STATISTICAL APPROACH TO THE AUTOMATION OF FLAW DETECTION

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INTRODUCTION

The detection of flaws in the presence of noise and other interfering signals can be enhanced by specifically taking into account the nature of these noise signals and designing a detection algorithm which performs optimally in the presence of that noise. In this paper, we present results of the application of this technique to a variety of specimens and show improvement in flaw detectability in the presence of grain scattering noise. We also discuss the use of this approach as a first step in the automation of flaw detection by virtue of its ability to recommend and evaluate measurement setups, perform optimum detection and provide confidence measures of the results.

BACKGROUND

The detection of the presence of flaws in structural materials is the most important function which nondestructive evaluation (NDE) performs. As structures are designed to meet higher performance criteria and as safety and life cycle cost factors become more important, it becomes necessary to detect smaller and more difficult to find flaws. It therefore becomes more likely that critical flaws will be increasingly difficult to distinguish from noise signals.

In addition, inspection productivity and performance can be improved if the inspection system can, in an automatic fashion, design and evaluate its own measurement methods. This would reduce the need for having a skilled operator carefully optimize the measurement process for each part inspected and/or provide a degree of adaptability which is not practical with conventional apparatus.

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In the previous year of this program, a statistical approach to the detection of flaws in the presence of noise was developed.[1] The approach is an extension of techniques used previously[1] for optimum characterization of flaws. A measurement model is defined which includes the flaw signal as well as all noise signals. This model is then calibrated for the particular specimen being tested and the particular apparatus being used for the test by means of a set of simple calibration measurements. Finally, a detection algorithm is calculated which is optimum for detecting the flaws of interest in the presence of the noise. This detection algorithm is then applied to each measured signal during the test.

A key assumption of this work is the modeling of the scattering amplitude of the flaw by one or a small number of time domain delta functions. This has been shown[2] to be a reasonable assumption for many flaws, and it causes the optimum detection algorithm to take the form of a simple convolution. This simplification makes it possible to implement the technique in a real time measurement apparatus.

The experimental results of last year's effort include[1] implementation of a practical form of the algorithm, demonstration of improved detection in the presence of electrical and A/D converter noise, and demonstration of real-time use of the algorithm in the digital ultrasonic instrument.

The goals of this year's effort were: 1) to demonstrate improved detection of flaws in the presence of material noise such as grain or pore scattering, 2) to determine the range of applicability of this approach, and 3) to evaluate the usefulness of the approach for automation of flaw detection.

THEORY

Measured ultrasonic signals contain a number of noise sources as well as the effects of diffraction and attenuation. In the measurement model, the measured signal M, as a function of frequency, is given by:

$$
\begin{array}{rll}
M = & X\, D_F\, P_F\, A_F & \text{Flaw signal} \\
& +\, X\, D_M\, P_M\, A_M & \text{Material noise} \\
& +\, N_E & \text{Electrical noise} \\
& +\, X\, D_E\, P_E\, A_E & \text{Echo noise} \\
& +\, N_{A/D} & \text{A/D converter noise} \\
& +\, N_{RFI} & \text{RF interference}
\end{array}
$$

where X is the response of the transducer and associated electronics, the D_x describe the diffraction associated with each signal, the P_x describe the propagation factors $\exp(ik\cdot r)$ for each signal, the A_x describe the scattering amplitudes of each type of scatterer, and the N_x describe the noise signal random variables.

The optimum filter has a spectrum of the form:

$$F = \frac{X^*\, D_F^*\, P_F^*}{C} \quad , \tag{1}$$

where * indicates complex conjugation and C is the power spectrum of the noise processes.

Detection is then performed by convolving measured signals with this filter. In the frequency domain, the statistical detection waveform is the inverse Fourier transform of:

$$D = F \cdot (M-A) \quad , \tag{2}$$

where A is the "average" component of the noise (i.e., unchanging from one location to another).

Attenuation Measurement

In order to estimate the signal amplitude at the flaw site in a material with attenuation, it is advisable to have an estimate of the attenuation for use in P_F. Two methods were used. For samples with low enough attenuation and a parallel back surface, the traditional method of measuring a front and two back surface echoes was used. For other samples, the following approach was used. The material noise signal returning from a given depth has a center frequency that decreases with depth. The attenuation was estimated at two depths (as described below) and taken to be approximately the attenuation of the frequency which is dominant at that depth. These two data were used to fit attenuation to a simple power law frequency dependence. The method of estimating the individual attenuations was to overplot the log amplitudes of the noise ensemble, fit a smooth envelope to this plot, measure the derivative of the envelope with respect to time, infer the depth dependence of the amplitude, and determine attenuation from $M(x+\Delta x) = M(x)\exp(-2\alpha\Delta x)$. The results agree with other measurements well enough for their intended purpose here.

EXPERIMENTAL RESULTS

Description of the Algorithm

The algorithm is an extension of the "research" algorithm described last year. A brief description of its current form follows. It is written in ISP and contains both a set-up phase for characterizing the signals and noises and defining the algorithm to be used, and a test phase in which the algorithm is applied to measured data to perform detection.

Set-Up Phase. The setup phase contains the following steps:

1. Estimate A, the time- and position-independent component of the noise. A can optionally be subtracted from each measured signal during the test phase.
2. Estimate the properties of the time-dependent components of the noise, such as electronic noise. This can be used to tailor the data acquisition process (e.g., via signal averaging).
3. Estimate the properties of the set of noises which vary during scanning. This is the noise which the detection algorithm must discriminate against. The estimated power spectrum of this noise is C in Eq. (1).

4. Estimate the system transfer function for this measurement geometry. This includes the effects of the transducer and associated electronics, and diffraction and attenuation during propagation to the flaw location and back. These components of the transfer function can be obtained either from reference measurements or theoretically, depending on what reference standards are available. In the worst case where no equivalent reference standard is available, the transducer and electronics properties are obtained from a reflection from a flat surface, the diffraction is either ignored because the measurement is being performed in the far field of the transducer, or calculated theoretically, and the attenuation is estimated from either through transmission or one-sided measurements.
5. Calculate the detection filter F using Eq. (1).

Test Phase. In the test phase, three types of detection algorithms are applied to each measured waveform. These are: 1) peak of the digitized (RF) waveform, 2) peak of the conventional video-detected waveform, and 3) peak of the statistical detection waveform. Video detection is performed digitally to simulate a conventional ultrasonic instrument. Statistical detection is performed according to Eq. (2). For ease of comparison, the statistical detection results shown below are presented in an envelope detection format.

Data was collected using the Ultrasonic Testbed.[3] A front surface echo was used for transducer calibration and a line scan over a flaw free region was used for noise calibration.

In order to test and debug the algorithms, ensembles of calibration and flaw waveforms were calculated theoretically and input to the detection algorithm.

Results

The available samples included the following: An austenitic stainless steel section from nuclear reactor piping,[4] Al castings with varying degrees of porosity,[5,6] diffusion-bonded reference specimens with built-in flaws,[7,8] and a Ni-based turbine engine material specimen.[9]

Transducer frequency and focus were varied to select an operating point where the flaw and noise signals were comparable, in order to show what improvement the statistical approach can provide.

The majority of the samples fell into one of two categories. In many cases, especially the Ti diffusion bonds, the flaws were intended for flaw characterization research and as a result are so large that any detection algorithm could easily detect them. In other cases, the noise in the material is so large that no method could detect the flaws. The remainder are described below.

Stainless Steel: The stainless steel sample is shown in Fig. 1. The flaw is a 2.5 mm deep EDM notch located on the far side of a 40 mm thick section. The inspection was performed using a 5 MHz longitudinal beam with an angle of incidence of 14° in the metal.

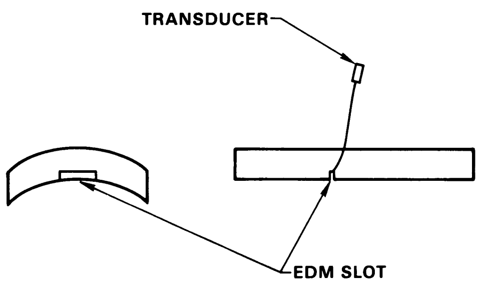

Fig. 1 Austenitic stainless steel sample with EDM notch.

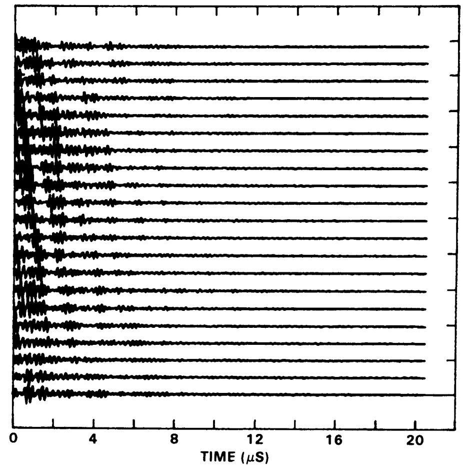

Fig. 2 B-scan of stainless steel sample in a flaw-free region showing grain scattering noise.

Figure 2 shows a set of waveforms collected as the transducer was scanned over a flaw free portion of the sample. The signals at the left are due to grain scattering. They decrease rapidly with time (depth) due to attenuation. The sloping pattern of correlation between lines is due to individual scatterers being visible to the angle beam transducer in several successive waveforms. This data was used to calibrate the noise component C of the measurement model.

Figure 3 shows the magnitude spectra of several of the signals used in developing the filter. The transducer spectrum peaks around 4 MHz. The field at the flaw (determined by correcting for diffraction and attenuation) is estimated to peak at less than 3 MHz, due primarily to attenuation. The noise power spectrum peaks at a much higher frequency due to the strong frequency dependence of grain scattering. These observations suggest that the best frequencies to use for detection will be the lower frequencies. The detection filter does indeed choose to use lower frequencies.

Figure 4 shows a set of waveforms collected by scanning over the flaw. In some of the waveforms, the flaw is visible above the background noise, in others it is not.

The degree of improvement in detectability is shown in Figs. 5-6. Figure 5 shows the results when the transducer is centered over the notch. If the sampled and video measurements were done with a properly calibrated distance-amplitude correction (DAC) curve, the flaw would be visible above the noise background with a signal/noise ratio of 2.5:1. If the DAC curve were not correct (for example due to unknown or varying attenuation), then the results would be worse. The statistical detection waveform has a signal/noise of 5:1. Figure 6 shows a location where the corner reflector signal of the notch is barely visible. It could not be reliably detected in the sampled or video waveforms, even with a correct DAC curve. The statistical algorithm detects it with a signal/noise ratio of 4:1.

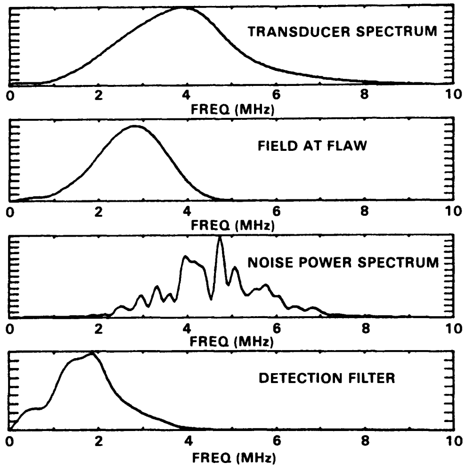

Fig. 3 Calculation of detection filter. Because noise is concentrated at higher frequencies, filter chooses lower frequencies for use in detection

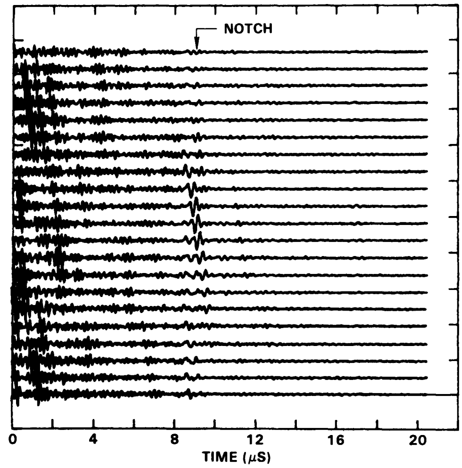

Fig. 4 B-scan over notch in stainless steel sample. Notch has more low frequency content than noise.

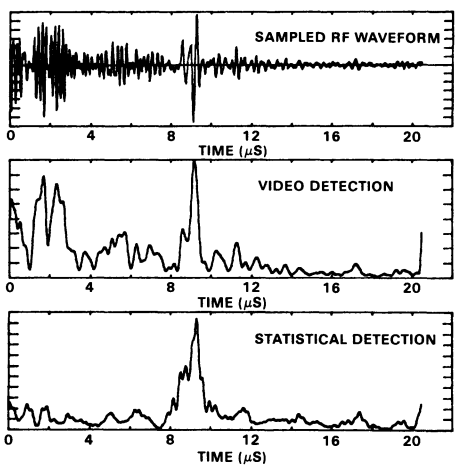

Fig. 5 Comparison of detection results over center of notch. Statistical approach improves detectability.

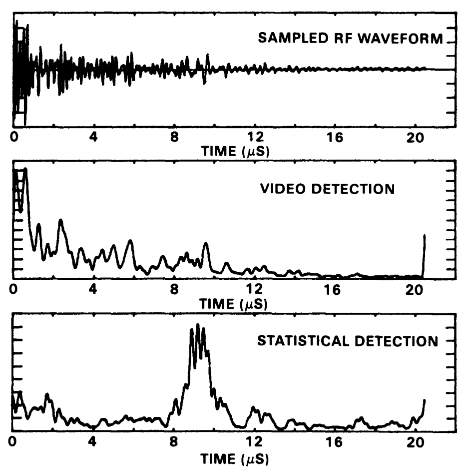

Fig. 6 Detection results near edge of notch.. Conventional approach does not detect flaw.

This degree of improvement in detectability was observed in all of the data taken with this specimen.

Castings: Several aluminum castings with intentionally large amounts of porosity were available.[5,6] The amount of porosity was as high as 6% and pore sizes were as large as 1 mm. Flaws were introduced by drilling round bottom holes in the back side of the samples. In several samples, the porosity was so extensive that not even the back surface of the sample could be seen, much less the flaw. In others, the porosity was not so high, but the individual pore sizes were very large. Because of the limited dimensions of the samples (typically 1 inch), the lowest frequency which could be used was 2.25 MHz. At this frequency, the pores are not in the Rayleigh (low ka) regime and therefore do not have the strong frequency dependence which allows their scattering to be separated from that of the flaw. In the one remaining cast sample, the porosity was so low that the flaw could be easily detected by any means.

Turbine engine materials: This specimen contains naturally occurring flaws in an unspecified Ni-based alloy. Attenuation measurements in the 10-25 MHz region show a frequency dependence of attenuation of $f^{1.6}$. This low power law dependence provided relatively little leverage for distinguishing flaws from noise and the detection filter developed reflected this. Grain size measurements were not available for this specimen and so the reason for the low power law dependence was not determined. Another interesting observation was that at 25 MHz, the limiting noise was asynchronous bursts of RF interference, presumably coming from nearby electrical equipment. Our detection filter is ineffective at eliminating this type of noise and this case points up the need to carefully engineer all aspects of a measurement system.

DISCUSSION AND CONCLUSIONS

With the set of samples and flaws available for these tests, we have shown one case where the statistical algorithm provides clearly improved flaw detection, and a number of cases where, for various well-understood reasons, the results are comparable to conventional detection. There are clearly other combinations of material properties and flaw sizes for which improved results would also occur, such as intermediate pore size castings. However, it has become clear that the benefits of the statistical approach are not limited to cases where detectability is improved over manually optimized conventional measurements. There is also a significant benefit that can result from using the statistical approach to automate the setup and operation of detection measurements.

In conventional flaw detection, the operator selects transducer frequency, diameter, degree of focus, etc. in order to have the best chance of detecting flaws. If he has sufficient knowledge, a wide variety of transducers, representative flaws in representative material, and sufficient time, he can usually do a good job. There are, however, a large number of factors which can interfere. These include the following: insufficient operator skill, the best transducer is not available, no suitable reference block is available, the sample's attenuation is unknown or different from that of the reference, the reference flaw is different from the target flaw, geometry effects such as the need to use the low frequency tail of a high frequency transducer, changing conditions such as sample-to-sample variations, depth variations or transverse variations during a scan, or the time and cost savings of reducing operator involvement.

The statistical approach presented in this paper provides the basis for an automated method of performing measurement design. The detection filter can be thought of as a method of evaluation of the chosen measurement setup: if the filter suggests that frequencies well below or well above the center frequency of the transducer are the best to use, then this could be used as a recommendation for the use of a different transducer. Going a step farther, the calibrated measurement model could be used directly to select the transducer and then, as in this paper, use it optimally. One benefit would be that the system could alert the operator if there is no available setup which can detect the flaws of interest. Because of the statistical nature of the model, it could also provide confidence measures of the liklihood of detecting flaws. This decision capability could, of course, be coupled to automated transducer selection equipment and automated signal processing hardware.

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