aspect of NDE, sizing, has been demonstrated in literature before [9].

Centrifugally Cast Stainless Steel

The signals for this part of the work were obtained from an ultrasonic database provided by EPRI [10]. The database has six files of which three are obtained using 1 MHz transducer and the other three files are obtained using 2.25 MHz transducer. Although all the files have been processed using SSP, only one signal will be presented to demonstrate how SSP can solve the ambiguity regarding the location of the targets.

The signals shown in Figure 1a is signal number 305 from the EPRI data file 'THIK2MHZ.KB1' which contains signals from thick (33.53 mm thick) welded plates using 2.25 MHz transducer. The signal in Fig. 1a clearly shows ambiguity regarding the number and the exact location of the echoes from anomalies in the material. For example, in Figs. 1a, the large ringing amplitude pattern in the middle indicates anomalous behavior. However, since the anomalous amplitudes are spread over almost three microseconds, and also since there is no clear separation of the echoes, it is not possible to draw conclusions regarding the exact location of the anomalies.

Signal in Figure 1b is the SSP processed signal of Figure 1a. The signal has been processed using 14 filters of approximately 0.1 MHz bandwidth each. The filter bank was located between 1.72 MHz and 2.23 MHz (the separation between filters was 0.04 MHz). The processed signal not only provides the exact location information but also shows clear indication of the presence of multiple echo pulses.

Thick Composite - Wing Spar

A signal obtained from a thick composite (approximately 19.05 mm thick-composite wing-spar) using 3.5 MHz transducer is shown in Fig. 2a. The signal shows the front surface echo, a back surface echo and another strong echo from inside the composite itself. The signal also shows strong material noise produced due to the interference of the ultrasonic waves by the material texture such as fibers, porosity, etc.

The signal in Fig. 2b is the result of Wiener filtering the signal in Fig. 2a. An experimentally obtained point spread function (PSF) was used for the generation of the Wiener filter as discussed in literature [11]. The result of Wiener filtering shows unsatisfactory performance due to the presence of substantial noise content.

Figure 2c is the result of SSP processing of the signal in Fig. 2a. The processing has been performed using 36 filters of 0.575 MHz bandwidth each, separated by 0.05 MHz. The filters are placed between 1.95 MHz and 3.66 MHz. The processed signal shows an excellent SNR enhancement compared to Fig. 2a.

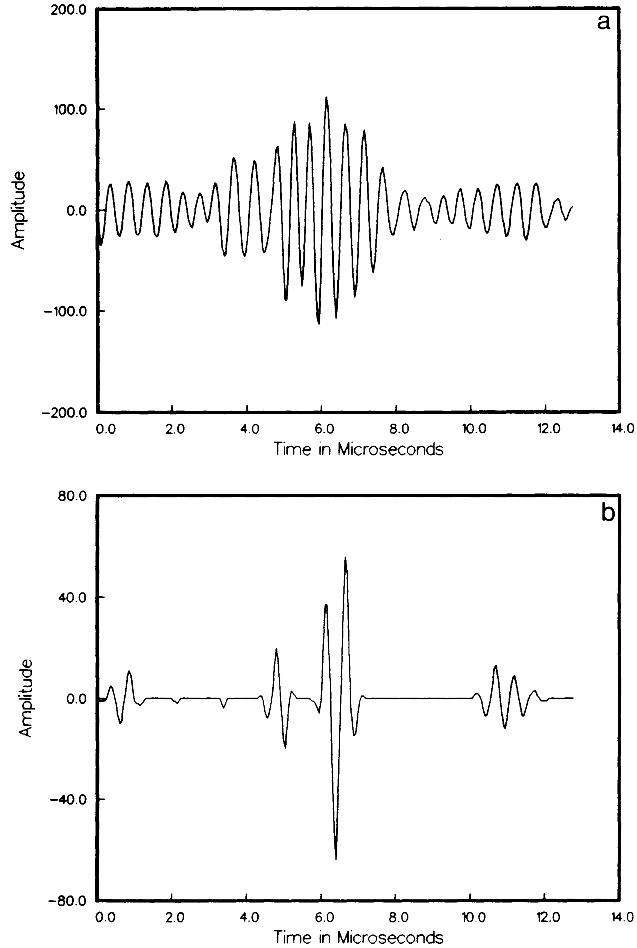

Figure 1 (a) Signal # 305 from the EPRI database file THIK2MHZ.KB1. The signal shows anomalous amplitude in the center. (b) SSP processed signal shown in Fig. 1a. The anomalous amplitude has now resolved into two reflectors showing accurate location of both the reflectors.

Figure 2d is the Wiener filtered result of processing the signal in Fig. 2c. The PSF used to generate the Wiener filter for Fig. 2d was obtained by SSP processing the PSF used for Fig. 2b. The result of Wiener filtering shown in Fig. 2d has superior performance compared to that in Fig. 2b.

The comparison of Fig. 2a with 2c and Fig. 2b with 2d provides two conclusions regarding the performance of SSP: first, SSP method of SNR enhancement is effective in an anisotropic material such as carbon-epoxy composite. Second, since the result of Wiener filtering using a SSP processed PSF is superior to that without processing, it is obvious that although SSP is a nonlinear processor, the nonlinearity is consistent as is obvious from the success of the 'system identification' process in Figs. 2c and 2d. Hence, SSP technique can be used as a preprocessor to enhance the SNR of signals that are going to be processed by such phase sensitive techniques as deconvolutions, feature extraction and classification methods and neural networks. The results of neural networks processing of SSP processed signals will be presented next.

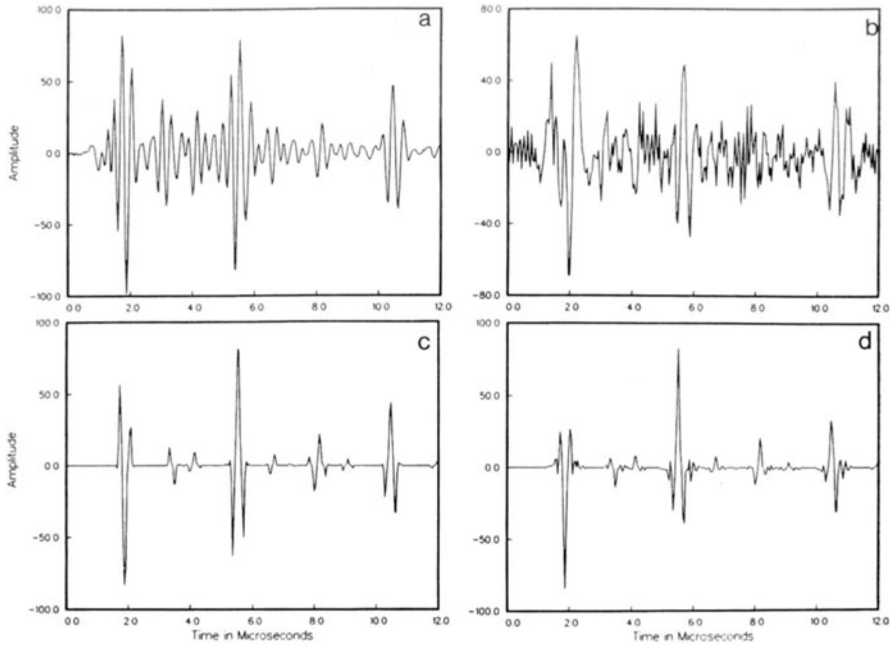

Figure 2 (a) A signal obtained from a thick composite (19.05 mm). The signal shows front wall, backwall and ultrasonic noise from within the sample (b) Wiener filtered result of processing the signal in Fig. 2a (c) Result of processing signal in Fig. 2a using SSP (d) Wiener filtered result of processing the signal in Fig. 2c. The PSF used for the Wiener filter was also processed by SSP.

Artificial Neural Networks - Impact Damage Characterization

Artificial neural networks (ANN) are well suited for anomaly detection and/or classification applications in NDE. There are several types of ANN that could be used in NDE. However, for the present study, back propagation (BP) algorithm has been used. The algorithm has been applied in the Fourier domain (magnitude spectrum) of the ultrasonic signals to eliminate time-delay variability due to surface undulations. Both the unprocessed signals and the corresponding SSP processed signals have been used for ANN analysis. The signals have been collected from an impact damaged composite as reported in an earlier publication [11] and is repeated here for the sake of completeness.

The sample used in this study is a 32-ply thick, quasi-isotropic, graphite-epoxy composite. The separation between ply interfaces in this sample is approximately 0.14 mm. Prior to ultrasonic inspection, the sample was intentionally damaged by a 5.4 Joule impact from a 12.7 mm diameter stainless steel ball on a pendulum impactor.

The impact-damaged graphite-epoxy composite was examined with a 3.5 MHz, 12.7 mm (0.50 in) diameter, 51 mm (2.0 in) focal length transducer operated in a pulse excitation mode. Step sizes for data collection were 0.10 mm (0.004 in) in each direction. A total of 40,000, 256-point-long RF A-scans (200 B-scans containing 200 A-scans each) were digitized, and were stored in the computer.

A C-scan image was generated by applying a broad software gate to the 40,000 unprocessed RF A-scans contained in a series of 200 B-scans obtained as discussed before. The gate was set up just past the front surface echo so as to interrogate the rest of the signal (excluding the backwall echo) in each A-scan collected. Thus, the gate setup will generate a single c-scan (Figure 3a) which includes the damages at all the various depths in the composite (ply-by-ply ANN analysis of the impact damage has been reported by this author in literature [12]). The C-scan in Fig. 3a will be used as a reference image to measure the accuracy of the output from the ANN.

A backpropagation (BP) ANN was used to process the data. The ANN was trained in an unsupervised self-learning mode [12]. The input layer contained 64 nodes while the output layer had two nodes. There was one hidden layer with seven nodes. The A-scan signals for the training were selected based on correlation analysis (see reference [12] for details). Two classes and five examples per class were used to train the network. The training and classifications were implemented in the Fourier domain of the A-scans which was implemented as follows: each A-scan was Fourier transformed and its magnitude spectrum was calculated. The magnitude spectra were the inputs to the network, both for training and classification.

The trained BP-ANN was used to classify all the A-scans obtained from the impact damaged composite panel. Figure 3b shows the resultant 'C-scan'. A comparison of Figs. 3a and 3b on a pixel-by-pixel basis reveals that the 'C-scan' produced by the ANN (Fig. 3b) has 71.11% accuracy of classification when a delamination is present (probability of detection) while the probability of false alarm (detection when none present) was 15.58%.

Split spectrum processing was applied to all the 40,000 A-scans collected from the impact damaged composite panel. A total of 21 filters of 1.63 MHz bandwidth each were applied. The filters were separated from one another by 0.195 MHz and the filterbank was placed between 1.76 MHz and 5.66 MHz. The SSP processed A-scans were Fourier transformed and the magnitude spectra were computed. The magnitude spectra formed the input to the BP-ANN network.

The magnitude spectra of the SSP processed A-scans were used as inputs to a BP-ANN which had the same architecture as discussed before. The network was trained again using the magnitude spectra of the SSP processed signals (a total of 10 training signals) as inputs. After training the network, the entire block of 40,000 SSP processed signals (magnitude spectra) were processed using the BP-ANN.

Figure 3c shows the output from the BP-ANN when the network is trained and used to classify SSP processed A-scan. A comparison of Figs. 3a and 3c on a pixel-by-pixel basis reveals that the 'C-scan' produced by the ANN (Fig. 3c) has 94.28% accuracy of classification when a delamination is present (probability of detection) while the probability of false alarm (detection when none present) was 8.73%. A comparison of theses probabilities from Figs. 3b and 3c is provided in Table 1.

CONCLUSIONS

The results presented in this paper demonstrate that although SSP is a nonlinear algorithm which will modify the amplitude and phase information of the A-scans in a nonlinear manner, the SSP processed A-scans can be still used in ANN and other AI methods and feature analysis techniques. This is possible because SSP is consistently nonlinear in processing the A-scans. The necessary condition for using SSP as a preprocessor would be to be consistent. That is, retrain the ANN with the processed signals or recalculate the feature values and descriminant functions for pattern recognition applications, use a SSP processed PSF for deconvolutions, and so on.

Table 1 Comparison of Probabilities of Detection (POD) and False Alarm (POFA) for the C-scans in Figs. 3b and 3c. The C-scan shown in Fig. 3a was used as a reference to calculate these probabilities.

Figure	POD	POFA
3b	71.11%	15.58%
3c	94.28%	8.73%

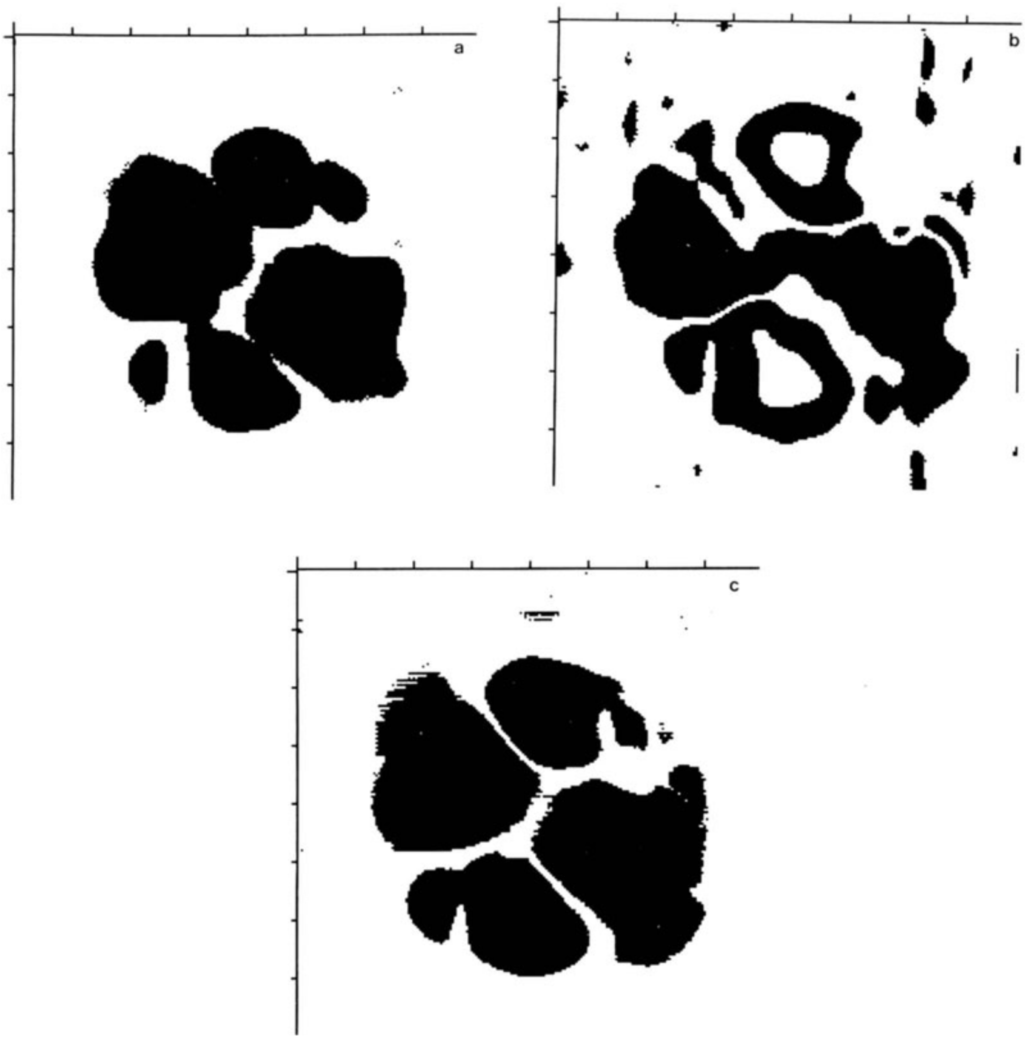

Figure 3 (a) Conventional C-scan of the impact damage in graphite-epoxy composit (b) C-scan produced by BP-ANN using unprocessed A-scans as inputs (c) C-scan produced by BP-ANN using SSP processed A-scans.

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