ABSTRACT

Algorithm development work is described for the initial phase of a two-part task, where these algorithm upgrades improved existing material characterization-related data collection by culling ultrasonic signals for quality and designing a more noise-resistant time-of-flight estimate. This prepares the existing factory-installed ultrasonic signal analysis system for future data collection and algorithm training, yielding a more comprehensive, real-time material characterization capability within this manufacturing setting.

Index Terms — Acousto-Ultrasonics, nondestructive evaluation, graphite reinforced plastic, time-of-flight, piezoelectric transducer, orthotropic/anisotropic materials, quadratic discriminant analysis (QDA)

1. INTRODUCTION

This paper describes the initial portion of a two-phase effort, which improves existing quality assurance-related data collection, in the form of ultrasonic time-of-flight (TOF), and prepares the factory-installed ultrasonic signal analysis capability for future data collection, training and eventually a more comprehensive and sophisticated orthotropic material characterization capability. Section 2 introduces the problem and purpose of this initial effort. Section 3 provides a short introduction to “Acousto-Ultrasonics,” a specific branch of nondestructive evaluation (NDE) science that is a combination of Acoustic-Emission and ultrasonic material characterization techniques. Section 4 lays out the processing procedures programmed to solve the problems defined in Section 2, while Section 5 covers the testing and evaluation of the procedures implemented. The paper closes with a summary and a way forward for the second phase of this two-phase effort.

2. PURPOSE

The initial purpose of this effort was to improve the consistency and accuracy of ultrasonic time-of-flight (TOF) data being collected by presently-installed piezoelectric transducers (PZT) in a factory setting, as illustrated in Figure 1. The problem was two-fold: 1) the arrival time of the leading ultrasonic wave mode was determined using a signal amplitude threshold that was susceptible to errors from spurious noise spikes and 2) unpredictable signal level variations, due to inconsistent transducer coupling, or lack of contact pressure to the product being inspected. This often resulted in signal amplitude loss, causing erroneous TOF data to skew NDE data collection results.

Figure 1 Acousto-Ultrasonic transducer/system configuration

An upgraded approach was decided upon, which consisted of three general processing goals: 1) precede all TOF estimates with a signal quality assessment; 2) replace the existing TOF algorithm with one that is amplitude-independent in order to cope with a higher noise environment, and 3) install a generalized signal analysis and pattern recognition-based capability into the factory firm-ware, so a large variety of product-specific material characterization problems can be addressed in the future, without having to resort to major hardware insertion efforts.

3. ACOUSTO-ULTRASONICS

The equipment layout shown in Figure 1 is a simplified picture of an Acousto-Ultrasonics (AU) configuration which excites multiple propagation modes within the product item (or section of item) being inspected. The system may consist of multiple, strategically placed PZT pairs defining specific propagation paths, with their own dedicated pulser-receiver channels. They could be air-coupled, laser-ultrasound, wheel or contact transducers, as dictated by the manufacturing information system (MIS) or as permitted by the specific NDE test scenario.

AU is applicable to a large range of NDE problems [1]; however, it was originally applied to the inspection and characterization of graphite-reinforced plastics (GRP). It was one of the few NDE techniques that could empirically correlate to mechanical strength, for both tensile [2] and compressive [3] test configurations. AU is especially suited towards evaluating bond integrity [4] and even detecting the growth of microro-corrosion in aircraft wing-skins [5]. The major application, however, is on a factory production line for PZT-calibrated [6],
in-line, rapid material characterization of manufactured parts; such as complex anisotropic GRP components with constant geometries but possibly flawed internal properties [7], [8]. It is interesting to note the similarities between AU waveforms collected from these earlier GRP components and both lower density anisotropic or naturally-occurring orthotropic material, currently being monitored. This should not come as a complete surprise, since flaws present in both are, in essence, a localized anisotropic feature. Therefore, the argument is being made that AU-type interrogation scenarios, coupled with similar signal processing/pattern recognition-based analyses, initially applied to GRP mass-production, should also be possible on low density products. The only difference is the center frequencies and bandwidths required, where GRP typically used broadband PZT crystals around 3 MHz; whereas the current center frequencies vary from 50 to 300 kHz depending upon the product application.

The advantage of AU is that it is very product-specific, which brings with it the disadvantage that large amounts of statistically-stable signal data are needed before effective pattern recognition-based NDE systems can be designed. Therefore, very often, the AU signal collection system has to be installed in the factory before the final AU NDE system can be totally implemented. This, in effect, is the current situation, where this first phase allows doing a better job of consistently estimating TOF and other basic parameters, while serving as an in-factory collection device. It then enables addressing a myriad of future NDE flaw classification applications, endemic to each manufacturing process and product, many of which may not have even been envisioned yet.

4. PROCESSING PROCEDURE

As noted earlier, our three primary goals are: 1) perform a signal collection integrity check, 2) if the signal is of acceptable quality, estimate the TOF using an amplitude-independent method, and, since many of these capabilities are being inserted into FPGA hardware, 3) install a generalized signal analysis/pattern recognition capability that will be adaptable to a multitude of future product-specific factory applications. The procedure depicted in Figure 2 achieves all three of these objectives.

First, the digitized signal is band-pass filtered across positive frequencies and transformed into an analytic signal in one operation. Being analytic, it simplifies the extraction of frequency-related features, as well as the calculation of a signal envelope, from which the TOF can be more reliably extracted without using a fixed amplitude threshold. The signal quality assessment is performed with the same type of QDA pattern recognition solution [9] that was used for the GRP material characterization problem [7]. The QDA solution to the signal quality problem may be considered over-kill; however, the main reason for using it now is to have an operating signal processing/pattern recognition capability installed within the FPGA firmware, allowing its future use on more sophisticated material characterization problems, while addressing the current need for a signal quality check that discards poor quality waveforms prior to executing TOF feature extraction.

Figure 3 demonstrates the processing result for a “good” quality AU signal sampled at 500 kHz, and its spectrogram. The upper panel plots the in-phase and quadrature-phase components, along with their magnitude envelope, from which a TOF = 253 was extracted. For this particular product propagation geometry (i.e. expected TOF was 180 to 330), samples 30 to 180 and 330 to 830 respectively defined regions of “noise-only” and “predominantly-signal.” From the 826 factory-collected signals that were visually evaluated, 725 were classified acceptable while 101 were rejected, because of signal activity in the “noise region” or poor signal amplitude, frequently, but not always, inhibiting correct TOF extraction. As an example, Figure 4 illustrates one of the visually rejected acquisitions, even though TOF was correctly estimated. Six features were extracted from these “signal” and “noise” regions, and a signal-to-noise feature quotient set was also appended, for a total of 18 features. All 18 were evaluated for Fisher ratio discriminating properties [10], resulting in 4 “winning” features, whose mean values are listed in Table 1.

<table>
<thead>
<tr>
<th>Group</th>
<th>ZCRs</th>
<th>f₁ (Hz)</th>
<th>R₁/E₁</th>
<th>Eₙ/E₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accepted</td>
<td>0.17393</td>
<td>21298</td>
<td>0.99461</td>
<td>599.9</td>
</tr>
<tr>
<td>Rejected</td>
<td>0.26948</td>
<td>27993</td>
<td>0.96183</td>
<td>4.3857</td>
</tr>
</tbody>
</table>

Three of the four features were from the “signal region” (samples 330-830); namely zero-crossing-rate (ZCR₁), frequency centroid (f₁), and an energy-normalized adjacent sample correlation value (R₁/E₁), and the fourth feature was the quotient of the signal and noise region energies (Eₙ/E₁). Both the R₁/E₁ and f₁ features are borrowed from aerospace work [11], where energy-normalized single-lag correlation of a complex signal, R₁/E₁, is a metric for sample-to-sample similarity (near unity for signals, lower with increasing noise), and the phase of R₁ may be converted into frequency, f₁, in Hz. Figures 3 and 4 include the frequency centroids for the noise (fₙ) and signal (f₁) regions as black and white lines in the spectrogram panels extending over the noise and signal regions, respectively.
Scatter plots of all four features listed in Table 1, are shown in the two 3-feature panels of Figure 5, with blue/dark dots and red/light crosses, being the “acceptable” (j = 1) and “rejected” (j = 2) signal groups, respectively. QDA-based pattern recognition distances [9] are then computed as:

\[
d_j(U) = \sum_{m=1}^{4} \left[ \left( \sum_{n=1}^{4} [u(m) - a(m,j)] [u(n) - a(n,j)] \right) \psi_{\text{mn}}^j \right],
\]

where \( U \) is the unknown signal feature vector, \( d_j(U) \) is the distance from \( U \) to the \( j^{th} \) (good/bad) signal group, \( u(m) \) is the \( m^{th} \) feature of \( U \), \( a(n,j) \) is the mean value of the \( n^{th} \) feature for the \( j^{th} \) (good/bad) signal group, and \( \psi_{\text{mn}}^j \) is the \( mn^{th} \) element of the inverse covariance matrix for the \( j^{th} \) signal group. Signal quality decisions are then made on the basis of the smallest distance: “accepted” if \( d_1(U) < d_2(U) \) and “rejected” if \( d_2(U) < d_1(U) \).

From Figure 4, it can be noted that although this signal acquisition did not “look” acceptable, the TOF algorithm, described next, successfully estimated the location of the “knee” in the signal envelope. The current manufacturing customer preferred some measure of control via a “soft” decision option, rather than having the minimum pattern recognition distance value being the final arbiter. Therefore, a confidence value is also computed that the user can then threshold; where confidence, \( C \), in the decision made for group \( j \) is computed as:

\[
C = 100 \% \times \left( 1 - 2 \times d_j(U) / [d_1(U) + d_2(U)] \right),
\]
given that \( d(U) \) is the smaller of the two \( (d_1(U), d_2(U)) \) pattern recognition distances.

Figure 4 demonstrates the resistance to noise of the “envelope knee-searching” TOF algorithm. Equation 3 has two adjacent 25-sample (50 μs) sliding windows used to calculate the mean of the envelope-squared \( (e^2) \) in each window. When the quotient of the two windows in the square brackets of equation 3 is maximized, the “knee,” and therefore, the TOF, has been bounded and found.

\[
\text{TOF} = \arg \max_p \left[ \frac{\sum_{i=p-24}^{p} e_i^2}{\sum_{k=p+1}^{p+26} e_k^2} \right],
\]

To stress the TOF algorithm further, the noise region (samples 30 to 180) was analyzed to determine its spectral color, from which a noise generator was developed. The top two panels of Figure 6 illustrate at true TOF = 238, at an initial SNR of 30.05 dB and the change to a TOF = 241 estimate at
SNR = 12.041 dB. With increasing noise, the TOF estimate tends to creep upward before totally failing. The multiple simulation results in the bottom panel indicate reasonably stable TOF estimates, down to an SNR of approximately 10 dB.

Figure 6 Artificially degrading the SNR of the signal to monitor TOF noise robustness

6. EVALUATION AND TESTING

As noted earlier, 725 of the 826 signal total were visually classified as acceptable, with 101 rejected. There were two product groups (464 and 362) making up the 826 signals. QDA training performed on the 464-signal product resulted in 93.5% and 95.4% correct classifications for the “good” and “bad” groups, respectively, when used as a test set. The same QDA was applied to the remaining (independent test) signals in the other product category, with 98.2% and 92% correct for “good” and “bad” signal groups, respectively. Because of the improved TOF algorithm, many of the 101 “rejected” waveforms yielded valid TOF numbers; on only 4 occasions of 725 “good” collects (~ 0.5%), did the TOF algorithm misidentify the true knee.

7. SUMMARY

This initial effort significantly reduced errors in TOF estimates and over-all data collection statistics by culling poor quality signal data. The collection, processing and classification capability, currently put in place at the factory during this first phase for our customer, opens up a wide variety of future quality assessment scenarios; where separate joint-time-frequency analyses [12] on individual AU signal plate wave modes can be used for more sophisticated feature extraction.

Applications include sorting product output for pricing (increasing return-on-investment), correlating with destructive mechanical tests for future strength prediction and also feeding back NDE information to the MIS for adaptive, real-time manufacturing process correction.

8. REFERENCES