FREQUENCY DIVERSE BAYESIAN ULTRASONIC FLAW DETECTION*

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ABSTRACT

When the range cell of an ultrasonic system contains many unresolved reflectors such as grains, fibers, etc., the detection of flaws embedded in the range cell is obscured by echoes scattered from the microstructure. In general, microstructure echoes (clutter) are random, and more sensitive to changes in frequency than flaw which is generally larger in size. Through split-spectrum processing, frequency diverse scattering information of both microstructure and flaw can be obtained. The statistical difference between clutter and flaw echoes has led to the development of a Bayes classifier which is quadratic and can incorporate the correlation properties of scattered echoes. The performance of the Bayes classifier has been examined for both experimental and computer simulated data, and is compared to other commonly used techniques such as mean, minimum, median and polarity detectors. It has been observed that the Bayes classifier exhibits superior performance, such that the flaw-to-clutter visibility has been improved by a margin of 5-15 dB when the measured flaw-to-clutter ratio is zero dB or less.

INTRODUCTION

Defect detection by ultrasonic techniques has been proven to be an effective means to assure the quality of materials nondestructively. However, the performance of ultrasound is limited when the level of echoes from the surrounding unwanted reflectors is comparable to or larger than that of the defect signal. Frequency diversity based on shifting the frequency of the transducer can decorrelate coherent noise and proper post detection processing will result in flaw-to-clutter ratio enhancement [1,2]. A practical method in implementing frequency diversity is by transmitting a broadband echo through the materials and bandpass filtering the received echoes over many sub-bands of frequencies [1]. Since the microstructure consists of unresolved and randomly distributed reflectors, the detected echoes exhibit randomness in amplitude and are sensitive to shifts in the transmitted frequency. In general, flaw echoes exhibit different scattering distributions as a function of frequency when compared with microstructure scattering. Therefore, at any given time, the outputs of bandpass filters can be represented as a random feature vector which contains information related to flaw and microstructure echoes. The statistical approach for flaw detection, utilizing the statistical properties of this feature vector, is to design flaw detection algorithms.

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In this paper, we focus on the use of the Bayes classifier designed for flaw detection and microstructure noise discrimination based on information collected from the output of bandpass filters of the split-spectrum processor (SSP). The performance of the Bayes classifier is examined using both computer simulation and experimental results.

THEORY OF BAYESIAN DETECTION

An effective method of obtaining frequency diverse information is through splitting the spectrum of broadband echoes. Since the power spectrum amplitude of the received echoes is not uniformly distributed, we use a set of weighting coefficients $\alpha_1, \alpha_2, \cdots, \alpha_K$, in order to obtain the equally-powered output signals. Then, the weighted, filtered outputs are passed to the Bayes classifier for optimal detection. The entire split-spectrum Bayes classification procedure is illustrated in Figure 1.

The feature vector at any given time t can be represented as:

$$Z = [z_1, z_2, \cdots, z_K]^T \tag{1}$$

where, $z_i = r_i(t)$, and is the i-th filter's output signal after normalization, and K is the total number of bandpass filters used in the split-spectrum technique. The design of the discriminant function can be accomplished with the Bayes decision rule which is optimum in the sense of minimizing the probability of error [2,3]. The Bayes classifier used for flaw detection is concerned with the following hypotheses at a specific time t_n,

H_0 : Flaw Plus Clutter Echoes
H_1 : Clutter Echoes

Using the above hypotheses, the criterion for decision making can be represented by:

$$\phi_{op}(Z) = \frac{p(Z/H_0)}{p(Z/H_1)} > \frac{P(H_1)}{P(H_0)} = TH \rightarrow H_0 \tag{2}$$

$$\phi_{op}(Z) = \frac{p(Z/H_0)}{p(Z/H_1)} < \frac{P(H_1)}{P(H_0)} = TH \rightarrow H_1 \tag{3}$$

where $\phi_{op}(Z)$ is the likelihood ratio which serves as the discriminant function for classification, $P(H_0)$ is the

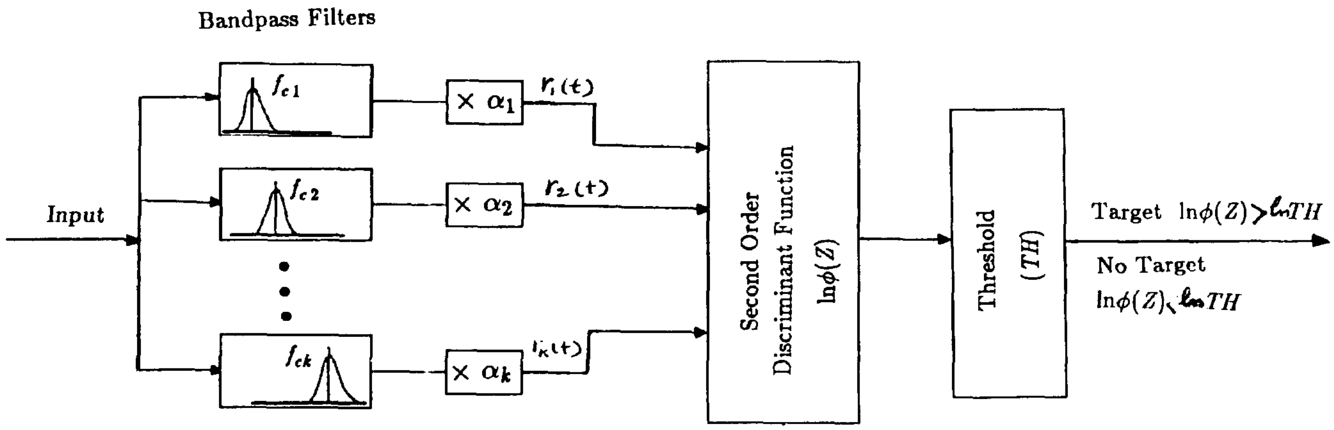

Fig. 1. System block diagram of the Bayes flaw detector using split-spectrum processing.

probability of the presence of flaw, $P(H_1)$ is the probability of the absence of flaw, and $P(H_1)/P(H_0)$ is the detection threshold, TH. The term $p(Z/H_0)$ is the probability density function of flaw-plus-clutter echoes, and $p(Z/H_1)$ is the probability density function of the clutter echoes.

We examined the histogram of the echoes at the output of each bandpass filter, and they were found to be Gaussian in shape with reasonable accuracy. Furthermore, we have observed that an insignificant correlation among the elements of feature vectors exists with reasonable accuracy. This has led to the assumption that the features from bandpass filters are jointly normal with different mean vectors and covariance matrices. For a normal distributed feature vector it is more convenient to write the discriminant function in Log form.

$$\ln\phi_{op}(Z) = \frac{1}{2}[(Z-M_0)^T\Sigma_0^{-1}(Z-M_0)]+\ln\frac{|\Sigma_0|}{|\Sigma_1|} -\frac{1}{2}[(Z-M_1)^T\Sigma_1^{-1}(Z-M_1)] \tag{4}$$

where Σ_0 and M_0 are the covariance matrix and the mean vector for the hypothesis H_0, Σ_1 and M_1 are the covariance matrix and the mean vector for the hypothesis H_1. The above equation is a second order discriminant function that will be used for flaw detection.

In this study, the Bayes classifier has been compared with other recently proposed frequency diverse flaw enhancement techniques such as averaging, the median detector, minimization methods, and polarity thresholding [1,4,5]. The mathematical expressions of these techniques are as follows:

Average detector:

$$\phi_{av}(t_n) = \frac{1}{K}\sum_{j=1}^{K} |r_j(t_n)| \tag{5}$$

Median detector:

$$\phi_{med}(t_n) = Median\ [\,|r_j(t_n)|,\ \ j = 1,2,...,K] \tag{6}$$

Minimum detector:

$$\phi_{\min}(t_n) = Minimum\ [\,|r_j(t_n)|,\ \ j = 1,2,...,K] \tag{7}$$

Polarity thresholding:

$$\phi_{pt}(t_n)=\begin{cases} r(t_n), & \text{if } r_j(t_n)>0 \text{ or } r_j(t_n)<0, \\ & \text{for all } j=1,2,....,K \\ 0, & otherwise \end{cases} \tag{8}$$

where t_n are discrete time instants with n=1, 2, ..., N.

COMPUTER SIMULATION AND DISCUSSION

Computer simulations were performed using signals with different clutter patterns and flaw positions. Furthermore, to best evaluate the performance of flaw detection algorithms, it has been assumed that the flaw signal covers the same frequency band as background grain echoes, although in certain experimental situations, flaw echoes may show different frequency content. If a flaw signal is present in certain frequency bands, it implies that for those frequency bands, a high flaw-to-clutter ratio exists. Consequently, simple bandpass filtering will improve the flaw visibility. In addition, the application of any flaw enhancement algorithms will result in satisfactory performance.

An example of the output signal using the above processing techniques applied to a simulated microstructure signal is shown in Figure 2. This result shows that the Bayes flaw detector out-performs other detectors. Since the performance of flaw enhancement algorithms is generally dependent on the clutter pattern, we have simulated a number of clutter signals with the same statistical properties. Furthermore, to achieve a more realistic picture of the performance, we have compared the Bayes classifier with the other flaw detection algorithms mentioned above. All flaw detection algorithms are examined using the same simulated signals, and the processed results are presented in Table I. This table presents the flaw-to-clutter ratio enhancement results from 20 independent simulations where the flaw echoes were embedded in different locations.

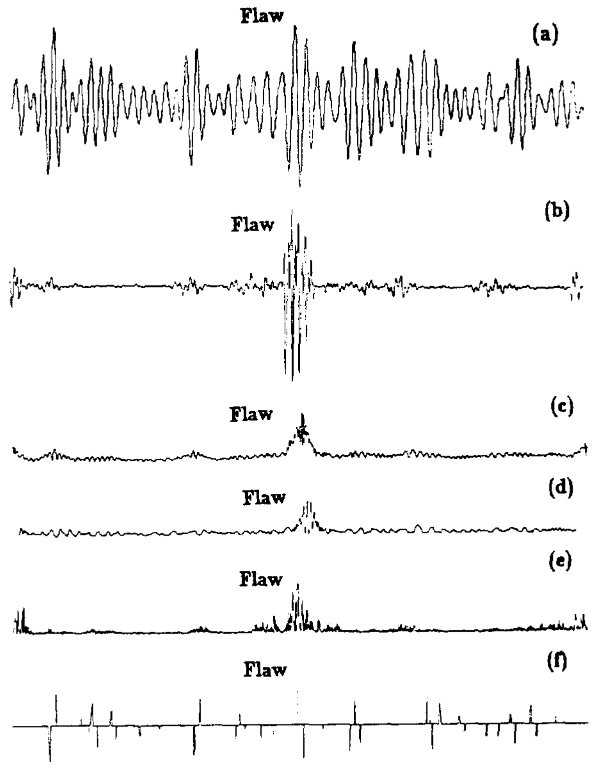

Fig. 2. A comparison of the performance of various signal processing schemes applied to a simulated signal with flaw echo; a) original signal, b) Bayes flaw detector, c) linear detector, d) median detector, e) minimization detector and f) polarity-thresholding.

The mean and standard deviation (SD) for each technique, i.e., Bayes detector, average detector, polarity thresholding, minimum and median detectors, is listed at the bottom of the table. A total of nine bandpass filters with a 2 MHz bandwidth, ranging from 0-14 MHz at frequency step 1.6 MHz, have been used for splitting the spectrum of returned echoes. For all simulated data the input flaw-to-clutter ratio is kept close to unity where the flaw echo is not recognizable by a direct visual inspection of the backscattered signal. It is evident that the performance of the Bayes detector is superior when compared to other flaw detection algorithms. The averaging method, minimum and median detectors provide only moderate improvement. The performance of polarity thresholding is unacceptable. This poor performance results from the fact that this method demands a change in the polarity of clutter echoes, but no change of polarity for flaw signals. In ultrasonic detection, polarity thresholding only works when the F/C is high and, under this condition, many techniques such as a simple threshold detection will be equally as good, if not better.

The performance of averaging techniques, and the minimum or median detector are highly dependent on the amplitude distribution function of returned echoes. Our previous analyses of these techniques indicate that these detectors are suboptimal and only perform well when certain conditions are satisfied [5]. As shown in Table I, the expected F/C enhancement using the Bayes detector is 5.57, while other detectors can only improve detection up to twice. It should be noted that the variance of Bayes performance is also significantly larger than that of the other detectors. This observation suggests that the performance of the Bayes detector is more sensitive to the parameters of the SSP or clutter patterns.

EXPERIMENTAL RESULTS

Experimental studies were conducted using steel specimens with an average clutter size about 50μm and a Panametric transducer with a 6.22 MHz center frequency and a 3-dB bandwidth of 2.75 MHz. Flaws are formed by drilling two different flat-bottom holes, one with a 1.5 mm diameter and 2.5 cm depth and the other with a 2.0 mm diameter and 1 cm depth into the specimen. The complex flaw is formed by drilling two adjacent holes with 1.5 mm diameters, 2.5 cm depths and a mutual distance about 3 mm into the specimen. Ultrasonic measurements were accomplished using the contact technique and data was acquired with a 100 MHz sampling frequency. Nine bandpass filters were used, with 3 dB bandwidth of 1 MHz and ranging from 0.6-9 MHz at frequency steps of 0.8 MHz. This range of frequency provides both flaw and microstructure noise in all nine bandpass channels. Test signals with different F/C ratios were obtained by slightly shifting the transducer beam path away from the flaw position at different directions in order to obtain a flaw-to-clutter ratio about zero dB (i.e., signal has poor F/C ratio). The training process of the optimal flaw detector was accomplished by measuring the clutter signal with and without flaw under the same equipment setting. An example of the output signal, from various signal processing techniques for an experimental measurement is displayed in Figure 3. We repeated these observations for many microstructure signals and results are shown in Table II. Note that trials 1-8 represent the signal from simple flaw and trials 9 and 10 represent the signal from a complex target (i.e., two adjacent flaws).

Inspection of Table II and Figure 3 suggests that the Bayes detector can improve the F/C ratio significantly when compared to other flaw enhancement algorithms. By comparing Figures 2 and 3, we see that the performance of the algorithm applied to experimental results is slightly better than the results of the computer simulation. In computer simulation, we restricted ourselves to the worst case in which the flaw echo exhibits no frequency shift with respect to clutter signal, and the bandwidth of the flaw echo is also the same as that of the clutter echoes. In practice this may not be the case, as often the flaw echoes exhibit a lower frequency band than that of the clutter echoes, which can be beneficial to the performance of the optimal detector.

CONCLUSIONS

We have shown that a second order discriminant function can be used for flaw detection in a situation where clutter echoes are highly dominating. Results show that for a situation in which flaw-to-clutter echoes are about zero dB and direct visual inspection is difficult, an enhancement as high as 15 dB can be obtained. Extensive computer simulations show that the Bayes classifier is an effective flaw detection technique, especially for a low flaw-to-clutter ratio signal.

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Table I. Flaw/Clutter Ratio Enhancement of Various Processing Techniques Using Simulated Signals

Trial NO.	Bayes Detector	Average Detector	Median Detector	Minimum Detector	Polarity Detector
1	2.62	1.07	1.09	2.39	0.42
2	4.40	1.37	1.34	1.80	0.98
3	6.17	1.21	1.82	2.20	0.93
4	10.83	1.03	1.22	3.24	0.56
5	1.79	1.08	1.56	1.13	0.39
6	3.82	1.57	1.46	1.60	0.82
7	3.19	1.06	0.97	2.63	0.20
8	6.09	1.02	1.05	2.36	0.29
9	7.49	1.06	1.08	2.27	0.13
10	7.88	0.97	1.01	1.99	0.29
11	3.34	1.59	1.51	1.45	0.68
12	4.86	1.07	1.28	1.81	0.28
13	7.54	1.04	1.24	1.83	0.22
14	8.04	1.02	1.08	2.08	0.19
15	7.99	1.00	1.19	1.55	0.24
16	7.98	1.05	1.17	1.75	0.31
17	8.41	1.06	1.24	1.96	0.19
18	3.28	1.08	1.20	2.20	0.11
19	2.68	1.04	1.08	2.20	0.11
20	3.25	1.02	1.07	2.19	0.03
Mean	5.57	1.12	1.23	2.03	0.36
SD	2.49	0.17	0.21	0.45	0.27

Table II. Flaw/Clutter Ratio Enhancement of Various Processing Techniques Using Experimental Results

Trial NO.	Bayes Detector	Average Detector	Median Detector	Minimum Detector
1	4.37	1.63	1.56	1.23
2	2.54	1.79	1.40	1.33
3	7.51	2.29	1.57	1.53
4	7.06	2.19	1.27	1.39
5	5.02	1.51	1.16	1.50
6	4.82	1.91	1.37	1.36
7	4.83	2.11	1.66	1.50
8	3.08	1.89	1.32	0.77
9	2.98	1.60	1.25	1.52
10	5.25	1.58	1.27	1.40
Mean	4.75	1.85	1.38	1.35
SD	1.56	0.26	0.16	0.21

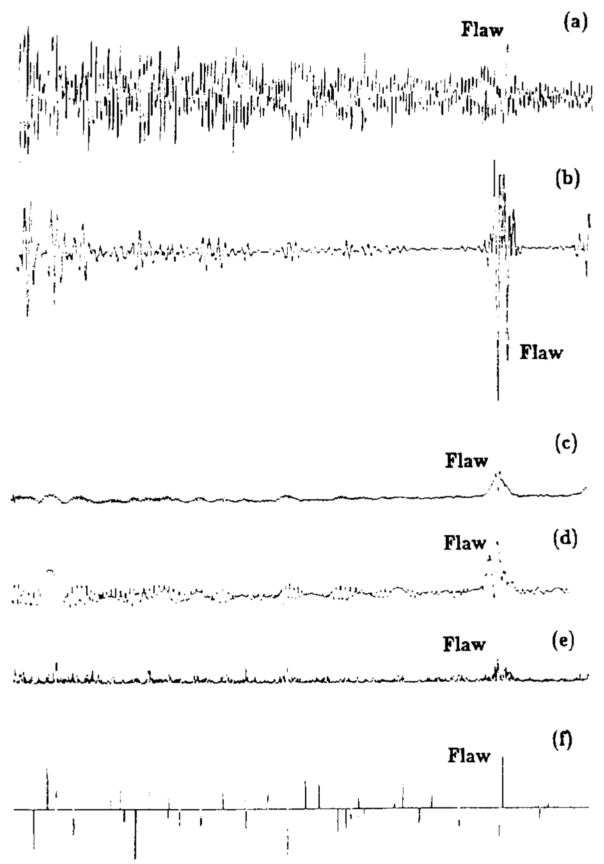

Fig. 3. A comparison of the performance of various signal processing schemes applied to an experimental measurement data; a) original signal, b) Bayes flaw detector, c) linear detector, d) median detector, e) minimization detector and f) polarity-thresholding.