Comparison of some non-adaptive deconvolution techniques for resolution enhancement of ultrasonic data

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A selection of well established deconvolution techniques are assessed for operation in the ultrasonic environment. Both time and frequency domain methods are compared under varying conditions of data format, design wavelet profile and signal-to-noise ratio, thereby providing insight into some of the difficulties associated with typical ultrasonic signals. Those algorithms which are best suited to particular ultrasonic applications and conditions are identified via a simulation approach, based around a linear systems model.

Keywords: signal processing; inverse filtering; deconvolution; resolution enhancement

The use of deconvolution techniques for resolution enhancement in ultrasonic applications has been subject to widespread investigation and is well documented in the literature. However, although a wide variety of methods are feasible, little information concerning their relative performance in relation to a typical ultrasonic environment is presently available. This work compares a selection of non-adaptive deconvolution algorithms when applied to realistic ultrasonic data. In the present context, the deconvolution objective is to enhance axial resolution in an ultrasonic system by suitable processing of the receiver output. A mathematical description of this unidimensional problem may be summarized as follows

\[ z(t) = w(t) * u(t) + n(t) \]  

where: \( z(t) \) corresponds to the total measured response from the receiving transducer or probe; \( w(t) \) defines the transducer pulse-echo impulse response (this function is sometimes termed the distortion wavelet and is obtained normally by measurement of the transducer impulse response from a suitable reflector positioned within the operational environment); \( u(t) \) is the acoustic impulse response from the target system under investigation; and \( n(t) \) represents measurement noise. This is assumed white and uncorrelated. Convolution is denoted by the asterisk symbol.

With a knowledge of both \( z(t) \) and \( w(t) \), the objective of the deconvolution process is to obtain \( u(t) \), with minimal distortion. Unfortunately, the inverse problem is highly ill-conditioned and some constraining or stabilization procedure is necessary if meaningful results are to be obtained. Consequently, the deconvolution techniques are required to produce a solution function \( u'(t) \), which is close in some sense to \( u(t) \). Such a solution may be generated by minimizing a particular norm of the following cost function

\[ J = |z(t) - w(t) * u'(t)| \]

A large number of deconvolution algorithms have been postulated as optimal solutions to this problem. The following well established techniques were selected as a basis for the comparison study:

1. the Wiener Pulse Shaping filter;
2. the Two-Sided Wiener filter;
3. the Weighted Least Squares (WLS) filter;
4. Mendel's Minimum Variance Deconvolution (MVD) algorithm;
5. Oldenburg's Frequency Domain Deconvolution algorithm; and

This list is by no means exhaustive and it is apparent that a number of alternative methods have been excluded. However, it is hoped that the work will serve as a basis of comparison for other deconvolution techniques which are omitted for reasons of space. Also, no attempt is made to discuss the algorithm derivations, as these are well documented in the listed publications. Moreover, with such a unidimensional approach to the deconvolution problem, \( w(t) \) must be spatially invariant for the inverse process to be valid throughout the sound field. In general, this is not the case and some degradation in algorithm performance is to be expected. The following additional points should be noted.

Both the Wiener shaping filter and frequency domain techniques operate by preselection of a desired output shape, usually an impulse, (denoting exact inversion), or
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A short duration gaussian bell. This desired response is denoted by \( d(t) \) in subsequent notation.

The Wiener Shaping, Two-Sided Wiener and WLS filters are the most straightforward from a design and operational viewpoint. They are each dependent upon the use of the \( L_2 \) norm for their derivation and are implemented using a fixed tap, FIR filter structure. The MVD is a two pass algorithm derived using a state space formulism for the deconvolution problem. It should be noted that the MVD algorithm can be implemented in a time varying environment and it should be termed strictly an adaptive deconvolution technique. However, when operating in its adaptive mode the kalman vectors associated with this algorithm will not reach the steady state condition required for a computationally cost effective implementation. For the purposes of this evaluation, the MVD algorithm is assumed to be working in its steady state, non-adaptive mode. Oldenburg’s frequency domain deconvolution algorithm is slightly different from the standard frequency domain techniques\(^{35,36} \), as it is derived by performing a strict \( L_2 \) minimization upon a physically meaningful cost function. Finally, the \( L_1 \) algorithm solves a set of constrained linear equations using the \( L_1 \) norm to generate the solution.

To assess relative performance in a realistic ultrasonic environment, the following areas were selected as a basis for comparison. Firstly, those algorithms which offer the highest resolution improvement are identified from a representative range of simulated pulse-echo data. Secondly, the influence of wavelet profile alteration on the design performance of individual algorithms is discussed and those techniques least influenced by violation of the spatial invariance assumption are identified. Thirdly, the performance of individual algorithms is compared using simulated ultrasonic data which has been contaminated with varying levels of wideband noise. Finally, a summary of the relative computational effort required to implement each technique is presented and those algorithms which best satisfy the inevitable compromise between performance and speed are indicated. Before continuing, the following general points relevant to the simulation approach should be noted.

For ease of data generation and algorithm comparison, all results were derived from a representative range of simulated ultrasonic data, obtained using the systems feedback approach described in References 21–23. This has been verified extensively on an experimental basis and is considered adequate for an accurate assessment of the various deconvolution algorithms. It is also important to note that the simulated data is always structured to contain a certain amount of random, contaminative noise. This is considered necessary since no practical deconvolution processing can take place under noise free conditions and unless otherwise indicated, a signal-to-noise (S/N) level of 100 dB is assumed. That is

\[
\text{Signal/noise (dB)} = 10 \log \left( \frac{\text{signal power}}{\text{noise power}} \right) \quad (3)
\]

Where average power over a specific time interval is used for both signal and noise quantities.

Each deconvolution algorithm thus requires a degree of stabilization to optimize performance in the presence of added noise. As a result, the ideal filter performance achieved via optimal design on noise free data is never realised. Moreover, it should be noted that most of the algorithms require input data which exhibits minimum delay characteristics. It may be shown\(^{37} \) that ultrasonic data obtained via conventional, ceramic based transducer structures cannot readily conform to a minimum delay format and a mixed delay pulse shape is generally evident. In consequence, an ideal impulse profile cannot be obtained from those deconvolution algorithms which require minimum delay data, even under conditions of zero additive noise.

All of the deconvolution algorithms with the exception of the \( L_1 \) technique generate a zero phase wavelet of the form shown in Figure 1. The axial resolution performance corresponding to each algorithm is assessed from this output. The technique adopted here is based upon the 20 dB (10%) modulation standard recommended by P.J. t’Hoen\(^{26} \), rather than the 6 dB (50%) modulation standard normally used, as it is considered more realistic in terms of final data quality. Figure 1 illustrates the use of this definition as a method of quantifying the resolution capability of a wavelet, where the interval denoted by \( T \) defines the time scale over which the amplitude is greater than or equal to 10% of the maximum amplitude. The processed wavelet is then said to possess a temporal resolution capability of \( T \) \( \mu \)s.

**Assessment of resolution enhancement**

The following two sets of ultrasonic data were employed for comparison purposes.

1 Ultrasonic data exhibiting narrow-band characteristics

This form of response is often encountered when a transducer is required to generate a high energy output. Such systems are often tuned, with a single peak in the spectral characteristics of \( w(t) \). Typical application areas are in sonar, and in some cases, the non-destructive testing and biomedical fields.

![Figure 1 Definition of wavelet resolution capability using the 20 dB modulation standard. \( T \) defines the resolution of the wavelet. Time scaling is in \( \mu \)s](image-url)
2 Ultrasonic data exhibiting wide-band characteristics

This type of data may be encountered when a transducer is required to generate a short waveform which automatically enhances the system resolution. Such a response function is common in non-destructive testing applications and in high resolution biomedical systems.

The time and frequency domain characteristics of test data generated via the linear systems model are shown in Figure 2, where (a, b) and (c, d) correspond to narrow-band and wide-band impulse response functions, respectively. In each case, the transducer centre frequency is normalized to 1 MHz, with a simulation sampling rate of 10 MHz.

Deconvolution performance on narrow-band data

The data profiles and associated resolution performance figures generated by the deconvolution algorithms are shown in Figure 3 and in Table I, column 1 respectively. There are two main points which emerge from these results. Firstly, the L1 technique (Table I/column 1/row 8 or T1/C1/R8), offers a resolution performance unmatched by any of the least squares based methods. Secondly, there is no clear performance difference among the other algorithms. The results do indicate however, that the Wiener Shaping filter (with $d(t)$ set to a gaussian bell) (T1/C1/R2), the WLS filter (T1/C1/R4) and the frequency domain filters (T1/C1/R6-7), have performed marginally better than the other, least square based algorithms.

Deconvolution performance on wide-band data

The resolution performance afforded by the deconvolution algorithms where the input data is relatively wide-band is summarized in Table 2. Examination of these results illustrates once again the high resolution performance afforded by the L1 technique and the general similarity in performance of the other methods. The results do indicate however, that those algorithms which are designed around a gaussian bell (T2/R2 and R7), demonstrate slightly superior performance. This is an expected result and can be explained in terms of the amplitude spectrum of the wide-band data, which maintains a higher amplitude as the frequency tends to zero. This, together with the fact that the spectrum of the desired response, (a gaussian bell) is lowpass, implies that the deconvolution procedure is able to employ effectively a larger proportion of the usable spectrum of $w(t)$ to generate the desired output. It should be noted also that the overall resolution performance figures obtained for the wide-band data are significantly better than those obtained under narrow-band conditions, even though each has the same fundamental resonant frequency. This is a direct result of the greater available bandwidth which can be used to produce the compressed output. As in the narrow-band case, each algorithm, (with the exception of the L1 technique), was observed to generate a similar output profile, typical of that shown in Figure 1.

Influence of wavelet profile variation on the performance of the deconvolution algorithms

It is useful to assess how changes in the transducer pulse echo response influence the performance of the deconvolution algorithms under investigation. Each inversion technique assumes that $w(t)$ remains constant, irrespective of where it is measured in the acoustic field. Such an
### Table 1: Resolution performance figures achieved using narrow-band ultrasonic data at various S/N levels

<table>
<thead>
<tr>
<th>Deconvolution technique</th>
<th>Resolution (µs)</th>
<th>100 dB</th>
<th>60 dB</th>
<th>30 dB</th>
<th>15 dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unprocessed 'noise free' wavelet</td>
<td>b.4</td>
<td>2.7</td>
<td>3.8</td>
<td>5.7</td>
<td>6.9</td>
</tr>
<tr>
<td>Wiener Shaping Filter</td>
<td>d(t) = Gaussian</td>
<td>1.9</td>
<td>1.7</td>
<td>1.5</td>
<td>2.0</td>
</tr>
<tr>
<td>Two Sided Wiener Filter</td>
<td>d(t) = Impulse</td>
<td>2.6</td>
<td>2.8</td>
<td>3.1</td>
<td>3.2</td>
</tr>
<tr>
<td>WLS Filter</td>
<td>d(t) = Impulse</td>
<td>2.4</td>
<td>2.5</td>
<td>2.6</td>
<td>2.7</td>
</tr>
<tr>
<td>MVD Algorithm</td>
<td>d(t) = Impulse</td>
<td>3.4</td>
<td>3.8</td>
<td>4.2</td>
<td>4.5</td>
</tr>
<tr>
<td>Frequency Domain Algorithm</td>
<td>d(t) = Impulse</td>
<td>1.9</td>
<td>1.9</td>
<td>1.9</td>
<td>1.9</td>
</tr>
<tr>
<td>L1 Algorithm</td>
<td>d(t) = Gaussian</td>
<td>1.9</td>
<td>1.9</td>
<td>1.9</td>
<td>1.9</td>
</tr>
</tbody>
</table>

### Table 2: Resolution performance figures achieved using wide band ultrasonic data at S/N level of 100 dB

<table>
<thead>
<tr>
<th>Deconvolution technique</th>
<th>Resolution performance (µs)</th>
<th>R</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unprocessed wavelet</td>
<td>1.63</td>
<td>W</td>
<td>0.96</td>
<td>R1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wiener Shaping Filter</td>
<td>d(t) = Impulse</td>
<td>0.96</td>
<td>R1</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two Sided Wiener Filter</td>
<td>d(t) = Gaussian</td>
<td>0.96</td>
<td>R1</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WLS Filter</td>
<td>d(t) = Impulse</td>
<td>0.96</td>
<td>R1</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVD Algorithm</td>
<td>d(t) = Impulse</td>
<td>0.96</td>
<td>R1</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency Domain Algorithm</td>
<td>d(t) = Impulse</td>
<td>0.96</td>
<td>R1</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1 Algorithm</td>
<td>d(t) = Gaussian</td>
<td>0.77</td>
<td>R1</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Assumptions and Methods

Assumption is generally invalid for the ultrasonic pulse echo environment, where changes in \( w(t) \) can be attributed to the physical characteristics of the piezoelectric transducer and to attenuation or scattering effects within the medium of propagation.

Several authors have investigated methods of introducing quantifiable, and if possible, physically representative modifications to \( w(t) \) in order to assess this effect. Herment et al. studied the robustness of their deconvolution algorithm with respect to changes in the wavelet profile by sampling the measurements at rates slightly offset from the designed rate, in an attempt to simulate the effect of dispersive attenuation in the medium of propagation. Oldenburg investigated the influence of frequency dependent attenuation in the medium of propagation to assess the performance of his frequency domain algorithm. In the following section, the influence of frequency related attenuation and transducer aperture diffraction is assessed with respect to deconvolution performance.

### Profile Variation as a Result of Spectral Attenuation

It is well established that the upper spectral components suffer selective attenuation as an ultrasonic pulse propagates through a given medium. Although the exact nature of the attenuation is a function of the transmission channel, it may be approximated in many cases by a power law and the medium acts effectively as a low pass filter, with characteristics proportional to the distance travelled by the acoustic pulse. To illustrate the influence of this behaviour on the selected algorithms, an 'ideal' ultrasonic wavelet was simulated under lossless conditions via the linear systems model. This data was then used as the design basis for a series of optimal inverse filters according to the various deconvolution methods. The loss free distortion wavelet was subsequently processed via a fourth order Butterworth low pass digital filter to approximate the influence of attenuation on the upper spectral components. The final stage involved deconvolving the lossy wavelet by each predesigned filter to assess how this form of profile alteration influenced algorithm performance.

The time and frequency domain characteristics of the distortion wavelet before and after low pass filtering are outlined in Figures 4a and b, respectively. A comparison

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Figure 4: Time and frequency domain characteristics of a simulated pulse echo response with frequency dependent decay. Attenuated data is denoted by the broken lines. Time scaling is in µs and frequency scaling in MHz.
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Table 3 Resolution performance figures illustrating the effect of frequency dependent attenuation on deconvolution performance

| Deconvolution technique | Unprocessed wavelet (µs) | Attenuated wavelet (µs) | R
|-------------------------|-------------------------|-------------------------|---
|                         |                         |                         | w

|                         | Unattenuated            | Attenuated              | w
|-------------------------|-------------------------|-------------------------|---
| Wiener Shaping Filter   | 2.83                    | 4.00                    | R1
| Two Sided Wiener Filter | 2.33                    | 2.17                    | R2
| WLS Filter              | 2.00                    | 3.00                    | R3
| MVD Algorithm           | 3.83                    | 3.33                    | R4
| Frequency Domain        | 2.00                    | 2.75                    | R5
| Algorithm               | 1.67                    | 4.00                    | R6
| LT Algorithm            | 0.2                     | 0.40                    | R7

of the amplitude spectra reveals significant attenuation of all frequency components above 1.5 MHz. The subsequent resolution performance after deconvolution processing is summarized in Table 3. An inspection of these results indicates a noticeable loss of resolution as a result of the filtering process. However, it is apparent also that the deconvolution outputs still afford a useful degree of wavelet compression and little associated distortion of the desired zero phase profile was observed. This would suggest that attenuation of high frequency information at these levels does not adversely influence the deconvolution performance. These results comply with those published by Oldenburg who reached a similar conclusion when examining the effect of high frequency attenuation on his particular algorithm.

Profile variation as a result of aperture diffraction

It is known that the acoustic wave profile generated by a transducer may undergo changes depending on where the profile is measured in the sound field. This phenomenon can be attributed to plane and edge wave interaction as a result of the finite aperture dimensions of the radiator. Furthermore, few transducers vibrate solely in a piston like fashion. Additional modes of vibration such as radial and head waves have been observed, particularly in the transducer near field. It should be noted that the nature of the reflector has an important bearing upon the degree to which diffraction effects influence the final receiver output. For example, a small, discrete reflector which has a fairly omnidirectional reflectivity will tend to produce larger variations in $w(t)$ than a large planar reflector which has a highly directional reflectivity. Such fluctuations are most apparent in the transducer near field and imply that the reflections from a particular structure placed at different points in the field will not remain constant, resulting in a different acoustic response from the same object as it is moved around in the field.

To illustrate some effects of aperture diffraction, consider the simulations outlined in Figure 5. These show the variations in the observed output voltage of a 1 MHz, 30 mm diameter disc transducer acting in the pulse echo mode and where the reflector is a small spherical object positioned 5 cm from the front face. Variations in the wavelet profile were introduced by simulating the effect of moving the reflector across the face of the transducer from $0^\circ$ (on-axis) through to $10^\circ$ (off-axis) while maintaining a constant separation distance.

![Figure 5](image)

For a meaningful comparison, it is necessary to obtain some figure of merit which will indicate the degree of similarity between the on-axis ($0^\circ$) transmit/receive impulse response (which all of the deconvolution algorithms will treat as the spatially invariant distortion function) and the various off-axis responses. The method adopted in this context involves cross correlation of the off-axis and on-axis data. Such a technique is by no means ideal, since it neglects the phase characteristics of the data sets being correlated. However, it is considered that it does offer a relative figure of merit which relates well to the performance of a particular deconvolution algorithm as the wavelet profile moves further from the ideal structure about which the inverse filter is designed. If the energy...
in each of the compared wave profiles is normalized to unity, then a cross correlation factor of 1 indicates perfect matching of the wavelets. Equation (4) defines the discrete cross correlation operation.

\[ g(k) = \sum_{j=-0}^{j} w_o(j)w_x(k+j) \]  

(4)

where: \( w_o(k) \) is the 0° on-axis pulse echo response; \( w_x(k) \) is the \( x^\circ \) off-axis pulse echo response; and \( g(k) \) is the resulting cross correlation vector.

Using this technique with the pulse-echo responses shown in Figure 5, the set of cross correlation factors defined in Table 4 was calculated. The results indicate that as the object is moved off axis, the associated cross correlation factors start to fall, thus quantifying the extent of spatial invariance.

For comparison purposes, each algorithm was designed such that the on-axis response of Figure 5a was optimally deconvolved. The same filters were then employed to process each wavelet outlined in Figures 5d–e. The resolution performance afforded by individual deconvolution algorithms when the input data corresponds to the design, axial response is summarized in Table 5, column 1. Actual response profiles after processing were very similar to those shown in Figure 3. That is, each output was centred at \( t = 0 \), with symmetry around the peak value, which was of uniform height in all cases.

The results shown in Table 5 also indicate that every algorithm suffers substantial performance degradation after processing off-axis data. The extent of this is further illustrated in Figure 6, for which the input data differed from the design distortion wavelet by a cross correlation factor of 0.943 (5° off-axis). An inspection of the output profiles indicates that each of the deconvolution algorithms has suffered a substantial decrease in all aspects of its performance. Firstly, the outputs have a significantly reduced resolution capacity over those obtained where the input data is the same as the assumed spatially

![Figure 6](image-url)
invariant response. Table 5 also shows a general trend of increasingly reduced resolution performance as the data becomes further removed from the on-axis response. This indicates that the use of the cross correlation factor as a measure of the variation in wavelet profile was a relatively effective means of quantifying the extent of variation. Secondly, the asymmetrical, non-uniform output profiles no longer satisfy the necessary requirements for unambiguous interpretation. A special note should be made concerning the performance of the L1 technique when w(t) no longer satisfies the spatial invariance assumption (see Figure 6b). In this case, the output shows little resemblance to the expected triangular response. As far as the other techniques are concerned, the results indicate that the WLS method, together with those which attempt to generate a gaussian bell, tend to be slightly more robust than their counterparts with respect to changes in the profile of w(t).

Influence of wide-band noise on deconvolution performance

This section attempts to examine and assess the relative performance of each of the deconvolution algorithms under conditions where the input data has been contaminated with wide-band noise. The noise problem is always present in any real ultrasonic system where measurement error can never be entirely eliminated. Signal-to-noise levels of 60, 30 and 15 dB, were selected as a basis for comparison, since these were considered to be representative of noise contaminated data covering most practical environments. In those applications where the S/N ratio is less than 15 dB, alternative noise reduction schemes such as matched filtering or even signal averaging may be considered before any deconvolution is performed. Such methods are not considered here.

The comparison employs two sets of results at each of the predefined S/N levels. The first set shows the deconvolution output of each algorithm, for a single, noisy, input wavelet. To illustrate further the effects under practical conditions, a second set of results outlines the performance of the algorithms when applied to pulse echo data received from a multilayered target system.

The multilayered system was chosen to comprise five nominal layers and the associated simulation impulse response u(t), is shown in Figure 7. The voltage generated by the receiving transducer is obtained by a convolution of u(t) and w(t). The final addition of white noise n(t), (arising from random noise and quantization), is used to simulate the measurement error associated with the data acquisition. This process is described by Equation (1).

Both sets of results utilize the simulated, narrow-band wavelet described in the previous section and illustrated in Figure 2a. The noise contaminated observations are outlined in Figure 8, where Figures 8a, c and e show the single wavelets and b, d and f show the observed responses from the multilayered system at S/N levels of 60, 30 and 15 dB, respectively. Inspection of these figures, apart from indicating the amount of noise on the data, clearly illustrates the inability of the transducer to resolve the structural properties of the layered target system. The deconvolution algorithms were then employed to reconstruct the layered system impulse response, u(t), from the noise contaminated data, z(t).

Deconvolution performance at 60 dB SNR

The resolution performance is summarized in T1/C2. Examination of these results indicates that each algorithm has suffered marginal loss of resolution compared to those achieved at a S/N level of 100 dB. The performance of each deconvolution algorithm on the multi-layered data shown in Figure 8b is compared in Figure 9. In each case, the main structural features have been extracted, with the L1 method again providing superior enhancement.

Deconvolution performance at 30 dB SNR

It is apparent from the results shown in T1/C3 that all of the algorithms have suffered a significant decline in
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Figure 9 Deconvolved layer reflectivity sequence at S/N = 60 dB. (a) Wiener Shaping Filter \( d(t) = \delta(t) \); (b) Wiener Shaping Filter, \( d(t) = \text{Gaussian Bell} \); (c) Two Sided Wiener Filter; (d) WLS Filter; (e) MVD Algorithm; (f) Frequency Domain Algorithm \( d(t) = \delta(t) \); (g) Frequency Domain Algorithm, \( d(t) = \text{Gaussian Bell} \); (h) L1 Algorithm. Time scaling is in \( \mu s \).

Figure 10 Deconvolved layer reflectivity sequence at S/N = 15 dB. (a) Wiener Shaping Filter, \( d(t) = \delta(t) \); (b) Wiener Shaping Filter, \( d(t) = \text{Gaussian Bell} \); (c) Two Sided Wiener Filter; (d) WLS Filter; (e) MVD Algorithm; (f) Frequency Domain Algorithm, \( d(t) = \delta(t) \); (g) Frequency Domain Algorithm, \( d(t) = \text{Gaussian Bell} \); (h) L1 Algorithm. Time scaling is in \( \mu s \).

Performance compared to that achieved at a S/N level of 60 dB. However, it was possible to resolve the major features of the layered system in all cases, with the L1 method providing the greatest resolution enhancement.

Deconvolution performance at 15 dB SNR

The single wavelet and multilayered results at this S/N level are shown in T1/C4 and Figure 10, respectively. It is apparent that there has been a noticeable increase in the output signal degradation compared to the results obtained at 30 dB. However, despite this loss of performance, the results indicate that the least square based algorithms are still capable of generating an output which approximates the major features of the layered system impulse response. The following additional observations may be made: the best performance at the 15 dB S/N level was achieved using the FIR filter based algorithms; and the L1 technique has started to break down at this S/N level. Referring to Figure 10h, it is apparent that the algorithm has been unable to extract two of the largest reflection events.

Discussion and conclusions

The results in the section on assessment of resolution enhancement show that the L1 method offers by far the greatest improvement in resolution. They also indicate that although the remainder are similar, optimum performance is dependent upon the spectral properties of \( w(t) \). In particular, the WLS is probably the best algorithm to use when the distortion function is narrow-band. However, when \( w(t) \) is wide-band, then those algorithms which attempt to generate a desired output in the shape of a gaussian bell, offer the best overall performance.

One further point of interest concerns the resolution performance of the algorithms when operating with non-minimum delay, ultrasonic data. The results did not indicate that either the Two-Sided Wiener filter or the MVD algorithm provide a better performance than any of the other, least squares based methods. This is rather surprising since both techniques are theoretically independent of the wavelet delay properties and a better performance would have been expected.

The results concerning high frequency attenuation indicate that at the levels investigated, this phenomenon does not produce a significant degradation in performance. On the other hand, the study of wavelet profile alteration caused by aperture diffraction indicated that no single deconvolution algorithm is particularly robust with respect to this phenomenon. All suffered a significant reduction in performance, both in terms of their resolution capacity and ability to produce unambiguous data. It should be noted however, that the WLS technique together with those algorithms which specify a gaussian bell as their desired output, tended to provide marginally superior performance. Special note should be made concerning the adverse effect of wavelet profile alteration on the performance of the L1 technique. Under circumstances where the data being deconvolved satisfies the spatial invariance assumption, then the L1 method results in the production of very high resolution data, in
which the deconvolved wavelet approximates an ideal impulse with no associated sidelobes. As a result of the exceptional resolution performance of this technique, the artifacts resulting from the alteration in wavelet profile are far more severe than those associated with any of the least squares methods, since any sizeable impulsive waveform on the L1 deconvolved output may be interpreted as a reflection event.

The results obtained in the section devoted to the effects of noise contamination indicate that S/N levels of 30 dB and above do not significantly influence the overall ability of any of the algorithms to resolve the major structural features of a target system. The FIR filter algorithms were found to be least sensitive to contaminative noise, providing reasonable results at all of the S/N levels examined. The L1 algorithm was found to give acceptable deconvolution results at S/N levels down to 30 dB but was observed to suffer a significant decline in performance at a S/N level of 15 dB. The MVD and frequency domain deconvolution algorithms performed reasonably well at all of the S/N levels examined.

To conclude, a brief summary describing the relative performance of each algorithm is presented together with a review of the relative computational effort required to implement each technique. Those algorithms which best satisfy the compromise between performance and speed are identified. A list of the computational requirements for a software implementation of each technique is presented in Table 6.

**Wiener Pulse Shaping Filter.** This technique has a number of attractive features, foremost of which is the speed and simplicity with which it can be designed and implemented. Furthermore, the algorithm was shown to be relatively insensitive to the effects of contaminative noise. It was found, however, that the choice of output shape, together with the spectral characteristics of w(t), are both important parameters, which if not taken into consideration, could result in the suboptimal performance of the filter. This technique is probably best suited to on-line applications (via dedicated hardware) due to the relatively high processing speed.

<table>
<thead>
<tr>
<th>Deconvolution method</th>
<th>CPU time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wiener Shaping Filter</td>
<td>0.04</td>
</tr>
<tr>
<td>Two Sided Wiener Filter</td>
<td>0.12</td>
</tr>
<tr>
<td>WLS Filter</td>
<td>0.04</td>
</tr>
<tr>
<td>MVD Algorithm</td>
<td>3.79</td>
</tr>
<tr>
<td>Frequency Domain Algorithm</td>
<td>0.08</td>
</tr>
<tr>
<td>L1 Algorithm</td>
<td>0.00 - 3.00</td>
</tr>
</tbody>
</table>

Table 6 Computation required for each algorithm

Length of distortion function, w(t) = 32 samples
Length of data to be processed, z(t) = 124 samples

The figures presented here were obtained by running the algorithms on a VAX 11/782 minicomputer. They are representative of the relative times required to run each of the algorithms on data sets of the length specified. They do not include the processor times required either for the design of the FIR filters or state vectors required by the MVD algorithm. The CPU time range quoted for the L1 algorithm represents a typical range which the algorithm may require to achieve the final output. Experience has indicated that the CPU times required when running the L1 algorithm depend both upon the types of constraints placed upon the output and upon the software package used to implement the algorithm.

**Two Sided Wiener Filter.** This filter was found to be only marginally better than the WPS filter in most of the categories of comparison. The performance was also dependent on the spectral characteristics of the distortion function. These facts, together with the threefold increase in computational effort, suggest that the WPS filter would be the preferable choice for most applications.

**Weighted Least Squares Filter.** Of the FIR methods, this technique provided the best overall performance. This was especially true when the filter was implemented using narrow-band data, as it consistently produced higher resolution results than any of the other algorithms, with the exception of the L1 technique. The WLS filter also proved to be fairly robust with respect to noise contamination and, to a lesser extent, wavelet profile alteration. The main drawback associated with this method is the relatively high amount of computation required to actually design the filter.

**Minimum Variance Deconvolution.** This technique performed fairly well in most of the categories of comparison. However, the achieved performance does not merit the increased computing power required for its implementation.

**Frequency Domain Deconvolution.** The performance of this technique was equivalent in most respects to that of the time domain counterparts with the exception that it proved marginally inferior at low S/N levels. However, the fact that all data has first to undergo a Fourier transform implies that it is not ideally suited to high speed applications. It can be used effectively however, in pseudo real-time applications as it is substantially faster than both the MVD and L1 techniques. One important advantage is the ability to deal quickly and readily with very long distortion functions, a property which makes it ideal for use in the design of special-purpose pre-processing systems.

**L1 Deconvolution.** This technique demonstrated the highest resolution capability and was also fairly robust with respect to wide-band noise contamination. It did prove, however, to be highly sensitive to changes in the profile of w(t) and great care has to be taken to ensure wavelet invariance. The algorithm also requires relatively large amounts of computing time and memory for its implementation. For this reason it cannot be seriously considered for any real time application. It could however, have an important role to play in those applications where processing time is not a critical factor.

Finally, it is apparent that the use of the non-adaptive deconvolution algorithms can result in an inaccurate representation of the structure of a target system, especially where the structure of interest lies within the transducer near field. Care should thus be taken when applying these deconvolution techniques to ultrasonic data to ensure that the transmit/receive response satisfies the spatial invariance assumption over the range of interest. This can be achieved by limiting the deconvolution procedure to measurements associated with the transducer far field, where diffraction related wavelet profile alteration is minimized. Alternatively, it may be possible to define accurately the wavelet w(t) at that point in the acoustic field corresponding to the position of the structure of interest. Clearly, these methods restrict the range over
which the deconvolution can be applied, and in the latter case is very difficult to implement in a practical system. An alternative method of tackling this problem could involve some form of time varying deconvolution algorithm such as an adaptive prediction error technique, which would not be constrained by the spatial invariance assumption. A number of adaptive techniques have in fact been investigated as part of the present study and this work will be reported at a later date.

A different approach involves treating the problem at the transducer level. A number of workers have investigated the design of 'diffraction-free' or plane wave transducers, with varying degrees of success. The design and manufacture of such devices is currently being investigated within the Strathclyde Group and it is anticipated that a combination of custom transducer design and adaptive processing will prove the optimal solution for fast, accurate deconvolution of ultrasonic data.

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