

NEW APPROACHES TO ULTRASONIC FLAW CLASSIFICATION USING SIGNAL PROCESSING,
MODELING, AND ARTIFICIAL INTELLIGENCE CONCEPTS

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INTRODUCTION

There are a number of modern approaches that can be used to characterize flaws in materials. For example, one method, which has been described recently by Wormley and Thompson [1], uses a model-based approach to obtain the "best fit" size and orientation parameters based on a simple equivalent shape such as ellipsoid. Before such sizing estimates can be activated, however, it is first necessary to determine if the unknown flaw being examined is a volumetric or crack-like flaw, since the sizing algorithm will be different for each case. This classification problem, although it is conceptually simpler than the more complete problem of flaw characterization, is, nevertheless, a difficult challenge because of the large number of parameters that can influence the resulting signals. A summary of our recent work on the flaw classification problem is given below. As will be shown, we have chosen to use a combination of signal processing, modeling and artificial intelligence tools to try to pare down the complexity of the ultrasonic responses and isolate those features that are dependent only on flaw-type.

SIGNAL PROCESSING AND MODELING

Since one of the major difficulties faced in trying to classify a flaw is the large number of possible flaws that might be represented by a given ultrasonic signal, there are basically two ways around this difficulty - either 1) find a set of features in the original data that are representative of flaw class only and do not depend on (or are weakly dependent on) other flaw parameters such as size, shape, etc., or 2) modify the original data to remove some of the dependency of other parameters. We are developing a combination of both approaches here.

We have used, for classification, two models for predicting the manner in which ultrasonic waves interact with flaws: the Kirchhoff approximation for cracks and the Born approximation for voids and inclusions. For simple shapes such as elliptical flat cracks and ellipsoidal volumetric flaws, these approximations predict ideal impulse responses such as shown in Fig. 1. Although these models are simple approximations of the scattering process and do not adequately represent these flaws, they do contain accurate information about the "leading edge" of the signal, i.e., the

first arriving waves. If we integrate once these model responses, we find that the Born approximation predicts that this leading edge response is given by

$$V(t) = A_0 + A_1 t + \dots \quad (1)$$

whereas the Kirchhoff approximation predicts that the leading edge response is

$$C(t) = A_2 t^{1/2} + A_3 t^{3/2} + \dots \quad (2)$$

A real leading edge response, however, will usually be a severely band-limited version of these ideal responses. This effect can be taken into

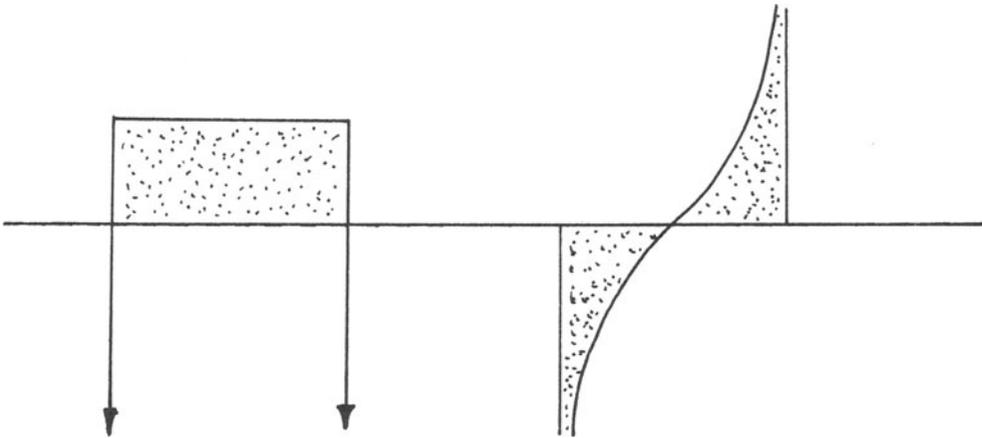


Fig. 1. Impulse responses of volumetric and crack-like flaws in the Born and Kirchhoff approximations, respectively.

account by convolving these ideal leading edge responses with a function $T(t)$ that represents the transducer:

$$V_b(t) = \int_0^t V(\tau) T(t-\tau) d\tau \quad (3)$$

$$C_b(t) = \int_0^t C(\tau) T(t-\tau) d\tau \quad (4)$$

By taking an unknown signal, integrating it, and looking at the leading edge response, we can then assume that it is a composite of the leading edge responses given by Eqs. (3) and (4), i.e., $M(t) = F(A_0, A_1, A_2, A_3)$. Then, by doing a least squares fit of the experimental data to this composite model, an estimate can be made if the flaw is a crack or not since, ideally, we have for (A_0, A_1, A_2, A_3)

$(A_0, A_1, 0, 0) \rightarrow$ void or inclusion

$(0, 0, A_2, A_3) \rightarrow$ crack

In implementing this type of classification scheme, since perfect results are never available, it is necessary to include confidence estimates in such predictions such as

$(4.57, 6.32, 0.12, 0.23) \rightarrow$ void or inclusion with a confidence factor of 0.8

To get such confidence factors, we are currently using synthetic data and varying noise levels, bandwidth, etc. Later work will use actual data to improve these estimates.

If the leading edge response classification scheme described above is by itself always a "good" indicator of flaw type then the classification problem can be solved simply. However, if the confidence estimate is low, then other additional information is needed in order to make a reliable classification. As mentioned previously, another approach one can take is to reduce the dependency of the data on other parameters. This can be accomplished in the following way. If the magnitude of the Fourier transform of the measured response is calculated, then phase differences due to errors in location of the zero of time origin are eliminated since if $F(f)$ is the Fourier transform of $f(t)$, it is well known that

$$|F[f(t);f]| = |F[f(t-t_0);f]|$$

where t_0 is a constant time shift.

Similarly, errors due to scaling (flaw size) can be eliminated by application of the Mellin transform, $M(p)$, to the magnitude of the Fourier transform data, since [2]

$$|M[F(f);p]| = |M[F(kf);p]|$$

where k is a scaling constant. Thus, the Fourier-Mellin domain is a particularly attractive domain for classification purposes since the data in this domain is independent of both flaw size and location. The calculation of this Mellin transform is also very computationally feasible since there is available the discrete Mellin transform in terms of the sampled values of F given by [2]

$$ipM(p) = \sum_{m=1}^{N-1} [\cos(p\ln k) + i \sin(p\ln k)] \Delta_m$$

where $\Delta_m = F(f_m) - F(f_{m+1})$.

We are currently implementing this Fourier-Mellin approach to extract flaw classification features from the ultrasonic response. These features are currently being obtained from the ideal responses of model studies. The models being used are based on simple modifications of the Born and Kirchhoff approximations. As mentioned previously, these approximations do not adequately represent the entire signal. But, it is just this entire signal which is needed to perform the Fourier-Mellin transform. Direct numerical modeling can give "exact" results but is too costly and time-consuming to be realistically employed in any classification method. However, it is possible to "fix up" the Born and Kirchhoff models without

introducing unduly burdensome calculations. This can be done by modifying these models by a factor which attempts to satisfy, in a least squares sense, the boundary conditions of the flaw being modeled. This factor acts essentially as a frequency dependent filter placed in front of the Born or Kirchhoff models and can be calculated directly as shown in [3].

ARTIFICIAL INTELLIGENCE

Using either the leading edge response or the flaw features extracted out of the Fourier-Mellin Domain, one is faced with the problem of how to use that information to reliably perform the classification process. The type of system that we are constructing is a rule-based system where the rules both define the features present in the measured response and the way in which those features are to be used in the decision-making process. This is in contrast to other types of classification and characterization systems of the "adaptive learning" type [4] where the important features are obtained by training a system, having numerous candidate features present, with the use of model-based and experimental data. We feel that the rule-based approach is more appropriate here, particularly when features based on fundamental principles, such as the leading edge response, are available. The development of this rule-based expert system is being done on a Symbolics 3670 workstation using both LISP and FORTRAN. Future work in this area will expand the expert system to encompass the entire flaw characterization process.

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REFERENCES

1. S. J. Wormley and D. O. Thompson, Review of Progress in Quantitative NDE 4A, D. O. Thompson and D. E. Chimenti, Eds., (Plenum Press, New York, 1985), p. 203.
2. P. E. Zwicke, IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. PAMI-5, 191 (1983).
3. P. M. Van den Berg, IEEE Trans. Antennas and Propagation, Vol. AP-32, 1063 (1984).
4. M. F. Whalen, L. J. O'Brien, and A. N. Mucciardi, Proc. DARPA/AFML Review of Progress in Quantitative NDE, AFWAL-TR-80-4078, 482 (1979).