Bayesian Separation of Lamb Wave Signatures

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Abstract

A persistent problem in the analysis of Lamb wave signatures in experimental data is the fact that several different modes appear simultaneously in the signal. The modes overlap in both the frequency and time domains. Attempts to separate the overlapping Lamb wave signatures by conventional signal processing methods have been unsatisfactory. This paper reports an exciting alternative to conventional methods. Severely overlapping Lamb waves are found to be readily separable by Bayesian parameter estimation. The authors have used linear-chirped Gaussian-windowed sinusoids as models of each Lamb wave mode. The separation algorithm allows each mode to be examined individually.

Keywords: laser-based ultrasonic, weld inspection, on-line inspection, Bayesian, separation

1. Introduction: Why do guided waves matter?

Ultrasonic waves come in two classes, bulk and guided, characterized by two different kinds of solutions to the same differential equations [1]. Bulk waves pass through the bulk of the medium and are not significantly constrained by boundary conditions. In contrast, the essential character of a guided wave is determined by its boundary conditions. Strangely, bulk waves, propagating through what amounts to an infinite medium, are limited to a finite number of possible modes. Remarkably, guided waves, constrained by finite boundaries, have infinitely many allowable modes.

This leads immediately to the question: Why do guided waves matter to NDE engineers? They matter because they're everywhere. Virtually every ultrasonic measurement involves an excitation transducer and a receive transducer at a boundary. The exciter launches guided waves whether or not the user wants them, and the receiver responds to them whether or not the user wants them. They are strong and persistent, and they often propagate along curvatures [2]. If the user is not interested in them, it is crucial to identify them so that they can be removed from the signal so that they do not obscure the signature of interest. Perhaps even more importantly, if they are of interest, we often end up with many modes. Trying to carefully contrive initial conditions such that only a desired mode is launched is costly, and in many cases impractical.

Not only are guided waves practically everywhere, but they can reveal a wealth of information. For example, an A0 mode Lamb wave propagating through a plate in a liquid medium could reveal force, pressure mass changes, fluid density, viscosity and elastic moduli [3]. However, there is a cost for such information. You need to know the mode under observation, and you need a model of the mode. Also, if the mode is one of many present, it needs to be separated from all the others.

The dispersiveness of guided waves reveals information about the properties of the medium. However, to make the best use of the information, it is necessary to be able to estimate the parameters of a specific mode in a specific signature. Such parameters include the frequency, chirp rate, envelope width, and the group time of arrival. Fourier analysis does not reveal this information; there is no straightforward method in the Fourier frequency domain to distinguish between the frequency broadening effects due to the windowing effect of the envelope, and those due to chirp.

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Thus, guided wave signatures present us with two problems, separating entangled modes and estimating the parameters of each mode. Remarkably, there exists a powerful technique for solving both problems simultaneously. The technique is Bayesian parameter estimation [4]. Why is Bayesian superior to more popular methods at separating overlapping signals or distinguishing weak signals from noise? Popular spectral analysis methods are equivalent to convolving the signature with a linear filter bank. An unavoidable effect of convolution is to broaden the signal. The effect of convolving two entangled signals is to broaden both at once. In other words, linear filtering entangled signals *makes them more entangled*. Bayesian spectral analysis is non-linear, equivalent to exponentiation. The practical effect is to push different components apart instead of squeezing them together.

2. Disentanglement

One of the major practical problems in the evaluation of signatures of guided waves is the fact that the signal of interest often overlaps many other signals [5]. The feature of interest produces a signal that contains desired information. However, other features also produce signals that overlap the signal of interest, but contain no relevant information. In addition, the signals are nonstationary. Finally, the signal of interest may be considerably weaker than the obscuring signals.

The key to the signal-processing problem is to separate the desired signal from the undesired signals while not destroying the desired information with the process. To appreciate the idea, consider a sensor signal composed of the sum of four overlapping Gabor functions plus low-level Gaussian noise. Also consider that the information of interest is contained in one of the Gabor functions. In this example, suppose that each of the Gabor functions is produced by a different physical feature and that we can tell something about the feature (for example, its location in space) by examining the parameters of the Gabor function associated with that specific feature. The problem is that we must disentangle the underlying Gabor functions given the overlapped signal. As shown in *Figure 1*, the signal is the sum of a low level of Gaussian noise and four Gabor functions with normalized frequencies of 0.025, 0.05, 0.025, and 0.05, and window peaks at time delays of 600, 1400, 1400, and 600 respectively. The components are not conveniently separable in either time or frequency domains.

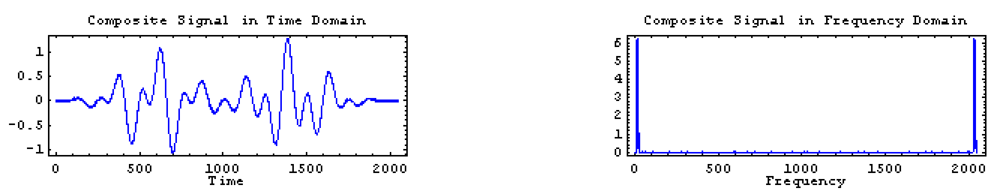

Figure 1. Signal overlapped in time and frequency

Suppose we have prior knowledge from our understanding of the underlying physical process that the signal should contain one or more Gabor functions, but we have no prior knowledge of the parameters such as frequency or the time of the window peak. By the methods of Bayesian parameter estimation, we can use the Gabor function as a model, and guess a frequency and a time. We can project the signal shown in *Figure 1* onto the model, and compute the log likelihood that the Gabor function with the guessed parameters fits the data. If we repeatedly guess sets of parameter values, and plot the resulting log likelihoods against the guessed parameter values, we obtain the plot shown in *Figure 2*.

Another way of saying this is that *Figure 2* is the projection into log likelihood space of the signal shown in *Figure 1*. When we examine this composite signal in log likelihood space, we see four well-separated components, and expect that we should be able to recover each component, one by one.

The two parameters are ω, the oscillation frequency (0-0.06) and τ, the time of occurrence (0-2000) of the event. The vertical dimension is log-likelihood.

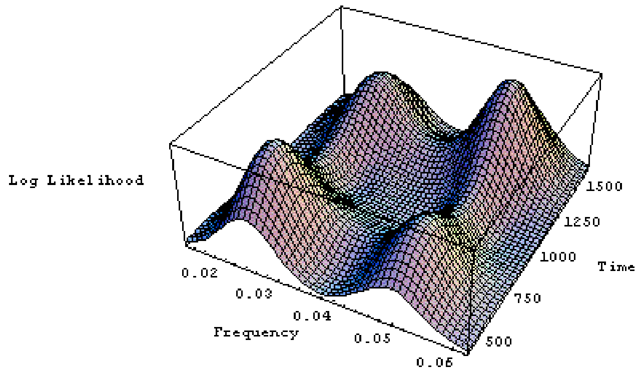

Figure 2. Likelihood of fit of signal to Gabor function

Given the signal shown in *Figure 1*, the most likely Gabor function that fits the signal, is the one whose parameters lead to the greatest log likelihood. Using a global optimizing algorithm, with the objective function being the log likelihood as a function of the time and frequency parameters, we can readily find the optimal combination of parameters. As indicated by the peak in *Figure 2*, the optimum value of the objective function occurs at a time of 605.4 and a frequency of 0.0248. The most likely Gabor function in the signal shown in *Figure 1* is plotted in the left-hand plot in *Figure 3*. This is the Gabor function whose parameters are found at the global optimum in *Figure 2*. When this estimated signal is subtracted from the signal in *Figure 1*, the residual in the right-hand plot of *Figure 3* is obtained.

Figure 3. Most likely signal and residual

Since we have reason to believe that the signal should contain several Gabor functions plus noise, we can apply precisely the same methods to the residual and obtain the next most likely signal and its residual with the next likeliest Gabor function removed. In *Figure 4* we see the results of repeating this process until the residual is reduced to noise. The other Gabor functions have times of 1397.9, 612.2, and 1400.9 and frequencies of 0.0251, 0.050, and 0.050. Only noise remains in the residual.

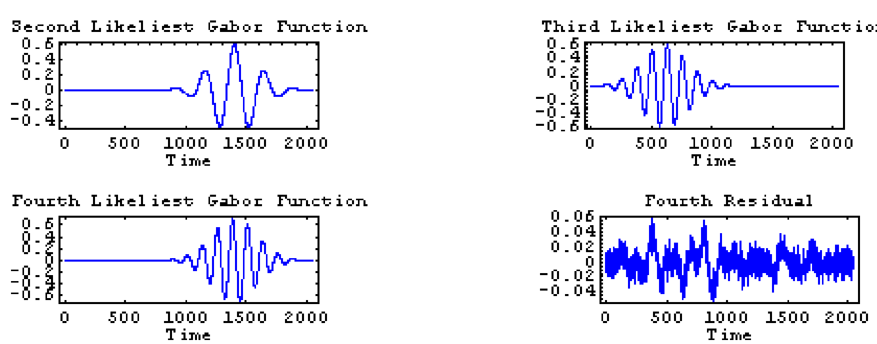

Figure 4. Other components of overlapped signal

3. Does it work in the real world?

The authors are investigating the use of Lamb waves to search for weld flaws [6]. The utility of a commercial weld flaw detector depends on its ability to consistently detect the signatures of different weld types. We have reported elsewhere that entangled Lamb wave modes could be readily separated by Bayesian parameter estimation [7]. The result that we report in this paper is that a specific mode structure can be associated with specific types of weld flaw.

In one experiment, we collected Lamb wave signatures for various samples. Sample 11 is a tailor-welded blank with a good weld with low porosity. Sample15 is a tailor-welded blank that is known to have high porosity from X-ray data. The model of each Lamb wave mode is assumed to be a Gaussian-windowed chirped sinusoid of the form

$$Ae^{-\frac{(t-\tau)^2}{\sigma^2}} \mathrm{Cos}\left[\alpha(t-\tau)^2 - (t-\tau)\omega\right] + Be^{-\frac{(t-\tau)^2}{\sigma^2}} \mathrm{Sin}\left[\alpha(t-\tau)^2 - (t-\tau)\omega\right] \quad (1)$$

where

t = the independent variable, and the parameters are
A and B = the amplitudes of the two components
τ = pulse group delay
σ = pulse width
ω = center frequency of oscillation
α = chirp rate

Each mode consists of a wave of this kind with a different set of values for the parameters.

Figure 5 is a plot of sample 15 scan 1. The rough plot is the raw data with the DC bias subtracted out. The smooth plot is the dominant mode, obtained from Bayesian parameter estimation. The plots show signal intensity versus time.

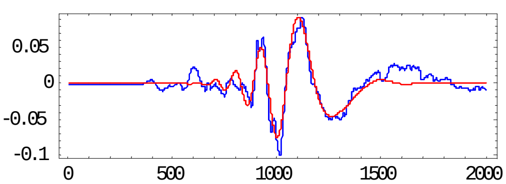

Figure 5. Sample 15 Scan 1

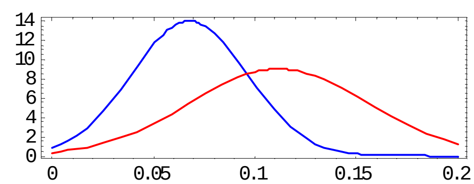

Figure 6. Distribution of frequencies in mode 5

For reliable pattern recognition, the relevant question is, do any of the parameters tend to cluster in an isolated region of parameter space? In particular, are the clusters well separated by class? What is desired in this case is a parameter value that is distinctly different for the class of high-porosity welds, and the class of good welds. In this experiment, the fifth likeliest mode showed the strongest tendency to form distinct clusters. The fifth mode for the good welds are very similar to each other. The fifth mode for the high-porosity welds are very similar to each other. However, the fifth modes for the two classes are unmistakably dissimilar.

Figure 6 is a plot of the Gaussian distributions based on the means and standard deviations of the dominant frequency of mode 5. To the left is Sample 15. To the right is sample 11. The frequencies of mode 5 tend to cluster, but the cluster for sample 11 does not appear to be especially well separated from the cluster for sample 15.

Can we find a parameter with tighter clusters? *Figure 7* is a plot of the Gaussian distributions based on the means and standard deviations of the percent energies in mode 1. To the right is Sample 15. To the left is sample 11. For a typical scan for sample 15, the first mode has about 80% of the signal energy. For a typical scan for sample 11, the first mode has about 60% of the signal energy. The percent energies in mode 1 form tighter and more separated clusters than the frequencies in mode 5.

Can we improve the classification by exploiting coincidence between parameters? If both the concentrations of energy in mode 1 and the frequencies in mode 5 are caused by the difference in porosity of the samples, then we would expect there to be an exploitable coincidence between the two features. If mode 1 has a high concentration of energy, *and* mode 5 has a low frequency, then it is much more likely that the signature is that of a high-porosity weld than that of a good weld.

Suppose that each scan of each sample is characterized by a feature vector consisting of the frequency of mode 5 and the percent energy of mode 1. *Figure 8* includes the plot of the feature vectors for both samples. Sample 15 appears in red in the original plot. Sample 11 appears in blue in the original plot. Horizontal axis is frequency of mode 5. Vertical axis is percent energy in mode 1.

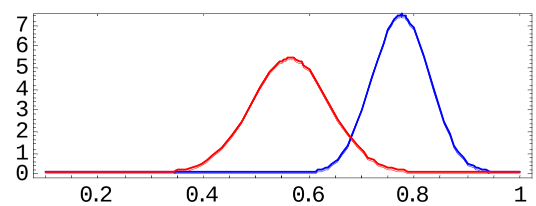

Figure 7. Distribution of percent energies in mode 1

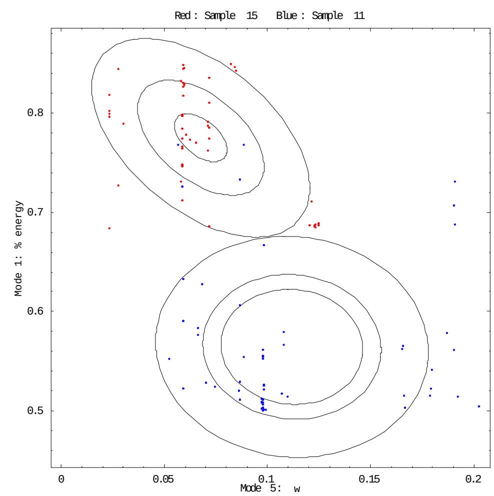

Figure 8. Weld features in 2D feature space

The quartile ellipses in *Figure 8* show the comparative compactness (or lack thereof) of the clusters. They are centered on the centroids of the sample lists for each class. The innermost ellipse encloses 25% of the samples of the class. The middle ellipse encloses 50% of the samples of the class. The outermost ellipse encloses 75% of the samples of the class. Notice that the 75th percentile ellipse for each class is outside the 75th percentile ellipse for the other. Thus, they are reasonably well separated. If we found yet another coincident parameter in the data, we could probably improve the separation of the classes further.

4. Conclusions and further research

The authors have detected various kinds of weld flaws in various specimens of tailor-welded blanks using the methods described in this paper. These results demonstrate capability to detect localized weld defects using a computationally efficient processing approach that can be implemented in real-time at the frequencies at which these signatures occur. We have also investigated the comparative reliability and computational cost of wavelet and Bayesian feature extraction methods.

While we have demonstrated in principle that weld defects are classifiable from their Lamb wave signatures, in future work we will seek to classify the whole range of possible defects encountered in commercial welding processes. The next step in this research is to construct a prototype of an on-line laser-based ultrasonic weld inspection device for tailor-welded blanks.

This work could lead to spin-offs for other on-line inspection in other processes. Additional follow-on research might include the examination of other types of continuous seam joints for distinguishing features. In addition, the Lamb-wave modeling and feature extraction would be directly applicable to inspection of other products fabricated from thin metal sheet.

5. Acknowledgments

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