Higher-Order Statistics-based Deconvolution of Ultrasonic Nondestructive Testing Signals

Ahmed Yamani
K.F.U.P.M. Box 1811
Dhahran 31261, Saudi Arabia
email:myamani@dpc.kfupm.edu.sa

Maamar Bettayeb
K.F.U.P.M. Box 1730
Dhahran 31261, Saudi Arabia
e-mail:maamarab @dpc.kfupm.edu.sa

Lahouari Ghouti
K.F.U.P.M. Box 1128
Dhahran 31261, Saudi Arabia
e-mail:g940143@dpc.kfupm.edu.sa

Abstract

Pulse-echo reflection techniques are used for ultrasonic flaw detection in most commercial instruments. As the measured pulse echo signal is assumed to be the result of linearly convolving the defect impulse response (IR) with the measurement system response, the objective is thus, to remove the effect of the measurement system through a deconvolution operation and extract the defect impulse response. The major drawbacks of conventional second-order statistics (SOS)-based deconvolution techniques are their inability to identify non-minimum phase systems, and their sensitivity to additive Gaussian noise. Our contribution is to show that higher-order statistics (HOS)-based deconvolution techniques are more suitable to unravel the effects of the measurement systems and the additive Gaussian noise. Synthetic as well as real ultrasonic signals are used to support this claim.

1. Introduction

Pulse-echo reflection techniques are used for ultrasonic flaw detection in most commercial instruments [1]. The ultrasonic wave, generated by a piezoelectric transducer coupled to the test specimen, propagates through the material and part of its energy is reflected if the wave encounters an inhomogeneity or discontinuity in its path, while the remainder is reflected by the back surface of the test specimen. A typical oscilloscope display is shown in Fig. 1. The first wavelet represents the initial voltage applied to the transducer in order to generate the wave, while the successive echoes represent the voltage generated by the reflected wave (from the flaw and the back echo respectively) impinging on the transducer. The flaw echo in Fig. 1 contains information regarding the material discontinuity that the ultrasonic wave has encountered in its path. For this, signal processing is used on the flaw echo only, and the other echoes are discarded from subsequent signal display.

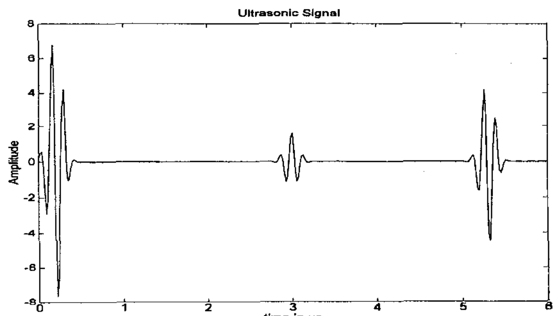

Fig. 1: Typical oscilloscope display of an ultrasonic examination.

Flaw echo signals are masked by the characteristics of the measuring instruments, the propagation paths taken by the ultrasonic wave, and are corrupted by additive noise. It is assumed that the measured flaw echo is obtained by linearly convolving the flaw or the defect impulse response with the measurement system response. Deconvolution operation therefore, seeks to undo the effect of the convolution and extract the defect impulse response which is essential for defect identification.

Conventional deconvolution techniques (CDT) such as least square, Wiener filter, and minimum variance deconvolution [2] are based on a priori knowledge of second-order statistics (SOS) of the noise and the input signal. In practice however, the acoustic noise due to scattering from the grains inside the propagation medium does not have a readily known statistic [3]. Moreover, ultrasonic pulse echoes are found to be non-minimum phase systems. SOS-based deconvolution techniques, being phase-blind cannot therefore, accurately estimate the defect impulse response.

The objective of this paper is to formulate the defect ultrasonic model in the polyspectrum domain where the processing is more suitable to unravel the effect of the measurement system and the additive Gaussian noise. Thereafter, the defect impulse response is recovered from its noise-free polyspectrum. Synthesized, as well as real ultrasonic signals are used to show that the proposed technique excels conventional SOS-based deconvolution techniques commonly used in NDT.

2. Theory

A measured ultrasonic flaw signal, $y(t)$, can be modeled as the convolution of the measurement system response function, $x(t)$, with the flaw's impulse response function, $h(t)$, plus noise, $N(t)$. This model can be written as

$$y(t) = x(t) \otimes h(t) + N(t) \tag{1}$$

where $\otimes$ denotes the convolution operation. With this model, defect of a particular geometry would be completely characterized by its impulse response. Estimation of $h(t)$ in (1), from the knowledge of $y(t)$, and $x(t)$ is variously known as system identification, filtering, or simply as deconvolution. Many deconvolution techniques have been developed in different engineering areas such as seismic exploration, military applications, and medical imaging. Chen [2] has studied the feasible applications of these deconvolution techniques to ultrasonic NDT, and has concluded that Wiener filter is a good candidate for such application. The main drawbacks of CDT are their inability to identify non-minimum phase systems, and their optimal implementation requires a priori knowledge of the noise statistics. These drawbacks can be completely alleviated when using HOS-based deconvolution techniques as is shown in this paper.

Equation (1) can be written in the polyspectrum domain as [4]

$$C_n^{\,y}(w_1, w_2, \ldots, w_{n-1}) = C_n^{\,x}(w_1, w_2, \ldots, w_{n-1}) H(w_1) H(w_2) \cdots H(w_{n-1}) H^*(w + w_2 + \ldots + w_{n-1}) + C_n^{\,N}(w_1, w_2, \cdots, w_{n-1}) \tag{2}$$

where $C_n^{\,s}(w_1, w_2, \ldots, w_{n-1})$ is the nth-order spectrum of the signal $s(t)$ (which could be $y(t)$, $x(t)$, or $N(t)$), $H(w)$ is the Fourier transform of the defect impulse response $h(t)$, and w is the angular frequency. Without loss of generality, (2) can be rewritten as

$$C_n^{\,y}(w_1, w_2, \ldots, w_{n-1}) = C_n^{\,x}(w_1, w_2, \ldots, w_{n-1}) C_n^{\,h}(w_1, w_2, \ldots, w_{n-1}) + C_n^{\,N}(w_1, w_2, \ldots w_{n-1}) \tag{3}$$

For Gaussian noise, the polyspectrum $(n>2)$, of $N(t)$ is zero and thus, the noise-free polyspectrum of the defect impulse response can be calculated from (3), and used to recover $h(t)$. Alternatively, if the bispectrum is used , i.e., $n=3$ above, then the noise does not have to be Gaussian to be filtered out from (2) and (3). It can have any symmetric probability density function (PDF). With one of these noise assumptions in mind, equation (2) and (3) represent the basis for the HOS-based deconvolution technique used in this paper.

3. Results

In this section, the HOS-based deconvolution technique is tested on synthesized as well as real ultrasonic signals obtained from artificial defects [2]. For computational efficiency, bispectra of the input-output signals are used only. In addition, as the recovery of a signal from its bispectrum is not a one-to-one transformation, we calculate the bicepstrum using the relationship between biceptrum and bispectrum defined by Pan and Nikias [5], thereafter, the defect impulse response is recovered using the bicepstral parameters [6].

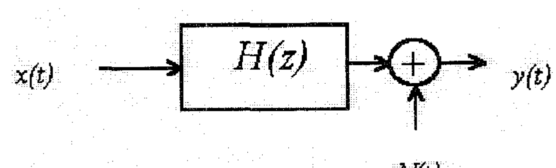

Fig. 2: The ultrasonic defect model

3.1 Synthesized Data

With reference to Fig. 2, the input signal, *x(t),* is taken as a Gaussian pulse that is amplitude modulating a single tone carrier whose frequency lies in the ultrasonic range. The noise, *N(t),* having a normally distributed PDF, is scaled by a constant, α , to account for different signal - to-noise ratios (SNR). Three different linear time-invariant systems are considered in this paper, namely:

- A non minimum phase moving average (MA) system whose transfer function is given by

$$H_{MA}(z) = 0.2197z^{2} - 0.747z + 0.6085 + 0.1533z^{-1} \quad (4)$$

- A minimum phase autoregressive (AR) system whose transfer function is given by

$$H_{AR}(z) = \frac{1}{1 - 0.7z^{-1} + 0.6z^{-2} - 0.3z^{-3}} \quad (5)$$

- A non minimum phase autoregressive moving average (ARMA) system whose transfer function is given by

$$H_{ARMA}(z) = \frac{1 - 3.25z^{-1} + 3.5399z^{-2} - 1.2487z^{-3}}{1 - 1.86z^{-1} + 1.47z^{-2} - 0.5246z^{-3}} \quad (6)$$

For a given SNR, the output signal, *y(t),* is computed using the model of Fig. 2. The bispectrum *(n=3)* of the system impulse response (SIR) is obtained from (3), and used to recover *h(t)* using the bicepstral parameters as stated above. To test the performance of the proposed technique, the variance of the error signal (between the true and estimated SIR signals of the MA system above) is computed for each SNR. Fig. 3 shows this result for a SNR as low as -5 dB. For comparison, a similar error variance is computed when the MA SIR is estimated using Wiener filter and is shown in the same figure. It can be clearly seen that the HOS-based deconvolution technique excels its counterpart CDT represented here by Wiener filter.

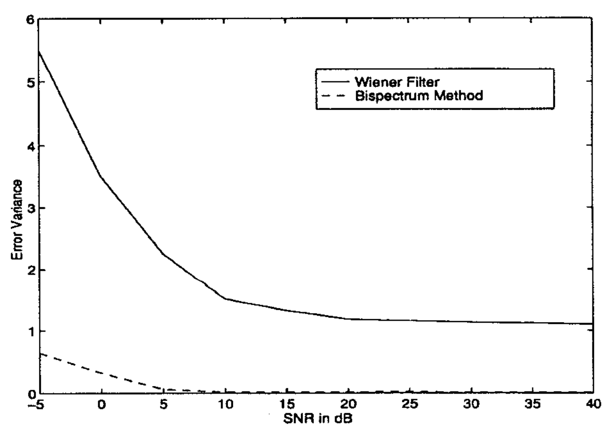

Fig.3: Error variance of the MA system impulse response.

To quantify the effect of these error variances on the estimated MA SIR, a plot of the later at a SNR=5dB is shown in Fig. 4. It can be seen that while the estimated impulse response obtained from the HOS technique is faithfully reproduced, the Wiener filter, at an error variance of about 2.2, fails completely.

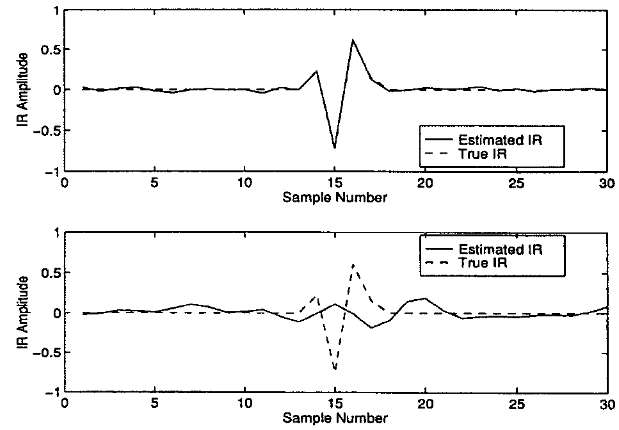

Fig. 4: MA system impulse responses obtained from HOS (top), and Wiener filter (bottom) deconvolution techniques for 5 dB SNR.

To complete this section, the AR and ARMA systems as defined by (5) and (6), are tested and their corresponding SIR estimated using the proposed technique for a SNR= 5 dB, are shown in Figs. 5 and 6 respectively.

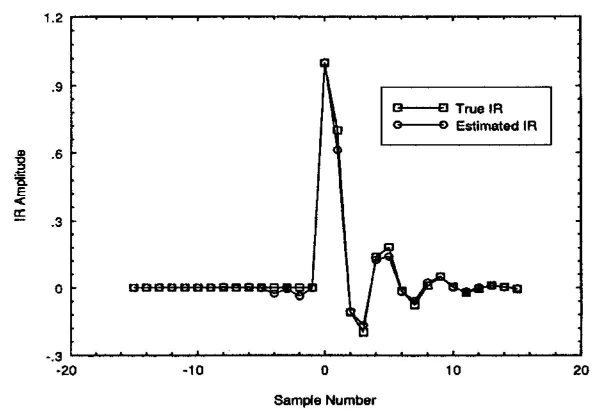

Fig. 5: AR system impulse response : true and estimated SIR for a SNR = 5 dB.

Again, the HOS-based deconvolution technique, with its potential of preserving the phase information, faithfully reproduces the SIR of both minimum (Fig. 5), and non minimum (Fig. 6) phase systems even at extremely low SNR. The small variations shown in Figs. 5 and 6 may be attributed to errors made in computing the cepstral parameters from the bicepstrum [5].

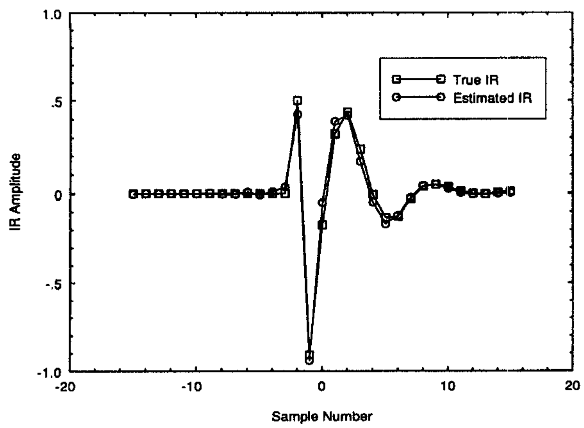

Fig.6 : ARMA system impulse response : true and estimated SIR for a SNR = 5 dB.

3.2 Real Ultrasonic Data

The proposed deconvolution technique is tested using real ultrasonic data [2], which is part of a larger data set obtained from the Army's Material Technology Laboratory, (Watertown, MA). The input signal, *x(t),* is measured in practice, from a flawless sample (A0), having the same characteristics as the specimen under test. It is referred to; sometimes; as the reference signal. Two artificial defects are considered; namely a flat-cut (A1), and an angular-cut hole (A2), in aluminum blocks, (see [2] for an illustration of these defect geometries). The center frequency of the transducer used is 15 MHz, and the A-scan signals contain 512 data points digitized at a rate of 100 MHz. The pulse-echo signals corresponding to A0, A1, and A2 samples are represented by T15A0, T15A1, and T15A2 respectively. For clarity, the signal T15A1 is shown in Fig. 7.

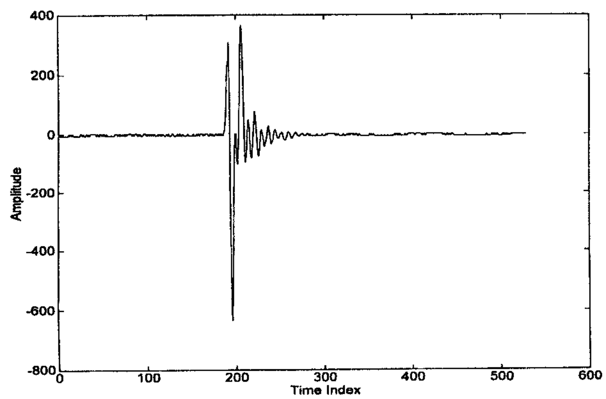

Fig. 7:Ultrasonic Pulse echo measured from sample A1.

When the bispectrum-based deconvolution technique is applied to real ultrasonic signals, namely; T15A1 and T15A2, with T15A0 taken as the reference signal, smooth, oscillation-free impulse responses are obtained as shown in Figs. 8 and 9. For comparison with CDT, the reader is referred to [7] where the same signals have been used.

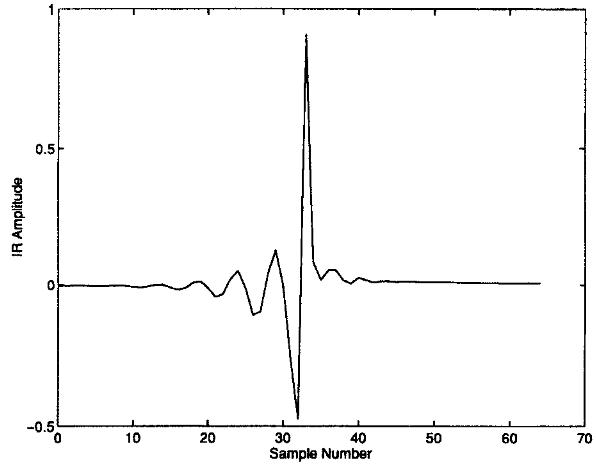

Fig. 8: Impulse response of the flat-cut hole (A1).

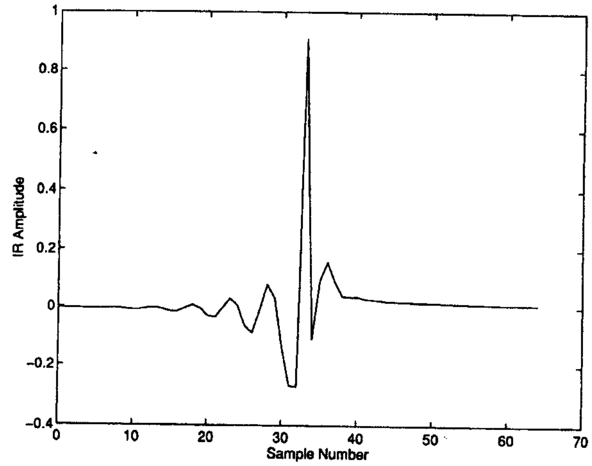

Fig. 9: Impulse response of the angular-cut hole (A2).

4. Conclusion

In this paper, we have shown that the drawbacks of the SOS-based CDT are completely removed when HOS-based deconvolution techniques are used. Synthesized, as well as real ultrasonic signals have been used to demonstrate this claim. Although we have focused on a non parametric deconvolution technique, and the bispectrum case of the polyspectra, higher-order based, parametric blind deconvolution techniques can also be used to remove the effect of the measured reference signal. Future work will be directed towards the influence of different reference signal models on the deconvolved defect impulse response using both polyspectra and polycepstra of real ultrasonic signals.

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5. References

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