Bayesian Separation of Lamb Wave Signatures in Laser Ultrasonics

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ABSTRACT

Laser-based ultrasonic (LBU) measurement shows great promise for on-line monitoring of weld quality in tailor-welded blanks. Tailor-welded blanks are steel blanks made from plates of differing thickness and/or properties butt-welded together; they are used in automobile manufacturing to produce body, frame, and closure panels. LBU uses a pulsed laser to generate the ultrasound and a continuous wave (CW) laser interferometer to detect the ultrasound at the point of interrogation to perform ultrasonic inspection. LBU enables in-process measurements since there is no sensor contact or near-contact with the workpiece. The authors are using laser-generated plate (Lamb) waves to propagate from one plate into the weld nugget as a means of detecting defects.

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 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 a linear-chirped Gaussian-windowed sinusoid as a model of the Lamb wave mode. For signatures captured in laser ultrasonic data in tailor-welded blanks, this has led to straightforward separation of multiple modes. Furthermore, the resulting parameter sets for the different modes reveal crucial characterizing features of the properties of the workpiece.

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

1. INTRODUCTION

The research reported in this paper considers the search for weld flaw signatures in laser–based ultrasonic (LBU) sensor output data. Consistent interpretation of sensor data must be model-based, where the model is in some reasonable sense a description of the underlying physical reality being observed. The various pops and bursts that appear in a sensor output have physical causes, and in ultrasonic observations, the physics of the causes is typically well understood. Signal processing must exploit this understanding to wring the maximum of new and relevant meaning from the sensor output data, and to provide an indication of confidence in the results.

Once the signature of interest is separated from everything else in the sensor signal, the detection of flaws in a workpiece is straightforward. Typically, the workpiece is scanned across a physical range by the sensor. Continuity of the mathematical properties of the signature across scans suggests an unflawed workpiece. The appearance of an abrupt discontinuity suggests the presence of a flaw.

The model-based signal processing strategy is in contrast with the "black-box" strategy that is widely popular in machine intelligence. Conventional wisdom says to feed a signal into the box, and a number pops out. With luck, the number may be useful. However, the algorithm is often surmised without respect to the underlying physical process. This empirical approach works for some data sets, but give no indication of whether or not it might break down for the next trial.

Remarkably, the "black box" strategy is not how biological intelligence operates. Biological intelligence is concerned with abstraction of meaning from data.[1] In fact, the key attribute of intelligent behavior is the extraction of meaning from sensory data.[2] "Black box" algorithms inherently cannot extract semantic meaning; they are entirely concerned with the syntactical

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process of swapping one set of symbols for another. As discussed in the next section, the search for a "black box" that can consistently process real-world sensor data is certain to be fruitless.

2. MODELING

In describing the properties of the formal Modeling Relation, Rosen tells us that modeling "is the art of bringing entailment structures into congruence."[3] However, his statement leaves us wondering what it really means. How does art enter into the picture; are we not instead supposed to be scientific? What is an entailment, much less an entailment structure? What does it mean that two different entailment structures are congruent? In what sense are they not identical? If they are not identical, what similarity between them causes us to declare them congruent? Why do these questions matter? If they do matter, then what should we do about them?

The first point to appreciate is that the Modeling Relation is a relation in the formal mathematical sense.[4] Suppose that A and B are sets, and that there exists a set, R, of ordered pairs, where the first element of each pair in R is an element of A, and the second element of each pair in R is an element of B. In mathematical notation: $a \in A$, $b \in B$, $(a,b) \in R \Leftrightarrow aRb$. In Rosen's Modeling Relation, the members a and b of each ordered pair in R are entailments from two different systems.

Entailments are the consequences of the order or organization of a system. There are two sorts of systems that might appear in the Modeling Relation: natural systems and formal systems. Natural systems are systems in physical reality that have causal linkages; if certain causes impinge upon a natural system, then the system will behave in a certain way, or produce certain effects. This consequential linkage of cause and effect in a natural system is a causal entailment. Formal systems are conceptual systems that have inferential linkages; if certain hypothetical propositions impinge upon a formal system, then they will produce certain consequential propositions in conclusion. This consequential linkage of hypothesis and conclusion in a formal system is an inferential entailment.

Entailment structures are inherent *within* a system; they are the distinguishing features that characterize the system.[5] They do not cross over from one system to another. This is represented in Figure 1, where we see a natural system distinguished by its structure of causal entailments, and a formal system distinguished by its structure of inferential entailments. The entailment structures of two distinct systems are distinct from one another; causes in one do not produce effects in the other. In fact, this provides the answer to one of the questions posed above. The distinguishing feature that provides identity to a system and distinguishes it from other systems is its self-contained entailment structure.

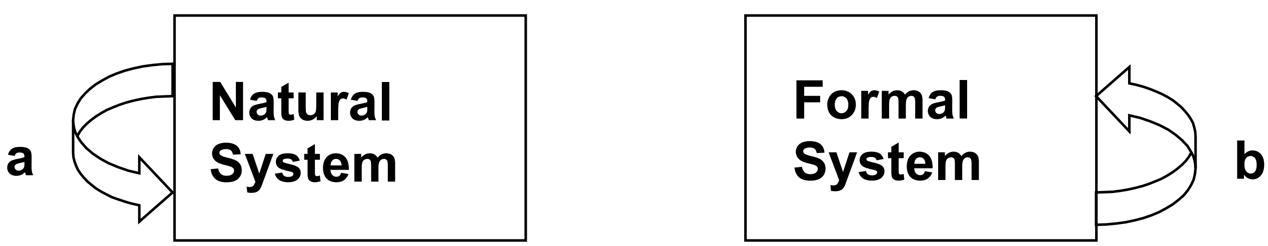
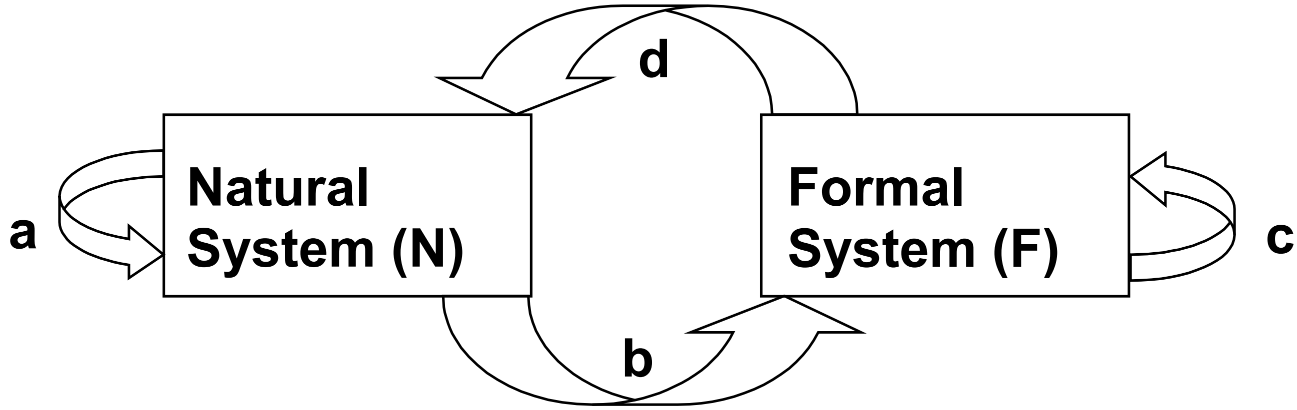


Figure 1. Entailment structures.

The fact that distinct systems are non-identical does not preclude them from being regarded as being in some sense similar. Similar systems should have distinguishing features that closely correspond to each other. Dissimilar systems should have distinguishing features that do not closely correspond to each other. As already noted, the distinguishing feature of a system is its entailment structure. Thus, we would expect similar systems to have entailment structures in which there is some degree of correspondence between the entailments.

To establish this correspondence, consider a system of encodings and decodings.[6] For example, we might have a system of encodings that encodes a set of phenomena in the natural system, N, in Figure 1, into a set of propositions in the formal system, F. We might also have a system of decodings that decodes a set of propositions in the formal system, F, into a set of phenomena in the natural system, N. Although the two systems remain independent in the sense that causes in one do not produce effects in the other, the two systems can be linked by the encodings and decodings as shown in Figure 2.



$$MR=\{(a,c) \mid a = b + c + d\}$$

Figure 2. Linked entailment structures.

This linkage between entailment structures provides the means of determining the similarity between two systems. Suppose that an event, e_1, in N can be encoded to a proposition, p_1, in F; we can think of the encoding arrow, b, in Figure 2 as a measurement on a natural system. Suppose further that the proposition, p_1, when applied to the inferential structure in F entails a consequential proposition, p_2, in F. In other words, the two propositions are entailed as an implication, c = (p_1 ->p_2), in F. Suppose that this entailed proposition, p_2, in F can be decoded into an event, e_2, in N; we can think of the decoding arrow, d, in Figure 2 as a prediction by a formal system.

Rosen defines congruency between the entailment structures in the following way.[7] Suppose that in the underlying reality the event e_1 in N causes event e_2 in N. In other words, the two events are entailed as a causal linkage, a = (e_1 ->e_2), in N. Suppose further that the linkages commute. Event e_1 is encoded by b to proposition p1, which implied proposition p_2, which decodes to event e_2, and that there is exact correspondence between the predicted event e_2, and the caused event e_2. The commutation is also described as a = b+c+d. If there exists no such entailment c in F, having a commutative relationship with some entailment a in N, then the two systems do not have congruent entailment structures. Entailment structures are congruent to the extent that such correspondences between entailments exist.

If such correspondences between the entailments in the two systems do exist, then we can learn something about one entailment structure by observing the other. This is the essence of Rosen's Modeling Relation. When it is applied to a formal system to obtain predictions about a natural system, the inferential entailments in the formal system correspond to the causal entailments in the natural system. Where the relationship holds up and where it breaks down are both understood. This is where the Modeling Relation differs from "black box" approaches. Construction of a "blackbox" makes no claims about the causal links in underlying reality, offers no understanding of the natural system it purports to describe, and offers no warning as to when the description will break down.

In contrast, for any valid Modeling Relation, the identification of the encodings and decodings between two systems is an act of discovery based on insight or understanding. The benefit of this understanding is the awareness of the specific entailments so described, and a clear indication of the scope of applicability (or non-applicability) of the formal system as a model. The cost of this understanding is that it is an art and not a science in the conventional sense; there is no automatic or algorithmic method for determining either the encodings or decodings. In fact, there is not even any necessity or assurance that the system of decodings can be obtained from some straightforward inversion of the encodings.

Both the cost and benefit of Rosen's formalism go to the question of why does it matter. We attempt to use formal systems to learn about natural systems because simply observing the natural system is either too slow, too costly, too dangerous, or too inaccessible. Formalism without understanding of the underlying reality is seductive. At a fraction of the cost of the real thing, it offers the illusion of understanding. However, pretending that a modeling relation between a formal system and a natural system when there is no congruency of entailment gives us results that we cannot trust, and on which we cannot afford to risk lives, safety, or vast sums of money.

3. ABSTRACTION OF MEANING

Detection of defects from sensor data is a process of abstraction of meaning from sensor output. If a defect or danger is in its field of view, a living creature abstracts the meaning that "something is wrong here," given a flow of data from its senses, and awareness of its context from prior experience. Can this kind of abstraction be implemented in an artificial system? Note what is actually being asked. This project is *not* an attempt to create or even simulate a living creature; it is an attempt to artificially produce a valuable behavior observed in some living creatures.

Landauer describes the abstraction of meaning as being organized into a hierarchy.[8] In increasing order of sophistication, the four levels of the hierarchy are data, information, knowledge and understanding. Qualitatively, information is when you can say it, knowledge is when you can do it, and understanding is when you can teach it. Fundamentally different types of processing are required within and between each level.

Data is the rawest or most elemental form of information. Observations of ontological events (real-world phenomena) produce a stream of epistemological atoms (data) according to some model of the measurement process. Conventional computer programs deal with data.

Information is data with an interpretive context. It is relatable to other collected data and to other available information. It can be processed to make new connections with other information or knowledge. The idea here is to find a formal space that is the best description of the data. Arguably, there are several available computational techniques that abstract information from data. Goldfarb's evolving transformation system is one example. It identifies class from exemplars of the class, providing a measure of distance between exemplars and distance between classes. It evolves transformation rules such that successive non-equivalent generations of formal spaces are produced until the one well suited to the data and the situation is found.[9] Bayesian parameter estimation is particularly well suited for converting sensor data to information. It can take prior knowledge (including associations observed in physical reality) into account. Most importantly, it provides a computed measure of how well a particular model describes the data.[10]

(Note: In this context, distance is a more general concept than the geometric distances between vectors, such as Manhattan or Euclidean distances. Two exemplars are members of the same class or have a small distance between them if it requires little effort to transform one exemplar into the other. Two exemplars are members of different classes or have a large distance between them if it requires great effort, or it is impossible to transform one exemplar into the other. Geometric distance is a special case of this concept of distance.)

Both of these computational methods all appear to be consistent with the need of a computing system in a complex environment to escape the trap of rigidity.[11] Both allow for *model expansion*, or building a system whose grounding can be arbitrarily "deepened." Both can map current structures onto new foundations. In particular, Bellman's description of cooperation between observed data and theoretical models in the spirit of a Kalman filter, producing a running model of the current state and an error estimate, is the quintessence of embedded Bayesian induction.

4. SIGNAL OVERLAP

One of the major problems in the evaluation of signals from ultrasonic sensors is the fact that the signal of interest is often overlapped with many other signals.[12] The feature of interest (such as a localized weld defect) produces a signal that contains desired information (such as the distance of the weld defect from the point of ultrasonic excitation). However, other features (such as the edges of the workpiece) also produce signals that overlap the signal of interest, but contain no relevant information. In addition, the signals are inherently nonstationary, and equally inseparable in the time domain and the Fourier frequency domain. 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 that is the sum of four overlapping Gabor functions plus a low-level Gaussian-distributed random function. Also consider that the information of interest is contained in one of the Gabor functions. (Note: A Gabor function is a Gaussian-windowed sinusoid. Its waveform is completely characterized by four parameters—the frequency and phase of the sinusoid and the peak location and width of the window.)

In this example, suppose 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 3, 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 the time or frequency domains.

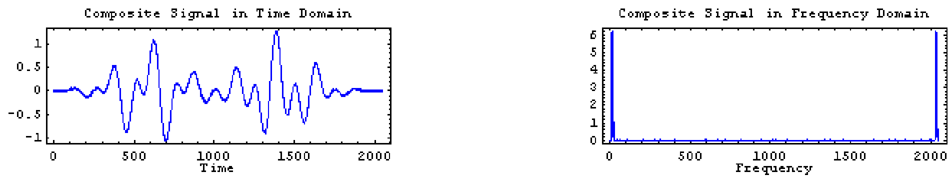


Figure 3. Signal overlapped in time and frequency.

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.[13] We can project the signal shown in Figure 3 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 4.

Another way of saying this is that Figure 4 is the projection into log likelihood space of the signal shown in Figure 3. 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 the log-likelihood that the observed data contains a Gabor function with the given pair of the parameter values.

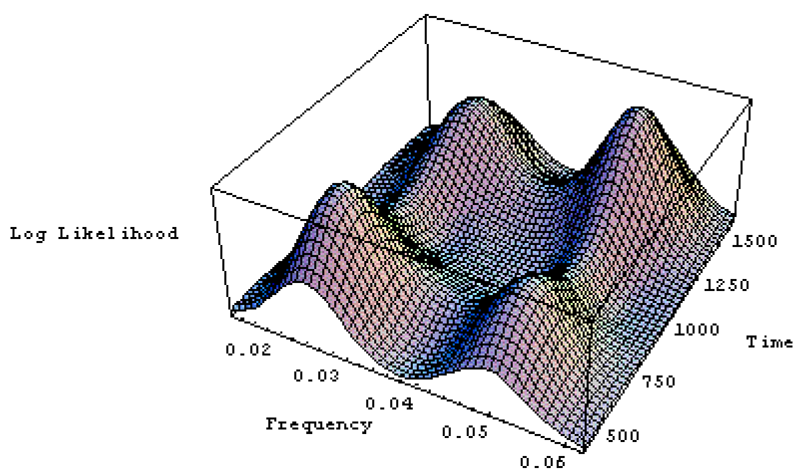


Figure 4. Likelihood of fit of signal to Gabor function.

Given the signal shown in Figure 3, 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. [Note that local optimization algorithms such as gradient descent are vulnerable to being trapped in local optima.] As indicated by the peak in Figure 4, 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 3 is plotted in the left-hand plot in Figure 5. This is the Gabor function whose parameters are found at the global optimum in Figure 4. When this estimated signal is subtracted from the signal in Figure 3, the residual in the right-hand plot of Figure 5 is obtained. Note that the most likely Gabor function has been separated from the signal without disturbing the other information in the signal.

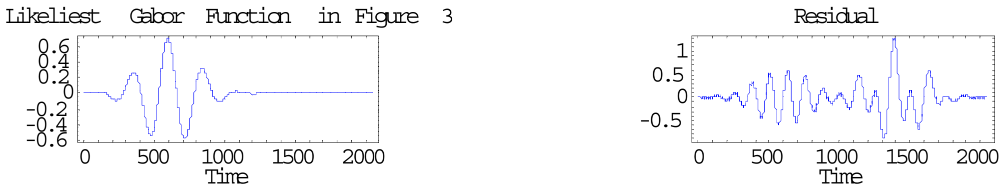


Figure 5. Most likely signal and residual.

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 6 we see the results of repeating this process until the residual is reduced to noise. The second through fourth likeliest Gabor functions have times of 1397.9, 612.2, and 1400.9 and frequencies of 0.0251, 0.050, and 0.050 respectively. The residual after removing the four likeliest Gabor functions is noise and cumulative rounding error.

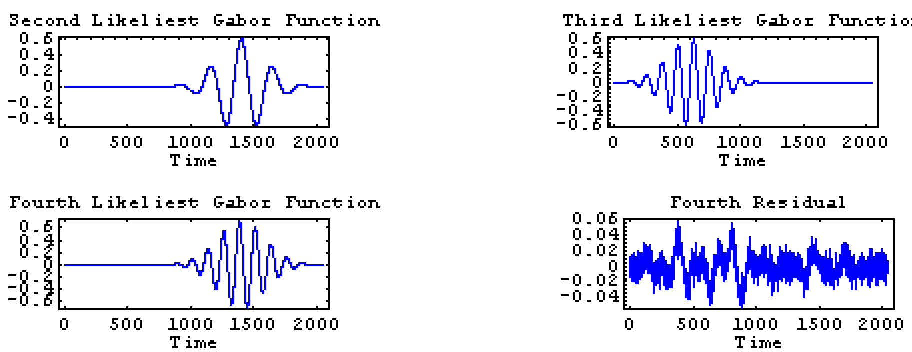


Figure 6. Other components of overlapped signal.

The point of the foregoing discussion is to demonstrate that overlapping signals can be separated without disturbing each other. However, the technique must be model-based. When we find an abrupt change in the behavior of the model, it should correspond to a change in the underlying causal entailments. In other words, it should provide a reliable signature of the defect in the signature data.

5. RESULTS

A typical result is shown in Figure 7. Each plot is the output voltage of a LBU photo-detector as a function of time, as the system makes 30 successive scans across a workpiece with a flawed weld. It would be very difficult to detect the flaw simply from a visual inspection of these raw data.

From the data for each of the 30 scans, the most likely model (or dominant component) was computed using Bayesian parameter estimation. For each scan, the waveform of the most probable model is a chirped Gaussian-windowed sinusoid. The most probable is taken to be the dominant component of the signal. These are plotted in Figure 8. This dominant component appears to be a biasing effect characterizing the experimental setup. As shown in Table 1, this component contains approximately 95% of the signal energy for each scan.

The second likeliest component for the data of each of the 30 scans is plotted in Figure 9. For each scan, the first residual is computed by subtracting the estimated data for the likeliest component from the original data for the scan. The most probable model of the residual computed by Bayesian parameter estimation is taken as the second likeliest component of the original signal. For each scan, the waveform of the second likeliest component is a non-chirped exponentially rising sinusoid. This appears to be a reflection of an exponentially decaying sinusoidal component off the back of the workpiece. As shown in Table 1, the second likeliest component contains approximately 2–3% of the signal energy for each scan.

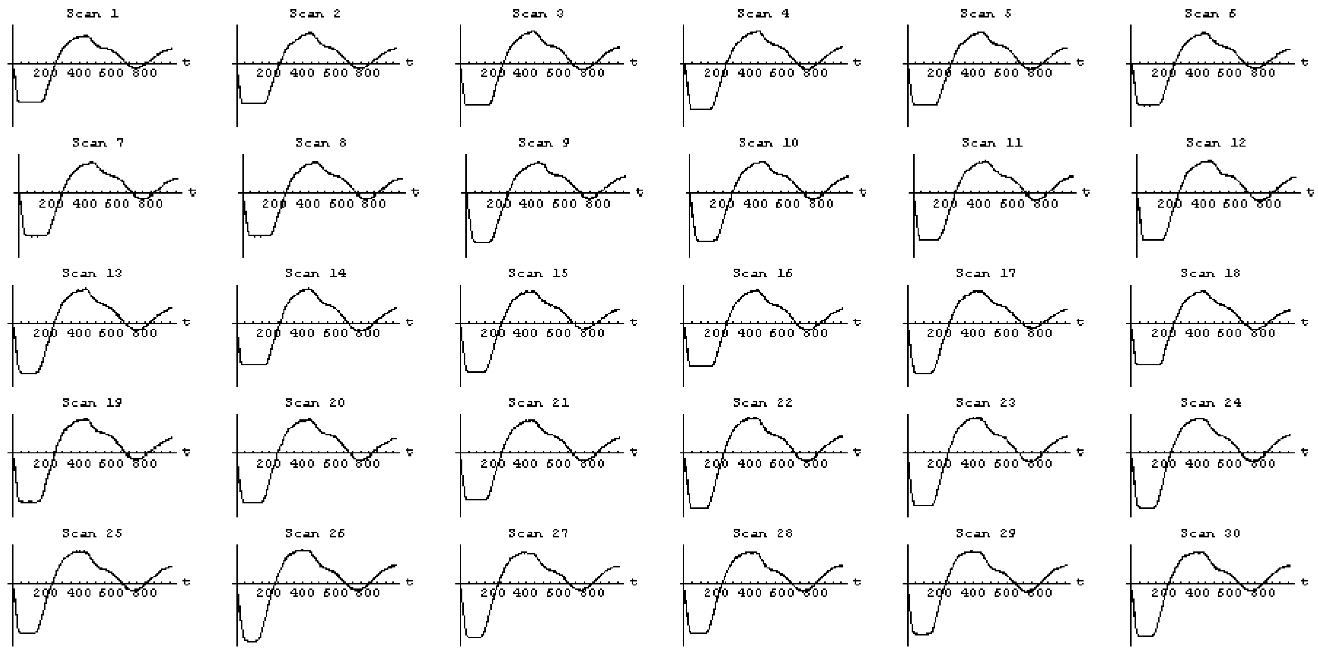


Figure 7. Successive scans across a flawed weld.

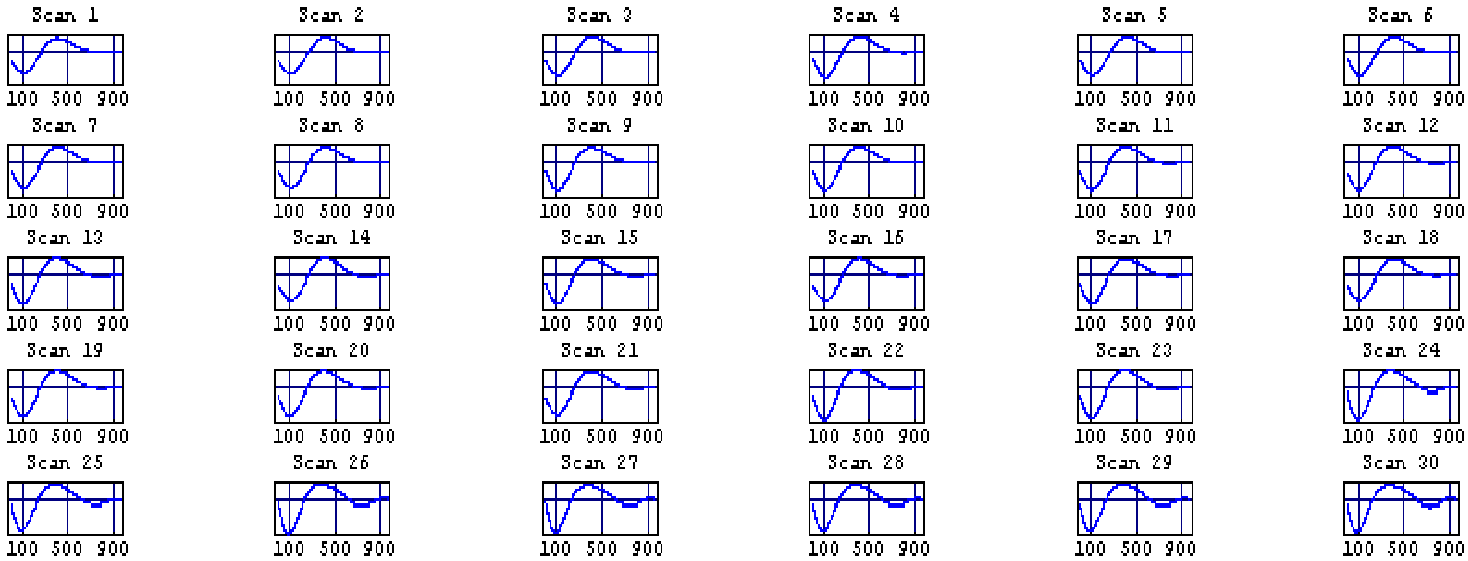


Figure 8. Likeliest component of each scan.

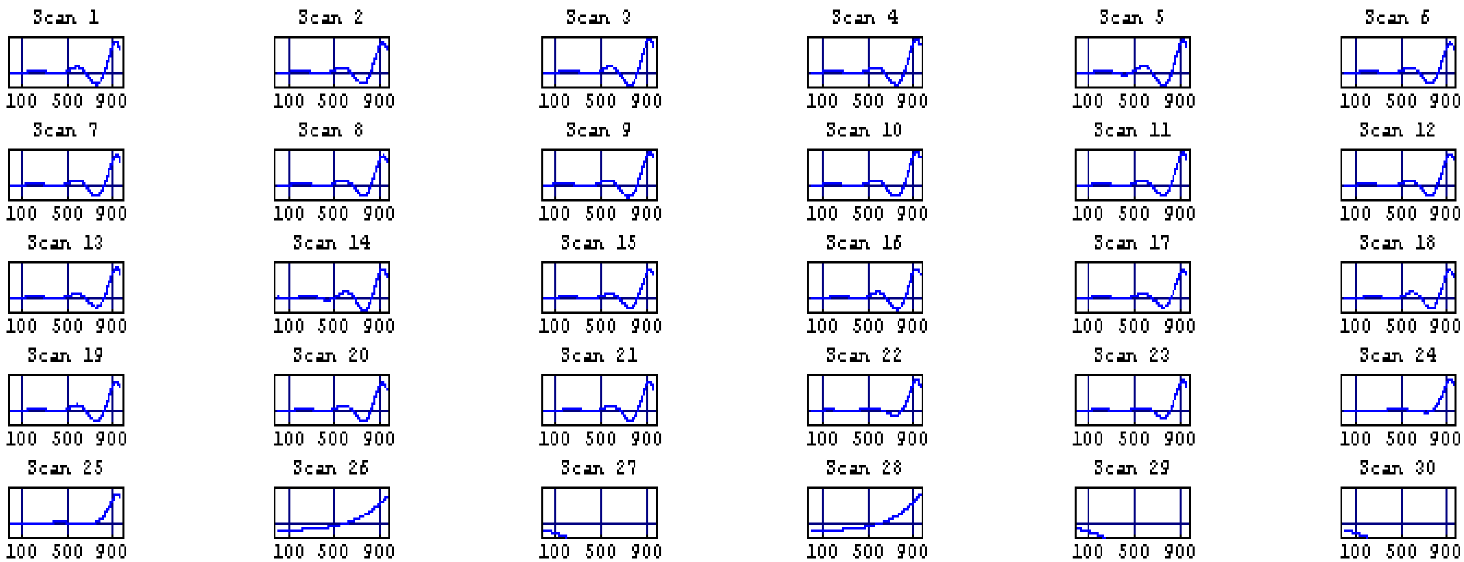


Figure 9. Second likeliest component of each scan.

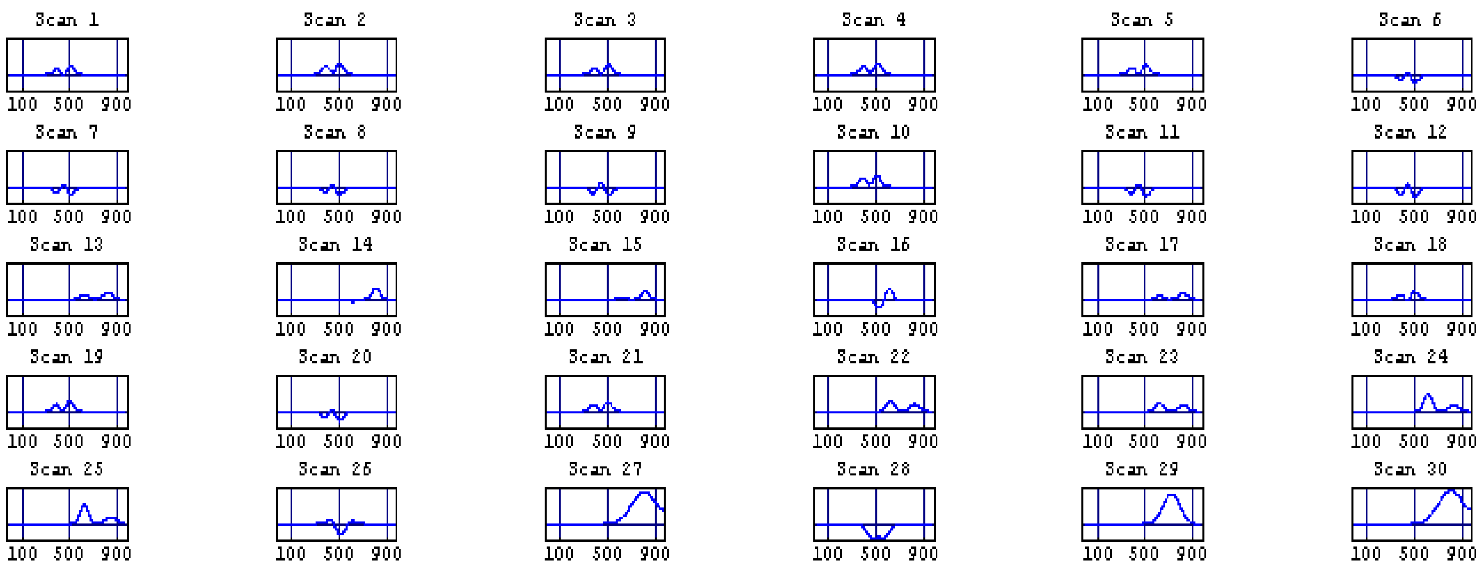


Figure 10. Third likeliest component of each scan.

Table 1. Percentage of energy in three likeliest components of each scan.

Scan	1st	2nd	3rd	Scan	1st	2nd	3rd	Scan	1st	2nd	3rd
1	94.6	3.4	0.2	11	95.1	3.	0.2	21	96.	2.3	0.2
2	94.8	3.2	0.2	12	95.4	2.7	0.2	22	96.3	1.9	0.2
3	94.5	3.5	0.2	13	96.2	2.1	0.1	23	96.1	2.	0.1
4	94.9	3.2	0.2	14	95.6	2.5	0.1	24	95.8	2.	0.6
5	94.7	3.4	0.2	15	96.4	2.1	0.1	25	95.6	2.	0.9
6	95.3	2.8	0.1	16	95.7	2.5	0.2	26	96.4	2.	0.2
7	95.3	2.8	0.1	17	96.6	2.	0.1	27	95.8	2.3	1.6
8	95.3	2.8	0.1	18	96.	2.3	0.1	28	94.9	2.7	0.3
9	95.2	3.1	0.2	19	96.3	2.1	0.2	29	95.4	2.3	1.7
10	95.1	3.1	0.2	20	96.3	2.1	0.2	30	95.7	2.3	1.6

The third likeliest component for the data of each of the 30 scans is plotted in Figure 10. For each scan, the second residual is computed by subtracting the estimated data for the second likeliest component from the first residual for the scan. The most probable model of the second residual computed by Bayesian parameter estimation is taken as the third likeliest component of the original signal. For each scan, the waveform of the third likeliest component is the sum of several Gaussian pulses. This appears to be a reflection off the weld. As shown in Table 1, the third likeliest component typically contains less than 1% of the signal energy for each scan.

Figure 10 reveals some interesting information about the workpiece. For the first 21 scans, the third likeliest component is located consistently (except for scans 14 and 15) in the neighborhood of time = 500. This is consistent with a visually detectable pinhole flaw in the weld in the vicinity of scan 14. The inconsistent location of the third likeliest component in scans 22 through 30 suggests other flaws in the workpiece that are not revealed by visual inspection.

6. APPLICATION TO INDUSTRIAL PROCESS CONTROL

The automotive industry is continually re-engineering its manufacturing processes to effect cost savings, enhance quality, reduce weight, and improve safety. One new process with all these attributes is associated with the fabrication of sheet metal panels for auto body manufacture. Different areas of the body have varying requirements for strength and corrosion resistance. Older manufacturing techniques either used single panels of sheet metal with stiffeners and protective coatings, or multiple panels with the proper characteristics which were attached separately to the body frame. In a new design-for-manufacturing approach, manufacturers are now producing large sheet metal panels or blanks made from smaller, individually engineered panels that are butt-welded together using a CO_2 or Nd:YAG laser welding process. With this approach, panels with differing thickness, metallurgy, or surface treatment can be joined to provide the desired attribute only in positions where it is required. Compared to conventional methods, the advantages of these tailor-welded sheet metal blanks are:

- less tooling and better integration of parts,
- forming with a single set of dies,
- reduction in manufacturing steps and in part count,
- superior dimensional control,
- reduction in overall weight,
- improved crash energy management,
- corrosion resistance, higher strength only where required,
- lower net cost, and
- better fit during assembly, resulting in less body noise.

In the United States, the production of tailor-welded blanks for 1997 is estimated to be 8 million blanks worth approximately \$25 million and made from 110,000 tons of sheet steel. The corresponding measure of welds produced is on the order of 10 miles per day.

In the blank welding process, the adjacent edges of the two panels to be welded are held at a fixed gap or in contact and the panels are then advanced under the stationary laser fixture. The most critical weld condition that must be controlled is the integrity and shape of the weld nugget formed between adjacent base metal surfaces. The desired transition from one surface to the other is smooth and flat, as shown in Figure 11. Here a concave or a convex surface is a sign of a lower strength weld. Typically, a concave surface can arise from poor fit-up or seam tracking, incomplete weld penetration or excessive weld penetration. Additionally, any crack or lack of fusion is a weld defect.

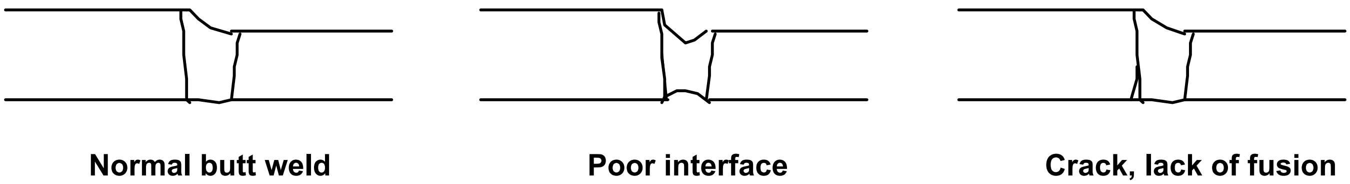


Figure 11. Schematic drawing of normal laser butt weld and poor weld with concave surfaces.

On-line monitoring of weld quality is a crucial unsolved problem in the manufacture of tailor-welded blanks. The goal is to be able to detect the full range of defects that may be present. At the current time, process monitors (e.g., weld speed, laser current) have been implemented, and control of these parameters to maintain the desired weld quality has been attempted. However, these open-loop controls are not sufficiently effective. As a further step in monitoring the weld process, a number of acoustic, optical, and ultrasonic sensors have been studied. Acoustic emission from the weld process (measured with an external microphone) was found to be noisy and not a full measure of weld quality. Optical sensors based on measurement of the spectral emission from the weld plasma or fusion zone have been investigated. Some correlation with weld quality has been observed, but the discrimination is not strong.

It is clear the need remains to implement a sensor that could directly measure the nugget integrity and surface profile, and thus determine the strength of the weld. One approach is to measure the deflection angle of a laser beam reflected from the nugget surface. Such an approach has been attempted, but poor surface quality has prevented reliable measurement of the surface profile. In addition, both sides of the blank would have to be interrogated. In the absence of any reliable automated sensor, welded blanks in the factory are now inspected by visual means on a statistical basis. Destructive sectioning with micrographic examination is sometimes used to augment the visual inspection. If defective welds are found then the output from the most or the entire shift must be inspected and the welder must be recalibrated. Clearly, this approach leads to added cost in energy, materials, and labor. As an alternative to this reactive welder maintenance approach, it would be desirable to develop a sensor that would monitor the desired weld property directly and allow proactive intervention to correct the weld process in real-time or to alert the operator that maintenance is required.

A technology that shows great promise for on-line measurement of weld quality in tailor-welded blanks is LBU. LBU is a technique for performing ultrasonic inspection using a pulsed laser to generate the ultrasound and a separate continuous wave (CW) laser interferometer to detect the ultrasound at the point of interrogation.[14] There are several significant advantages for the application of LBU. No sensor contact (or near-contact) with the workpiece is required, thereby allowing in-process measurements in the harsh welder environment (i.e., high temperatures, turbulent atmospheric environment, vibrating parts with rapid lateral motion). Both free-space and fiber-based delivery of optical energy can be implemented.

The authors are investigating the use of laser-generated plate (Lamb) waves propagating from one plate into the weld nugget as a means of determining the surface profile. The investigation is considering a number of inspection architectures based on processing signals from selected plate waves, which are either reflected from, or transmitted through the weld zone. One goal is to identify the simplest generation technique, wave mode, wave propagation geometry, feature extraction process, and pattern recognition algorithm that will provide effective identification of defective welds. It is anticipated that these measurements can be implemented just downstream from the weld cell (see Figure 12), so that weld quality data can be fed back to control critical weld parameters (or alert the operator of a problem requiring maintenance). Any deviation or defects from the desired surface profile can then be corrected before defective parts are produced.

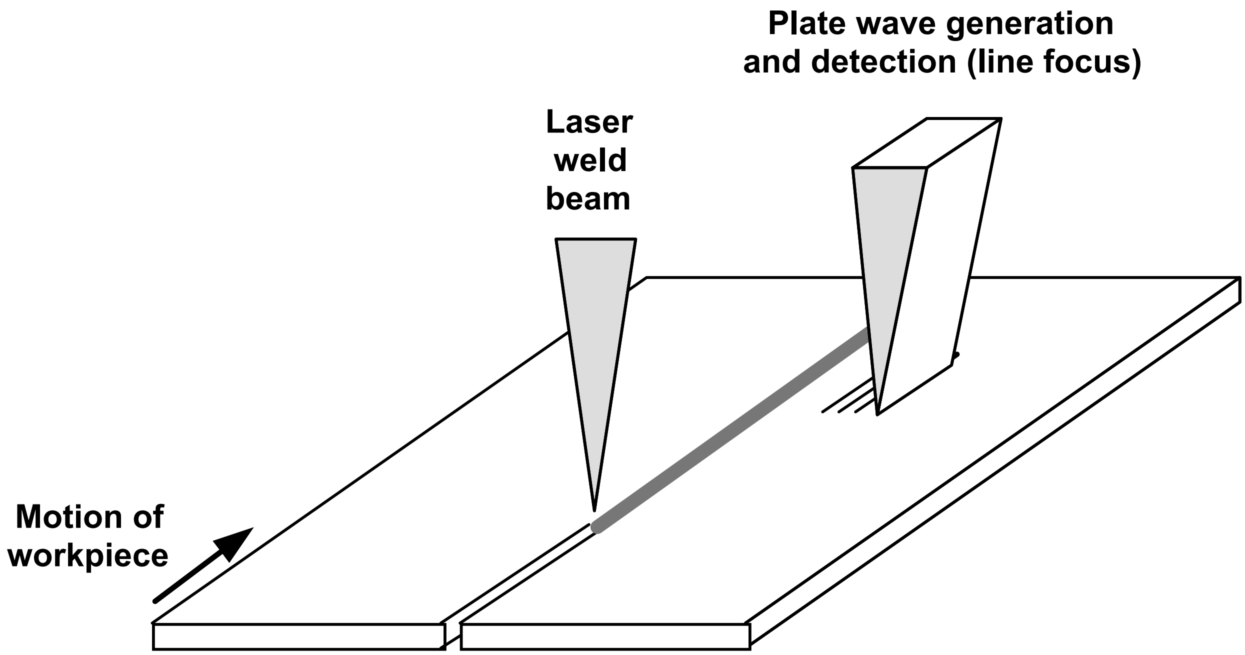


Figure 12. Schematic diagram of weld inspection geometry using reflected plate waves.
The gap between the sheet metal panels is exaggerated.

Recent advances in optical receiver technology can overcome some of the disadvantages of conventional laser-ultrasonic methods.[14] Adaptive interferometric receivers under development at Lasson allow the processing of speckled signal beams that result from the interrogation of machined surfaces. In conventional interferometric receivers, speckle is a source of phase error that can greatly reduce the receiver signal-to-noise ratio. In conventional LBU technology, multiple speckles can be avoided by focusing tightly to a single speckle, but this approach has the risk of signal "dropouts" due to the presence of "dark speckles." The other major advantage of the new adaptive receivers is that they are insensitive to noise at lower frequencies caused by workpiece vibration and by welder-induced turbulence in the path of the receiver probe laser. One challenge in implementing LBU for process control is the relatively low signal-to-noise ratio. This problem could be overcome by using more sophisticated signal processing for LBU than has been used in the past.[15]

7. 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. In ongoing research we are identifying the connection between the wavelet-based models and the underlying physical processes.[16] We will also investigate the comparative reliability and computational cost of wavelet and Bayesian feature extraction methods.

In future work we will seek to classify individual defects, including those encountered in the welding process. We will also devise a practical implementation of the signal-processing algorithm in real-time. The ultimate goal of this research is to construct a prototype of an on-line LBU 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.

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