STATISTICAL FLAW DETECTION:
APPLICATION TO FLAWS BELOW CURVED SURFACES

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I. INTRODUCTION

The detection of the presence of flaws in structural materials is the most important function which Non-Destructive Evaluation (NDE) performs. As structures are designed to 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. This paper presents a practical approach to the optimum detection of flaws in the presence of noise signals. A decision theoretic approach (described in more detail in a companion paper by Fertig, et al.1) is used to derive a detection algorithm which is adapted to the noise environment in which a particular measurement is being made. An automatic procedure for characterizing the noises and developing the optimum detection algorithm is presented. Two implementations of this approach have been tested on experimental data and show substantial improvement over conventional detection techniques. One is a flexible algorithm used for research purposes, and the other is a real-time algorithm suitable for field implementation.

This work was sponsored by the Center for Advanced Nondestructive Evaluation, operated by the Ames Laboratory, USDOE, for the Defense Advanced Research Projects Agency at the Air Force Wright Aeronautical Laboratories/Materials Laboratories under Contract No. W-7405-ENG-82 with Iowa State University.
II. THEORY

Ultrasonic measurements of small flaws are usually limited by the presence of one or a number of noise processes. The problem of flaw detection (or flaw characterization) is therefore one of distinguishing the flaw information from the accompanying noise information. The statistical approach to NDE involves taking specific account of the statistical nature of the noise processes when designing flaw detection or flaw characterization algorithms. The statistical approach has been used to develop a number of flaw characterization algorithms. This paper describes the use of the same approach for flaw detection.

The first step in developing a statistical approach to flaw detection (or characterization) is to create a measurement model which describes both the signals due to the flaw and the signals due to noise sources. The second step is to calibrate the model by performing a set of measurements which determine the instrumental properties of the measurement system and the statistical properties of the noise mechanisms. The third step is to derive an algorithm which performs the detection (or characterization) in an optimal manner with respect to the signals and noises present.

The measurement model used in this paper is the following (expressed in the frequency domain):

\[
M = X D_F A_F + X A_M + X A_E + N
\]  

(1)

where

- \(M\) is the measured signal,
- \(X\) is the response of the transducer and its associated electronics,
- \(D_F\) includes the diffraction, attenuation and other factors involved in the propagation of the sound to the flaw and back,
- \(A_F\) is the scattering amplitude of the flaw,
- \(A_M\) describes the material noise scatterers, including propagation factors,
- \(A_E\) describes "echo" noise such as geometrics or ringdown, and
- \(N\) is random electronic noise.

This notation differs from that used in Ref. 1 in that Ref. 1's term "\(p\)" is the product of our terms "\(X\)" and "\(D\)" and that we explicitly include a term which describes the "echo noise".

The derivation of an optimum detection algorithm is done in a decision theoretic manner. A detailed description of this derivation is given in Ref. 1. A summary follows: The full problem of distinguishing all flaws larger than a certain size from smaller flaws or no flaw at all generally leads to a mathematically intractable problem. Therefore, a key simplification has been made which leads to detection algorithms which can be implemented in real time.
hardware. This assumption is based on the observation that much of the energy scattered from flaws comes from localized areas of the flaw, such as the front surface of a volumetric flaw or the tip diffraction of a crack. As a result, this scattering is impulse-like. We have therefore used a simplified flaw model in which the impulse response of the flaw is modeled as a delta function or a set of a small number of delta functions. This leads to detection algorithms which are of the form of a convolution of the measured signal with a filter function. For the case of modeling the flaw as a single delta function, the filter function is:

$$F(\omega) = \frac{X(\omega) D(\omega)}{C(\omega)}$$  \hspace{1cm} (2)

where $C(\omega)$ is the power spectrum of the noise sources which can't be eliminated by preprocessing and $*$ indicates complex conjugation.

Detection then consists of thresholding the quantity:

$$S(t) = \sum_{\omega} M(\omega) F(\omega) \exp(j\omega t) .$$  \hspace{1cm} (3)

This corresponds to a type of matched filter for the detection of impulsive scatterers.

The advantages of the statistical approach are the following:
1. More accurate detection and characterization of flaws.
2. Automatic adaptation to the particular sample being tested and to the particular instrumentation being used.
3. Statistical algorithms can give confidence measures which can indicate the level of confidence which should be placed in any given estimate which the algorithm makes.

Among the practical implications of the statistical approach are:
1. The ability to detect and size smaller flaws.
2. The ability to detect and size flaws in noisier materials.
3. Increased inspection speed because less highly focussed transducers are needed to detect a given flaw.
4. Less exacting requirements on instrumentation, because the algorithms adapt to the properties of the instrumentation.

The limitations of the statistical approach include:
1. Large flaws can be detected by conventional means. The statistical approach is not needed.
2. Very small flaws will not be detected even by the statistical approach. There is, therefore, a range of flaw sizes for which the technique is appropriate.
3. The statistical approach requires digital processing of the measured data. Currently, this requires more expensive hardware than analog processing, but the margin is narrowing.
III. IMPLEMENTATION ON MEASURED DATA

In order for statistical flaw detection to be of practical use, two things must be proven. First, it must be shown that a significant improvement in flaw detection can be achieved on experimentally measured data, given the limitations of this data. Second, it must be possible to implement the method in algorithms and hardware which operate fast enough to be of use in practical NDE situations.

In this program, we have developed two implementations of statistical flaw detection. The first is a "research algorithm" which is written in the ISP signal processing language and provides a flexible vehicle for examining the performance of a variety of forms of detection algorithms, statistical and conventional. The second is a real time algorithm which is implemented in the Digital Ultrasonic Instrument (DUI).

A. Research algorithm

The first form in which the statistical approach to flaw detection has been implemented is a general purpose algorithm, written in ISP, by means of which a number of variations of the algorithm were tested and evaluated. The algorithm consists of a setup or training phase, followed by a testing phase.

1. The setup phase consists of the following parts:
   a. Estimate electrical and A/D converter noise from a set of waveforms collected at a single location on the sample. The algorithm calculates the mean waveform and the variance waveform of this set. The variance waveform is used to estimate of the power spectrum of the electrical and A/D converter noise and can be used to select the amount of signal averaging to be used in subsequent measurements so as to reduce the amount of these noises to a desired level.
   b. Estimate echo noise and material noise from a set of waveforms collected at a variety of nominally identical flaw free locations in the specimen. The algorithm again calculates the mean and variance waveforms. The mean waveform is an estimate of the echo noise (noise which is independent of position). It is saved and subtracted from each new data waveform that is acquired. The variance waveform is used to estimate of the power spectrum of the remaining noises and is used for $C(\omega)$ in the detection filter.
   c. The system response $X(\omega)$ is measured by means of the reflection of the sound beam from a flat surface in the far field of an unfocussed transducer or at the focus of a focussed transducer.
   d. The diffraction $D(\omega)$ which the sound beam undergoes in reaching the flaw location is calculated using formulae developed by Thompson, et.al.\textsuperscript{9}
Note that if the flaw is sufficiently in the far field of the transducer at all frequencies of interest, then $D(\omega)$ is the same for flaw and system response measurements and can be ignored. To the extent that the flaw is not in the far field, the diffraction can be determined theoretically, as described in the previous paragraph, or experimentally, by means of a scatterer of known properties at the exact distance of the flaw. Both of these approaches are limited because, in practice, it is difficult either to know the sound field well enough to reproduce near field effects theoretically, or to have a scatterer whose properties and position are known accurately enough to reproduce them theoretically.

e. The detection filter $F(\omega)$ (Eq. 2) is now calculated from the quantities determined above.

f. A detection threshold must be set. This can be done either theoretically using the measurement model or experimentally using reference specimens as is currently done in most NDE measurements. Neither approach is entirely satisfactory because in neither case can one be sure that the conditions in the test piece have been accurately duplicated. Because the purpose of our measurements was to study the algorithms rather than to detect specific flaws, a threshold was not selected, but rather the detection function itself was displayed for analysis.

2. The test phase consists of the following parts:
   a. A candidate waveform is acquired.
   b. The echo noise is subtracted from it.
   c. Two detection algorithms are then applied to the data: video detection and statistical detection. Video detection is performed by rectification followed by low pass filtering using a frequency domain Hanning window centered at zero frequency and with halfwidth equal to twice the transducer center frequency. The statistical detection is performed by filtering the signal using the filter $F(\omega)$ defined above.
   d. A display is provided of the waveforms at various steps in the computation process and of the waveforms output by each algorithm.

B. Real-time algorithm

In order for a detection technique to be of practical use, it must be able to be implemented in a form which will operate at the speed at which conventional ultrasonic inspections are performed. In order to demonstrate this capability and in order to provide for more rapid testing of the statistical approach, a real-time version of these algorithms has been implemented. This part of the work was funded by the CANDIS program. The algorithms were implemented on the Digital Ultrasonic Instrument (DUI), which is a high speed all-digital instrument for performing sophisticated calcula-
tions on ultrasonic signals. The DUI controls the motion of the Ultrasonic Test Bed\textsuperscript{12} in order to scan over the specimens under test. The detection algorithms implemented on the DUI are simpler than the research algorithm described above and therefore serve as a test of what simplifications can be made in the original algorithm in order to speed the computations without significantly reducing the quality of the results. The real-time algorithm also consists of a set-up or training phase, and by a testing phase.

1. In the set-up phase, the DUI guides the operator through the series of measurements required to design the detection filter:
   a. The DUI first asks the operator to provide an echo from a flat surface in order to determine the system response. The DUI provides an oscilloscope display of the waveform to guide him in his adjustments of the instrument. When the operator signals that he has the correct signal, the DUI acquires it, calculates its frequency spectrum and inserts it into the detection filter. No attempt is made to correct for diffraction in this algorithm, as it is assumed that the flaw is sufficiently in the far field of an unfocussed transducer or sufficiently close to the focus of a focussed transducer that such a correction is not needed.
   b. The DUI then asks the operator for a region of the sample over which to make a coarsely spaced scan in order to determine the noise present in the sample. It is desirable that there be few or no flaws in this region. The DUI scans the region, calculates the variance of the noise waveforms and thus determines \( C(\omega) \). In this algorithm the echo noise was not estimated and saved for the purpose of later subtraction, although this capability has been demonstrated in the DUI before.
   c. The DUI then calculates the detection filter.
   d. Because the algorithm also calculates the video detection waveform, it is necessary to calculate the required lowpass filter. In order to do this, the DUI asks the operator the center frequency of the transducer, although it could as well have measured this from the system response spectrum.

2. In the testing phase, the DUI performs the following steps:
   a. The Testbed is scanned to the next position to be measured.
   b. The waveform is acquired, with optional signal averaging.
   c. Three detection algorithms are applied to the waveform:
      - Peak of the sampled rf waveform
      - Peak of the video waveform
      - Peak of the statistical waveform
   The three peak values are stored for each point inspected. The sampled rf waveform is included in the set because it would be the easiest to implement in a digital system.
   d. At the end of the scan, three graphs are plotted. Each is the peak output of one of the detection algorithms.
IV. RESULTS

This section presents two sets of results. First are the results of applying the research version of the statistical detection algorithm to a set of data in which the level of electrical and A/D converter noise have been varied by changing the amount of signal averaging used in acquiring the data. Second, we present the results of using the real time algorithm while scanning a specimen.

The specimen used in these measurements is a block of plastic in which crack-like flaws have been induced by laser damage (Figure 1). The sample has a cylindrically cut surface which simulates the borehole of turbine engine components. The flaw on which these measurements is based is a crack 0.5 mm in diameter. Optical inspection shows it to be very flat and very nearly circular. The normal to the crack is inclined at an angle of 60° with respect to the normal to the cylindrical surface.

A. Results of the research version of the algorithm

The flaw is fairly easy to detect using a properly selected focussed transducer. In order to provide a greater challenge for the detection algorithm, the measurements were performed in a less than optimum manner. First, an unfocussed transducer was used, giving a smaller S/N than a focussed one would have. Recall that one of the benefits which is expected from the use of the statistical approach is that faster scanning will be possible by the use of less highly focussed transducers. Second, the transducer diameter was large (0.5 in), further decreasing the flaw signal relative to the noise. Third, the flaw was located at the first near-field null of the transducer at approximately the transducer's center frequency (5 MHz). The result is that the flaw signal is only approximately 1 LSB in amplitude at the input to the A/D converter.

Figure 2 shows a set of 6 waveforms acquired with varying amounts of signal averaging while the transducer was aimed at the flaw. Each is labeled with a relative signal-to-noise ratio based on the amount of signal averaging used. The flaw is visible at 34 μs in the higher S/N cases. At the beginning of the waveform is some "echo" noise due to the ringdown of the front surface echo. In the lower S/N cases, the quantization noise of the A/D converter is clearly visible.

The analysis of the noise processes gave the following results: Figure 3 shows the mean and the power spectrum of the variance of a set of waveforms collected with the transducer at a fixed position. The mean contains echo noise, material noise and the flaw. The noise power spectrum is a measure of the electrical and A/D converter noise. The sharp structure at 12.5 Mhz is due to clock noise in the A/D converter (Biomation 8100). Figure 4 shows the mean and
Fig. 1. Plastic test specimen with laser induced crack.

Fig. 2. Set of flaw signals with varying amounts of noise provided by varying the amount of signal averaging.

Fig. 3. Mean and noise power spectrum of a set of waveforms collected at a fixed position.

Fig. 4. Mean and noise power spectrum of a set of waveforms collected at various flaw free positions.

the power spectrum of the variance of a set of waveforms collected as the transducer was moved to a variety of flaw free locations. The mean in this case is the echo noise which can be removed from measured data by subtraction. The variance contains all of the random noises present in the signal, including material, electrical and A/D converter. It is this waveform that is used as the basis for the noise power spectrum C(ω) in the detection filter.
Figure 5 shows the steps involved in determining the system response function. The first two curves are the reference waveform obtained from a flat surface echo and its spectrum. The third curve is the calculated diffraction $D$ for the flaw location. Note the near field null at 5 MHz. The fourth curve is the product $XD$.

Figure 6 contains the remainder of the steps involved in preparing the detection filter. The first curve is the measured noise spectrum (from figure 4). Because it is an estimate based on a small number of samples, it is not as smooth as the expectation of the noise process itself. We have therefore smoothed it by means of a low pass filter applied to the spectrum (second curve). Finally, the filter function $F$ is calculated (third curve). Note that the A/D clock noise will be completely eliminated from the measured data because the transducer has no energy at 12.5 MHz and therefore the filter ignores this frequency.

Figure 7 shows the results of applying the algorithm to the waveform labeled "6dB". The upper curve is the measured waveform. The middle curve is the result of applying video (envelope) detection and the lower curve is the result of the statistical detection algorithm. Video detection does not clearly distinguish the flaw, but a significant response due to the front surface ringdown is seen. The statistical approach, on the other hand, shows the flaw clearly standing out above all the other noises.

![Fig. 5. Signals used in calibration of detection algorithm: a) system response from flat surface echo, b) spectrum $|X|$ of a), c) calculated diffraction $|D|$ at flaw location, d) $|XD|$.](image1)

![Fig. 6. Additional calibration signals: a) Estimated noise spectrum $C(\omega)$, b) smoothed noise spectrum, c) filter function $|(XD)*/C|$.](image2)
The results of applying the two algorithms to the six data waveforms are summarized in Fig. 8. The horizontal axis is the nominal signal-to-noise of the waveform. The vertical axis is the measured performance of the algorithm, expressed as the peak height of the detected signal at the time when the flaw is known to be present, divided by the peak height of the detected signal at any other time during the measurement. (In computing this measure, the detected signal due to front surface ringdown has been ignored, since this is not present in many measurement situations.) The circles show the results for the statistical detection algorithm. For the two lowest S/N cases, the flaw was not detected. The squares show the results for the video detection algorithm. It is likely that this algorithm did not detect the flaw in any of the four lowest S/N cases. The solid curves are a theoretical calculation of the expected (S+N)/N for various values of S/N. Each curve was fit to the corresponding set of results by varying S (i.e. sliding the curve horizontally). The curves for the two algorithms are separated by 16 dB, indicating that the inherent ability of the statistical algorithm to separate signals from noise is about 16 dB better than for video detection in this case.
B. Results of the Real-Time Algorithm

The real time algorithm was used in conjunction with the Ultrasonic Testbed to scan a transducer over the specimen containing the flaw described above. The pivot point of the transducer manipulator was positioned at the center of curvature of the cylindrical surface of the sample and the transducer was then scanned over a 25° angular range which included the flaw. Figure 9 shows the peak amplitude of the signals produced by each of the three detection algorithms as a function of position. Neither the raw digitized r.f. waveform nor the video waveform detected the presence of the crack. The statistical algorithm, on the other hand, did detect it, with a signal-to-noise of about 12 dB.

V. CONCLUSIONS

The method presented here makes use of an explicit knowledge of the noise processes in order to design a flaw detection algorithm which optimally detects flaws in the presence of such noise. A key assumption which makes the approach implementable in a simple form is to model the flaw as having an impulse response function which consists of a set of delta functions.

Experimental results using this statistical approach show a significant improvement in the detectability of a crack-like flaw relative to the results obtained with conventional video detection. This approach promises to provide a number of advantages in practical testing situations, including detection of smaller flaws, faster scanning due to the use of less highly focused transducers, and less need for operator optimization of the measurement process.
REFERENCES:

10. CANDIS is an acronym for Computer Aided Non-Destructive Inspection System. CANDIS is a Technology Modernization Program within the B1-B Contract F33657-81-C-0210.
12. The Ultrasonic Testbed is an automated immersion testing system developed under Air Force Contract F33615-78-C-5164.
13. This sample was provided by Dave Hsu of Colorado State Univ.

DISCUSSION:

From the Floor: You mentioned getting rid of the echo noise by subtraction. If there's any motion in the transducer, that turns into a differentiation that can be a very noisy process. Do you anticipate any problems with that?

R.K. Elsley: The question was about the practical aspect of implementing subtraction. Of course, you can do the subtraction
either in the time or frequency domain because it is a linear process.

Now about jiggles in the transducer which produce the effect that the signal doesn't arrive at quite the same time when you do subtraction. That certainly does happen. One of the techniques that we have used in some of this processing is to specifically time align the signal before doing the subtraction. Again, it requires a little extra computation capability, but by doing time aligning, we can use subtraction in a variety of areas such as in this kind of processing and phased array imaging. We can often get 25 DB of suppression of unwanted signals by careful subtraction.

P.M. Gammell (Sigma Research): I notice you are looking for signals which are below the least significant data recorded. Am I correct that this process actually requires the existence of noise and requires that the noise have certain statistics?

R.K. Elsley: Yes, I would agree. That's not my choice for doing such measurements, of course. It was just a trick to use to get added signal-to-noise for testing the algorithm, but I agree with your statement.

J.A. Simmons (National Bureau of Standards): Can you use this method to improve on time resolution or positioning resolution for the flaw?

R.K. Elsley: Yes. For example, one of the items that is needed to do the Born inversion is a very accurate measure of the location of the center of the flaw. The correct way to do that is by using the low frequency data. We have a statistically based approach for making an optimal estimate of where the center of the flaw is based on low frequency data. That's one that is specifically addressed by this technique.