ORTHOGONAL SIGNAL DECOMPOSITION COUPLED WITH BAYES AND FUZZY DISCRIMINANT CLASSIFIERS FOR ULTRASONIC FLAW DETECTION

Han C. Sun and J. Saniie

Electrical and Computer Engineering Department
Illinois Institute of Technology
Chicago, Illinois 60616

Abstract

The performance of an ultrasonic flaw detection system is valued by its success in differentiating flaw echoes from those scattered by microstructures (e.g. grain scattering or clutter). In order to successfully detect and classify the target echoes from background noise, an effective feature extracting method and a robust decision process are required. In this study, we present a comparative evaluation of three orthogonal signal decomposition methods: constant B (bandwidth); constant E (energy); and constant Q (i.e., ratio of bandwidth to center frequency), spanning the entire frequency band of the signal. An efficient method of implementing orthogonal decomposition using the Haar filter is presented in this paper. Orthogonal decomposition of the signal offers feature vectors suitable for classification and signal evaluation. The differences observed in the probability density function of clutter and the flaw echoes resulting from orthogonal decomposition are utilized to design the Bayes and fuzzy discriminant classifiers for flaw detection. These classifiers show good sensitivities in detecting flaw echoes in the presence of strong clutter where the signal-to-noise ratio is about zero dB. In this paper we present a mathematical derivation for these techniques and experimental results to demonstrate their application in ultrasonic nondestructive testing.

I. Introduction

In the problems of ultrasonic flaw detection, the backscattered ultrasonic signal is affected by the distribution of the grains, characteristics of the target echoes, as well as the frequency dependent absorption and scattering properties of the test materials [1]. These factors cause signal diversity in both time and frequency domains. Therefore, the success of ultrasonic flaw detection depends on the effeteness of a signal processing algorithm revealing the signal diversity and the development of a robust classification algorithm. This leads us to perform time-frequency analysis and apply statistical processing in order to detect flaw echoes in the presence of microstructure scattering [2]. The emergence of the multirate filter band [3] presents a useful tool to decompose the ultrasonic signal on the time-frequency plane. The advantages of using a wavelet packet include the orthogonal decomposition, the full coverage of the entire signal bands, and the flexibility in choosing the filter bands. The first two advantages guarantee that no information related to clutter and flaw will be lost and no redundant information will be involved. Taking advantage of the flexibility in choosing the filter bands, we have explored three methods of signal decomposition, namely constant bandwidth (B), constant energy (E), and constant relative bandwidth to center frequency (Q).

In the implementation of signal decomposition filters, The Haar filter bank [4] is used. The frequency response of the Haar filter bank is a sinc function suitable for the study of the shape, location, and strength of an impulse-like signal such as an ultrasonic echo. A critical factor in the design of these signal decomposition methods is the number of the filter bands. A higher number of filter bands generates more signals for evaluation and flaw detection, but this reduces the bandwidth and causes a high level of interference among neighboring echoes (an undesirable property). Therefore, for a particular nondestructive testing application, the number of filters must be properly evaluated using experimental data.

The decomposed signals on the time-frequency plane can be treated as signal feature vectors and can be used to investigate and thereby to extract the target information. In particular, we have examined the statistical characteristics of target and clutter signals in order to develop a fuzzy discriminant function as an alternative method to the standard Bayes classifier [5]. To develop the fuzzy discriminant function, the first order statistical parameters have been utilized to design the fuzzy membership function [6], and then the fuzzy discriminant function can be designed according to the characteristics of the membership function.

II. Signal Decomposition Algorithm

In this study, ultrasonic signals are decomposed on the time-frequency plane. Then the decomposed signals, served as signal features, are fed to the fuzzy discriminant function or Bayes classifier to detect flaw echoes in the presence of clutter.

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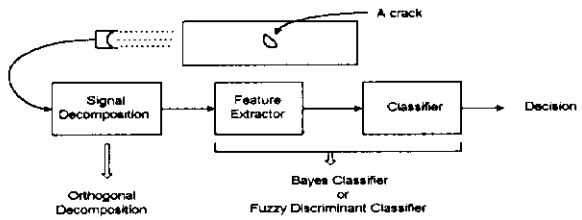

Fig. 1. A General Block Diagram of Ultrasonic Flaw Detection System

Figure 1 shows a general block diagram of signal decomposition and pattern classification for ultrasonic flaw detection. The decomposition is achieved by projecting signals onto the basis functions of the time-frequency plane. In particular, wavelets are chosen to be the basis functions, due to their desirable time-frequency localization properties which spread the signals on the time-frequency plane according to their frequency and spatial range.

The orthogonal expansion of an ultrasonic signal can be represented [4] as

$$x(k)=\sum_{j,m\in z}\langle\psi_{jm},x\rangle\psi_{jm}(k) \qquad (1)$$

where $<\psi_{jm},x>$ is the projection (i.e., inner product) and $\psi_{jm}(k)$ is the wavelet function. The wavelets are generated from one fundamental basis function $\psi(k)$ by dilations and translations :

$$\psi_{jm}(k)=\psi_j(k-m)=2^{\frac{-j}{2}}\psi(2^{-j}k-m) \qquad (2)$$

where j & m represent the index of dilation(i.e., frequency) and translation(i.e., position), respectively. In order to make an orthogonal decomposition, and for the purpose of decomposing impulse-liked ultrasonic signals, the Haar basis is chosen. Haar filters can be implemented efficiently and real-time by using the quadrature mirror filters (QMF) [7] as shown in Figure 2.

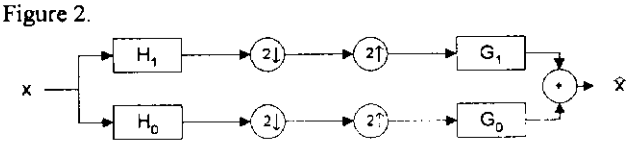

Fig. 2. Two Channel Filter Banks

In this figure, the lowpass filter H_0 and the highpass filter H_1 are called analysis filters. The output of H_0 and H_1 are down-sampled by a factor of 2 due to the reduction of their bandwidth by the analysis filters. Then the decimated signals are up-sampled by inserting a 0 between each sample of the signal and applying it to the synthesis filters, G_0 and G_1.

To satisfy the perfect reconstruction, the following two conditions must be held

$$G_0(z)H_0(-z)+G_1(z)H_1(-z)=0 \qquad (3)$$

$$G_0(z)H_0(z)+G_1(z)H_1(z)=2z^{-l} \qquad (4)$$

Satisfying above conditions, the coefficients for the Haar filter are

$$g_0[k]=(\delta[k]+\delta[k-1])/\sqrt{2},\quad g_1[k]=(\delta[k]-\delta[k-1])/\sqrt{2}$$

$$h_i[k]=g_i[-k],\quad i=0,1$$

Haar filter banks offer important practical advantages such as orthogonal property, FIR, and real-time implementation capability. Furthermore, the Haar filter banks can be applied in sequence leading to a multiresolution decomposition as shown in Figure 3. In this figure, three realization methods are presented by cascading the two channel filter banks in order to obtain constant B, constant E, and constant Q decompositions of ultrasonic signals.

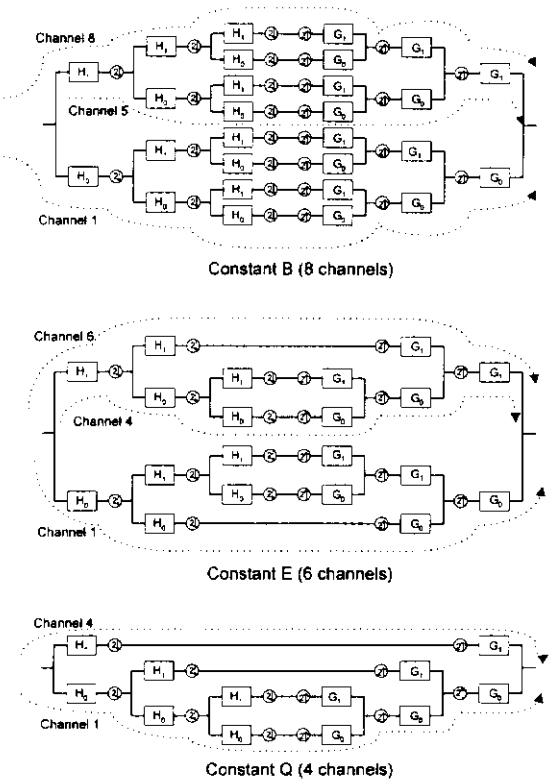

Fig 3 Examples of Constant B, E, and Q Decompositions

After the signals have been decomposed on the time-frequency plane, the signal features can be utilized for target detection. The following section presents the Bayes classifier and the fuzzy discriminant function based on time-frequency features to detect the ultrasonic flaw echoes.

III. Fuzzy Discriminant Function vs. Bayes Classifier

The Bayes classifier has been successfully used in the application of ultrasonic flaw detection [5]. The development of the Bayes classifier is based on the statistical difference between clutter and flaw echoes. The statistical parameters are collected utilizing the decomposed signal on the time-frequency plane. The block diagram of the Bayes classifier is shown in Figure 4.

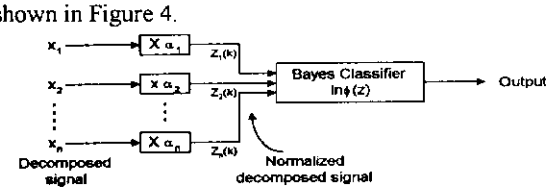

Fig. 4. The Block Diagram of Bayes Classifier

It should be noted that since the power spectrum amplitude of the received echoes is not uniformly distributed, we use the weighting coefficients, α_i, to obtain equally powered output (i.e., normalized decomposed signal) as shown in Figure 4. This normalization allows each channel to contribute equally to the decision process.

The output for the Bayes classifier [5] is

$$\ln\phi(z) = -\tfrac{1}{2}[(z-M_0)^T\Sigma_0^{-1}(z-M_0)] + \tfrac{1}{2}[(z-M_1)^T\Sigma_1^{-1}(z-M_1)] + \tfrac{1}{2}\ln(|\Sigma_0|/|\Sigma_1|) \quad (5)$$

where Σ_i and M_i are the covariance matrix and mean vector.

As an alternative to the Bayes classifier we have developed a fuzzy discriminant function for ultrasonic flaw detection and pattern recognition. Since 1965, when Zadeh [8] introduced fuzzy sets, the theory of fuzzy sets has been used by many investigators [9, 10] to solve problems such as artificial intelligence, control, and pattern classification.

Fuzzy sets are characterized by a class of membership functions which assign a grade (ranging between zero to one) to each member element, and these grades are worked as pointers to indicate the existing possibility of certain signal features.

Mathematically, a fuzzy set A [8] can be written in the form

$$f_A = (u_1 = f_1(z_1),\quad u_2 = f_2(z_2),\quad \cdots u_n = f_n(z_n)) \quad (6)$$

where u_i $i=1\ldots n$ is the grade of membership function f_i, and z_i is the decomposed signal. For the application of ultrasonic echo detection, designing the membership function for each filter channel is a critical step in the performance of membership function. We decomposed the scattered ultrasonic signals using constant B, constant E, and constant Q analyses and examined the histogram at the output of the filters which are found to be Gaussian in shape. Furthermore, the filter outputs are orthogonal and uncorrelated. Hence, this lead us to assume that the distribution of the decomposed output (i.e., membership function) is Gaussian with zero cross-correlation, and different means (m_i) and variances (σ_i) :

$$f_i(z) = \exp(-(\frac{z-m_{i_y}}{\sqrt{2}\sigma_{i_y}})^2) \quad (7)$$

In the above equation, the Gaussian membership function has been normalized to have a maximum value of 1. This equalizes the amplitude on each channel, and such moralization provides the membership grades between 0 and 1.

In this paper we have modified the fuzzy entropy [6] and the fuzzy discriminant function which allows a decision to be made from the information provided by the fuzzy sets. This fuzzy discriminant function is defined as,

$$H^p = \frac{H_T^p}{H_C^p} = \frac{\prod u_{T,i}^p \exp(1-u_{T,i}^p)}{\prod u_{C,i}^p \exp(1-u_{C,i}^p)} \quad (8)$$

where u is the output of membership functions, i is the number of channels, and p is the order created to enhance the difference between H_T and H_C. H_C is the fuzzy entropy of clutter and H_T is the fuzzy entropy of target echoes. In practice, a careful examination of the discriminant function will reveal the optimal value for the selection of the power factor p.

IV. Experimental Results and Discussion

The experimental studies have been conducted using a Panametrics broadband transducer with 5-MHz center frequency. The specimen examined in this study is a steel block type 1018 with average grain size of 50μm. The specimen has two small holes of 1-mm diameter located near the back surface of the steel block. The experimental data has a length of 2048 points sampled at 100MHz. It should be noted that the scattered energy from the holes is not fully directed toward the transducer, and consequently, the signal to clutter ratio of this measurement is about 0dB. The frequency range used for signal decomposition is from 0 to 9.375MHz. In this study 4-channel decomposition and 6-channel decomposition are used and the channel bandwidths are displayed in Figure 5.

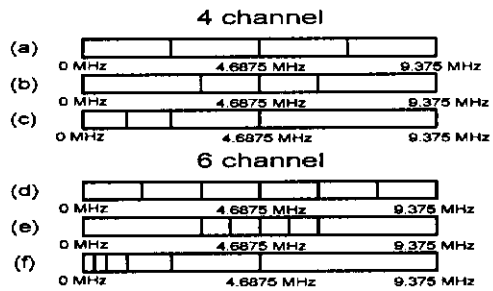

Fig. 5. Display of channel Bandwidth
(a) 4 channel constant B bandwidth
(b) 4 channel constant E bandwidth
(c) 4 channel constant Q bandwidth
(d) 6 channel constant B bandwidth
(e) 6 channel constant E bandwidth
(f) 6 channel constant Q bandwidth

Experimental results are shown in Figures 6 and 7. In each figure, the results are obtained using the Bayes classifier and the fuzzy discriminant classifier.

From the experimental results, we can learn that the technique of signal decomposition combined the statistical processing is a very useful method for analyzing ultrasonic signals with time-frequency distributions. The performance of 4-channel decomposition is better than that of 6-channel decomposition. This is due to the fact that the 4-channel pattern recognition algorithms contain less interference among neighboring echoes than the 6-channel decomposition. Therefore, in the design of a flaw detection system the selection of both the number of filters and the filter bandwidth are critical parameters in signal decomposition and target detection. This requirement may be achieved by incorporating the a priori knowledge of the frequency component of target echoes relative to clutter.

V. Conclusion

In this paper, we have presented three different orthogonal signal decomposition methods combined with the fuzzy discriminant function and the Bayes classifier for ultrasonic flaw detection. In order to make the constant B, E, and Q decompositions, rearranging the filters is necessary and these arrangements have been presented in Section II. Each arrangement presents signal features on the time-frequency

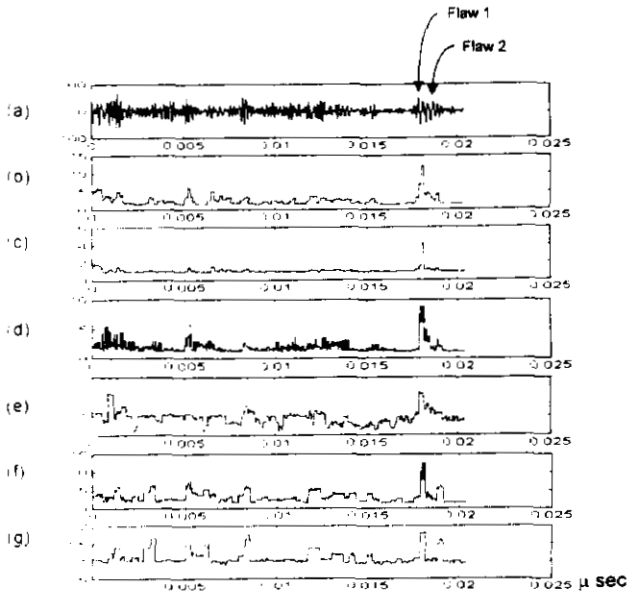

Fig 6 The experimental result by using 4 channel decomposition
(a) The experimental ultrasonic signal.
(b) The output of using constant B and Bayes classifier.
(c) The output of using constant B and Fuzzy discriminant classifier.
(d) The output of using constant E and Bayes classifier.
(e) The output of using constant E and Fuzzy discriminant classifier.
(f) The output of using constant Q and Bayes classifier.
(g) The output of using constant Q and Fuzzy discriminant classifier.

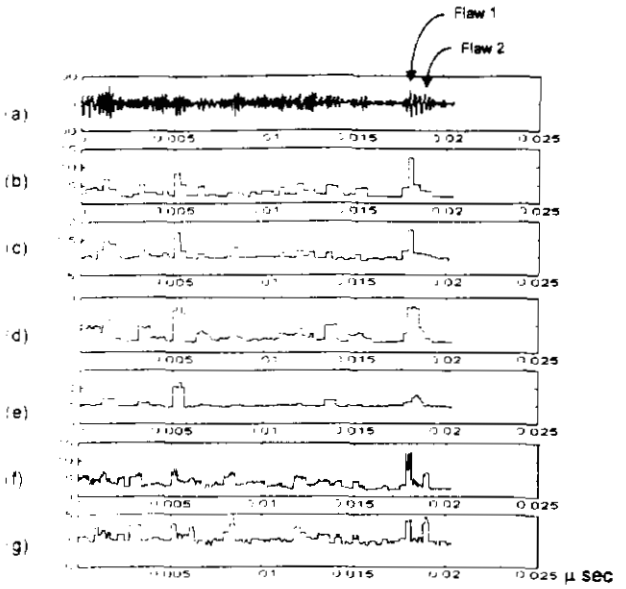

Fig 7 The experimental result by using 6 channel decomposition
(a) The experimental ultrasonic signal.
(b) The output of using constant B and Bayes classifier.
(c) The output of using constant B and Fuzzy discriminant classifier.
(d) The output of using constant E and Bayes classifier.
(e) The output of using constant E and Fuzzy discriminant classifier.
(f) The output of using constant Q and Bayes classifier.
(g) The output of using constant Q and Fuzzy discriminant classifier.

plane according to the time-frequency properties of the signal. Then, the Bayes classifier or fuzzy discriminant function can use these decomposed signals to make the detection decision. The experimental results show that these methods are capable of detecting the flaw echoes in the presence of a high level of microstructure scattering. Due to the randomness of the backscattered signal, some variation in the performance of the algorithm should be anticipated. This uncertainty in performance can be reduced by carefully evaluating experimental data and tuning the parameters by incorporating the a priori knowledge of clutter and target signal characteristics [11].

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