Wavelet and wavelet-packet analysis 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. As might be expected, the transient nature of Lamb waves makes them readily tractable to wavelet analysis. The authors have used discrete wavelet and wavelet packet analysis to untangle the Lamb wave signature. For signatures of Lamb waves captured in laser ultrasonic data in tailor-welded blanks, this has led to straightforward detection of weld defects. Furthermore, both techniques are realizable in the highly parallel cascaded-lattice architecture, and are well suited for on-line real-time monitoring of laser ultrasonic signals.

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

1. INTRODUCTION

In many measurement problems, the signals being measured are oscillating bursts. This suggests that wavelet analysis might produce acceptable performance for an on-line instrument. The wavelet basis function is an oscillating burst and the discrete wavelet transform is implemented as a bank of computationally inexpensive finite impulse response (FIR) digital filters.

The idea behind wavelet analysis is that the signal can be considered as the weighted sum of overlapping wavelet functions.[1] In fact, any signal of finite bandwidth and finite duration can be completely characterized as a weighted sum of a finite number of scaled and shifted versions of the underlying wavelet. The concept is similar to Fourier analysis, in which the time series signal can be considered a weighted sum of sinusoids at various frequencies, with the transform coefficients being the weights. The practical meaning of the wavelet transform of a signal is that each coefficient of the transform is the weight, or relative amount of information the wavelet at that particular value of scale and shift contributes to the overall signal.

For many of the results reported in this paper, the wavelet analysis was performed with the Daubechies 10-coefficient least asymmetric discrete wavelet.[2] Discrete wavelets are not expressible in closed form. Plots of the wavelet and its corresponding scaling function were computed with Daubechies cascade algorithm, and are shown in Figure 1.

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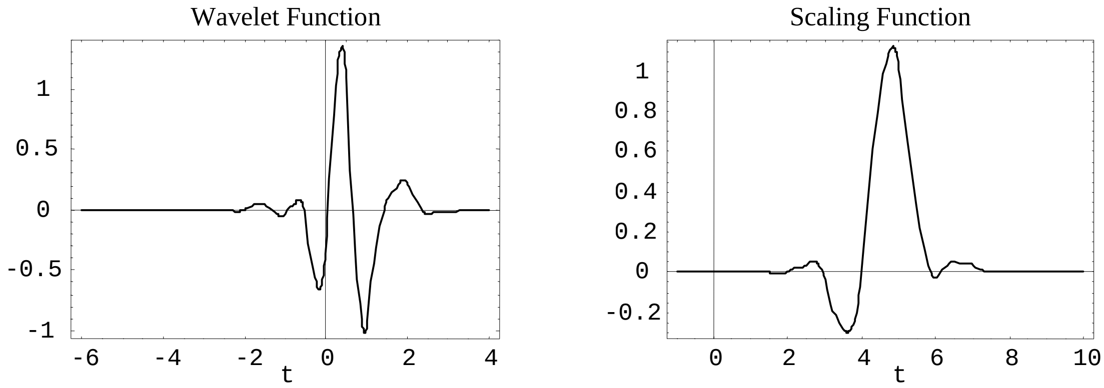


Figure 1. Wavelet and scaling functions for 10-coefficient least asymmetric wavelet.

Suppose that a time-domain input consists of a list of 960 evenly-spaced samples of a band-limited signal. The discrete wavelet analysis results in a list of 960 wavelet-domain coefficients output in response to each 960-element time series input signal. As sinusoids at different frequencies are orthogonal to each other, so also are scaled and translated versions of these wavelet functions orthogonal to each other. This means that Parseval's theorem holds for discrete wavelet transform; the amount of energy in the signal in the wavelet domain is exactly the same as the amount of energy in the signal in time domain.

The discrete wavelet packet transform is a generalization of the discrete wavelet transform. As shown in Figure 2, each stage of both the wavelet transform and the wavelet packet transform consists of an elemental pair of filters (high-pass and low-pass) that splits the input signal into two decimated orthogonal components. The low-pass output is an approximation of the input signal. The high-pass output contains the details of the input signal that are missing from the approximation. There is no information in the two outputs that overlaps, and nothing is lost. The input signal can be exactly reconstructed from the two outputs.

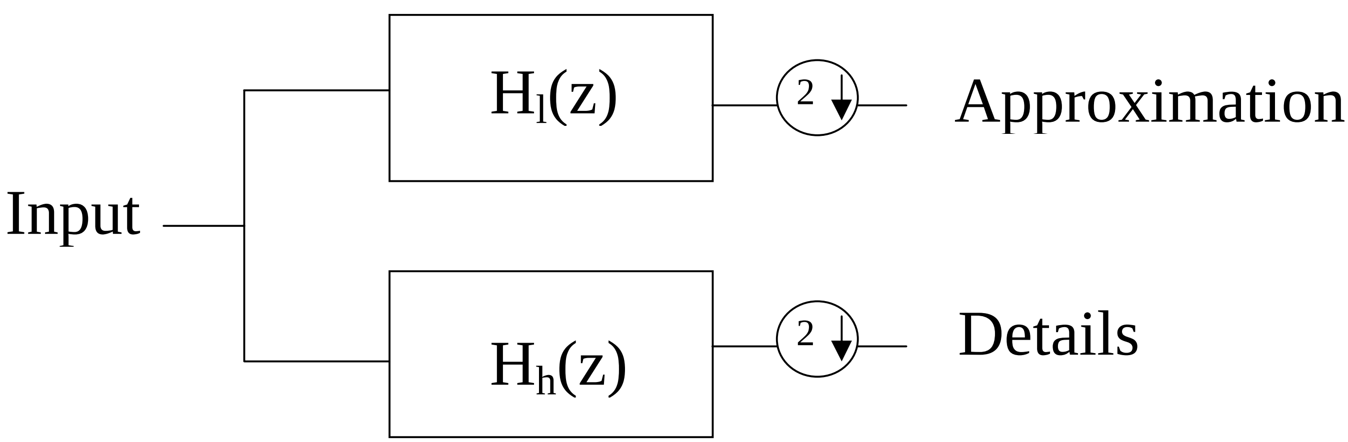


Figure 2. Elemental filter pair.

The discrete wavelet transform is implemented by cascading the elemental filter pairs as shown in Figure 3, and the wavelet packet is implemented by cascading them as shown in Figure 4. In the wavelet transform configuration, the low-pass output of the preceding stage is fed into an identical copy of the elemental filter pair. Thus the first approximation is further approximated, and the second set of details consists of the information present in the first approximation but absent from the second. In wavelet parlance, the output of the first high-pass filter is the set of wavelet transform coefficients of the input signal at the finest scale. The output of the next high-pass filter is the set of wavelet transform coefficients of the input signal at the next finer scale. The output of the final low-pass filter is the set of scaling function coefficients. The cascade can be repeated as often as necessary, and all the outputs are orthogonal.

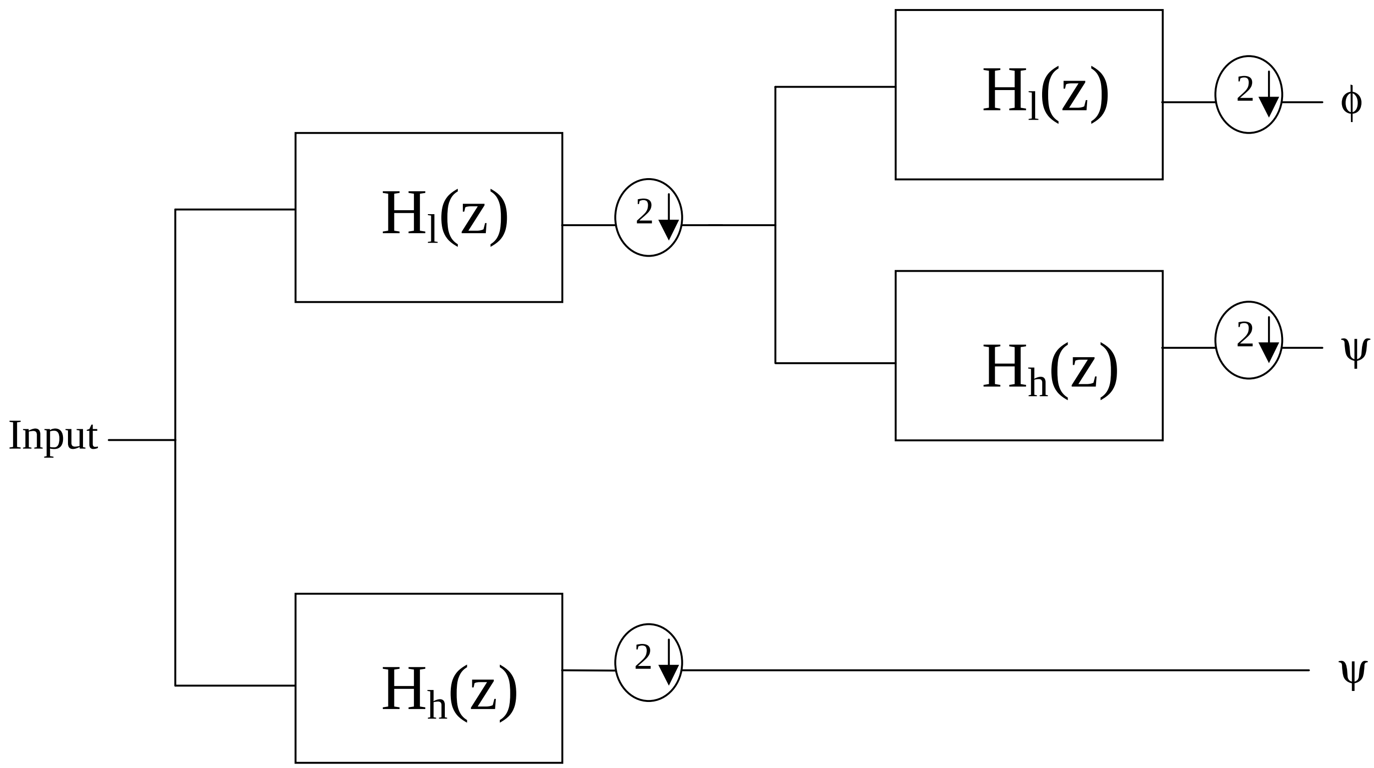


Figure 3. Implementation of the discrete wavelet transform.

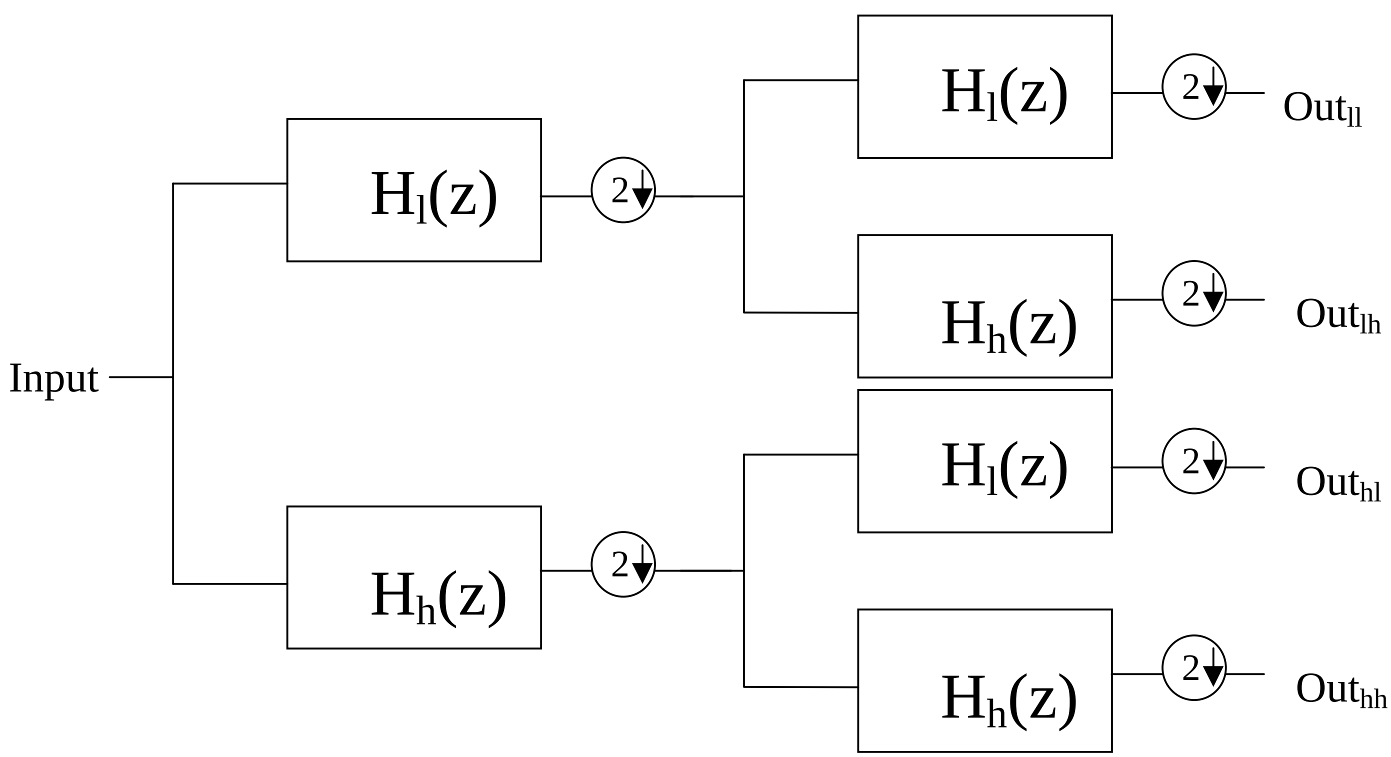


Figure 4. Implementation of the wavelet packet transform.

There is no fundamental reason why the high-pass output of the elemental filter pair cannot be split as well, and nothing to prevent repeating this process as often as necessary. A filter bank in which at least some of the high-pass outputs are split into other approximations and details implements the wavelet packet transform.[3] If the high-pass output is split whenever the low-pass output is split, then the system is a complete wavelet packet transform. However, it is not necessary for the wavelet packet to be complete. A more efficient representation of the signal may be obtained by leaving out some of the filter pairs in the cascade. Irrespective of how many filter pairs are included, all outputs are orthogonal.

For any given input signal, there is an optimal configuration of filter pairs that represents most of the input signal energy with the fewest coefficients. This is known as the best basis wavelet packet. The best basis is determined by finding the configuration of filter pairs whose output has the highest entropy.[4]

Energy is regarded as proportional to the information in the signal. Suppose that a signal's energy consists of three major elements. In addition to the energy of the desired signal, there may be coherent or non-random signals produced as undesired, but unavoidable biasing artifacts due to the hardware. Also, there may be broadband high-frequency energy that is typically regarded as random noise. If these three energies are separable in wavelet space, then the undesired bias and noise components of the sensor output signal can be identified and subtracted from the original sensor output. What remains is the signal of interest with its features unobscured.

2. CUMULATIVE ENERGY

The reason for transforming a time-series into another domain is to try to find a more compact representation of the information in the data. The performance of the different transforms can be compared by considering how effectively each compresses the same data set. The rationale for using data compression for the first step in pattern recognition feature selection is that it is more effective to search for features in a short list of numbers than a long list.

The effectiveness of several transforms was compared by taking the same list of 960 numbers (generated by a laser ultrasonic sensor), and producing an output list of 960 numbers. In each output list, there are relatively few big numbers, and relatively many numbers close to zero. The idea is that the useful information is in the few big numbers, and that the many small ones can be zeroed out without much loss of the underlying information. This is the conceptual basis for data compression.

The wavelet packet, the discrete wavelet, and the discrete Fourier transform are all orthogonal. Since Parseval's theorem holds, the energy in the output data set is identical to the energy in the input data set. For each transform output data set, the cumulative energy function counts up the cumulative energy in the output coefficients as energy is accumulated by counting energies, starting from the energy of the greatest transform coefficient, and moving to the smallest.[5] In the following example, we compute the normalized cumulative energy of the wavelet packet transform, the discrete wavelet transform, and the discrete Fourier transform of the same signal from a laser ultrasonic sensor.

In the upper left of Figure 5, as the plot of the first 200 members of the cumulative energy list shows, for the output of the best basis wavelet packet transform, virtually all of the information is contained in the biggest 135 members. The other 825 members are very close to zero. The upper right of Figure 5 shows the cumulative energy for the discrete wavelet transform, using the same input signal, and the same elemental filter pair (Daubechies least asymmetric 10-coefficient filter and its paraunitary companion). The lower left of Figure 5 is for the Fourier transform; it is clearly far less effective than the other two at compressing the signal. The lower right shows all three cumulative energies overlaid. The best basis wavelet packet transform is only marginally superior to the wavelet transform for this data set, and not worth the added cost compared to the wavelet transform.

For a transient signal, such as an oscillating burst, it is expected that most of the energy in the signal will be concentrated in relatively few of the wavelet coefficients, with all the others having values very close to zero. For the wavelet packet, the wavelet transform, and the Fourier transform, how many of the 960 coefficients in the transform space hold a given percentage of the information in the signal? For this particular signal, the wavelet packet and wavelet transform need 9 coefficients, and the Fourier transform needs 31 coefficients to contain 90% of the information in the signal. For the same signal, the wavelet packet and wavelet transform need 14 coefficients, and the Fourier transform needs 65 coefficients to contain 95% of the information in the signal. The wavelet packet needs 66 coefficients, and wavelet transform need 71coefficients, and the Fourier transform needs 232 coefficients to contain 99% of the information in the signal. The results in Figure 5 are typical of many laser ultrasonic signatures of Lamb waves in thin steel sheets.

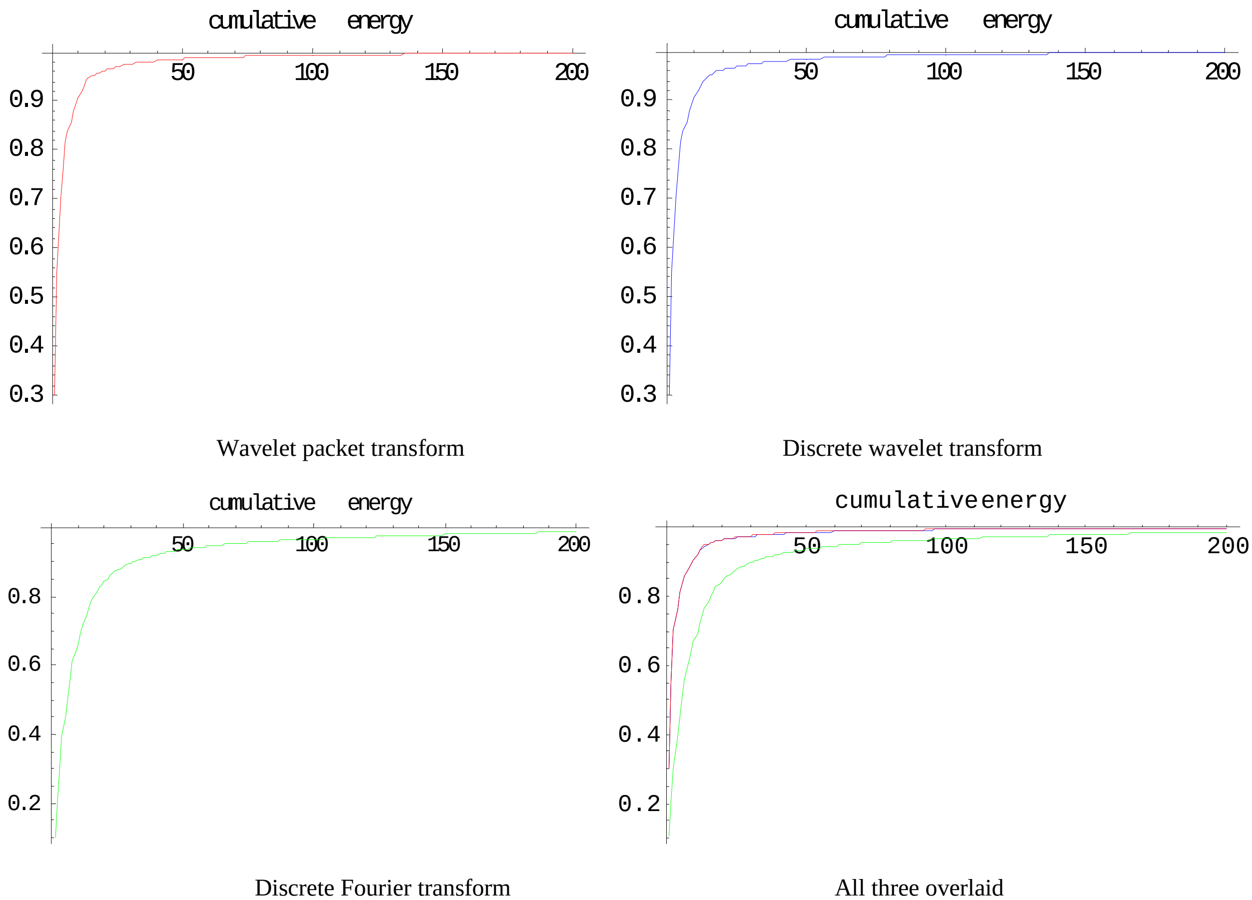


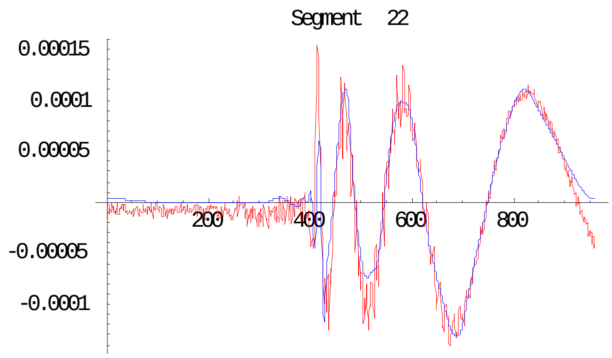
Figure 5. Cumulative energy of the same signal in different transform spaces.

One interpretation of any transform is that it is a measure of how much a given signal looks like the basis function of the transformation. Shown in Figure 1 is the wavelet function and scaling function that result from Daubechies least asymmetric 10-coefficient filter. An ultrasonic wave in steel looks much more like this than it looks like a sinusoid. Thus, it is reasonable to expect that the wavelet transform and/or the wavelet packet should be more effective than the Fourier transform at extracting laser ultrasonic signatures out of noisy and biased data.

3. DONOHO DENOISING

The compression effect is also the basis for Donoho denoising.[6] Donoho says that for a wavelet transform of a noisy signal, the big coefficients hold the information and the small coefficients hold the noise. Since the wavelet compresses the information, a signal spread out in the time domain will be very compactly represented in the wavelet domain. On the other hand, noise is approximately evenly randomly distributed throughout both the wavelet and the time domains. The problem with Donoho's technique is that it is a bit of an art to decide where to draw the line between big coefficients and small ones.

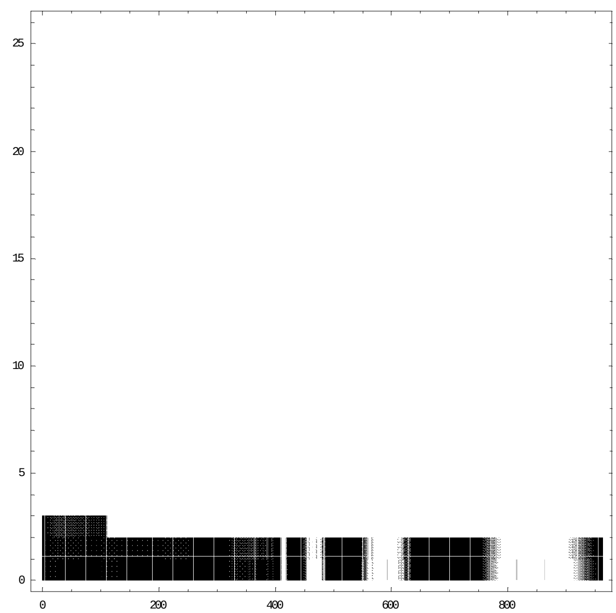
Suppose we try to denoise with the best basis wavelet packet, by declaring that the biggest coefficients holding 90% of the total energy of the signal constitute the "information." In the left-hand plot of Figure 6, the jagged line is the original time series. The smooth line is constructed by taking the wavelet packet transform and identifying and retaining the 9 coefficients that hold 90% of the energy in transform space and zeroing-out the 951 coefficients that contain the other 10% of the energy. The "denoised" time series is recovered by taking the inverse wavelet packet transform of the zeroed-out list. It is noted that the high frequency features of the time domain signal are mostly preserved (unlike the more traditional method of denoising by low-pass filtering), and noise is substantially reduced. However, it appears that there is some information being lost when we discard that last 10% of the energy.

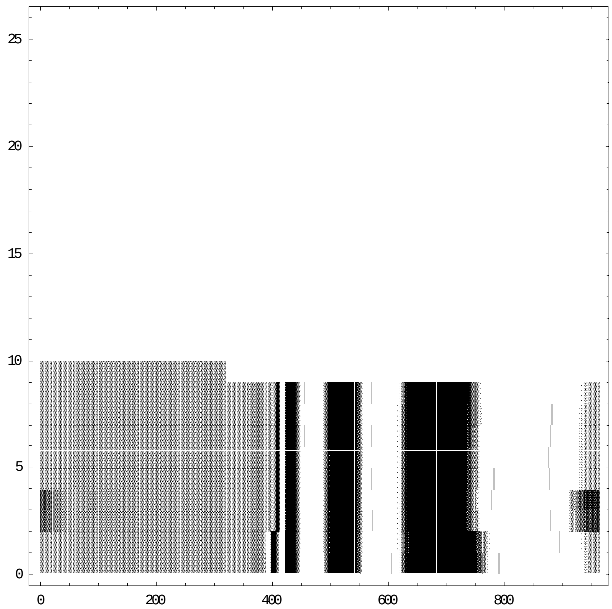


90% recovery

Figure 6. Denoising a laser ultrasonic signal.

The signal shown in Figure 6 is the 22^{nd} of a set of 26 time series collected for a particular specimen. As seen in Figure 7, it is fairly typical of the entire set. Figure 7 is a density plot of the same experimental data that was used to generate Figure 6. The horizontal axis is time, and the vertical axis is the index of the data set. Grey level is the signal strength. The plot shows the signals recovered from a set of 26 time series by using the Donoho algorithm to recover the signal from the wavelet packet coefficients containing 98% of the energy of the original signals. The smooth signal on the right hand side of Figure 6 can be interpreted as a section through Figure 7 at index 22.





25
20
15
10
5
0
0
200
400
600
800

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 9. Either 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.

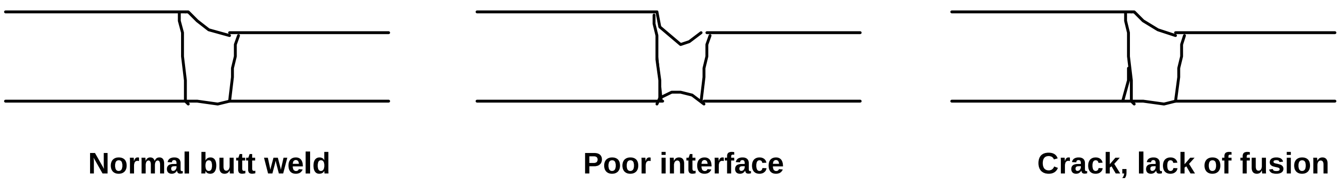


Figure 9. Schematic drawing of normal laser butt weld and poor weld with concave surfaces.

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 laser-based ultrasound (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.[7] 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 10), 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.

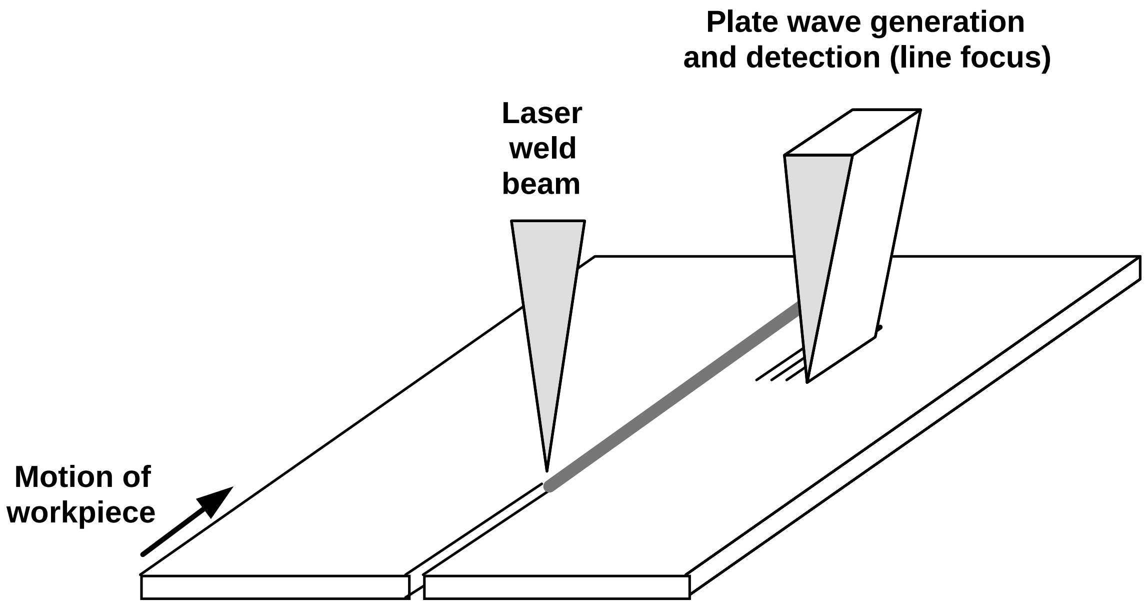


Figure 10. Schematic diagram of weld inspection geometry using reflected plate waves.
The gap between the sheet metal panels is exaggerated.

Recent advances in optical receiver technology can overcome some of the disadvantages of conventional laser-ultrasonic methods.[7] 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.[8] The signals produced by the LBU receiver are nonstationary transients in the time-domain, and real-time wavelet analysis should lead to the most efficient method of feature extraction. Furthermore, embedded wavelet processes are implementible in real-time hardware and are effective for many pattern recognition problems for transient signals in severe noise.[9-11]

6. 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 Bayesian-derived models and the underlying physical processes.[12] 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.

ACKNOWLEDGMENTS

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