Seismic wavelet estimation

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ABSTRACT

In this paper, four methods of seismic wavelet estimation are investigated: the statistical method, the full wavelet method, the constant phase method and the Roy White method. The influences of algorithm parameters and data types on the wavelet estimation are also analyzed. It turns out that different wavelet estimation methods may give different results. They are influenced differently by parameter values and the data used. The best method needs to be determined for the dataset at hand and different parameter values need to be tested by trial and error. What is more, a minimum-phase wavelet is modeled as a linear-phase wavelet, which may make minimum-phase wavelet estimation more simple and robust.

INTRODUCTION

The seismic wavelet is the important link between seismic data and stratigraphy as well as rock properties of the subsurface. Seismic wavelet estimation is done to deconvolve the seismic trace, tie the well log to the seismic data, design inversion operator and etc.

In the stationary case, the seismic trace $s(t)$ can be modeled by the convolution of the seismic wavelet $w(t)$ and the reflectivity $r(t)$ plus noise $n(t)$ (Sheriff and Geldart, 1995)

$$s(t) = w(t) \bullet r(t) + n(t). \tag{1}$$

Here we ignore all the other physical effects of wave propagation such as wavefront spreading, transmission loss, multiples, attenuation, and anything else conceivable. Noise $n(t)$ is assumed to be white and stationary.

Two kinds of idealized wavelets are most common in geophysics. One is the minimum -phase wavelet, which models the recorded seismic wavelet. It has no energy before time zero and has the majority of its energy concentrated at the front. The other is the constant-phase wavelet, which models the residual wavelet after deconvolution. It has energy before time zero and has a constant-phase across dominant frequencies. Among constant-phase wavelets, the zero-phase wavelet, which is symmetrical about time zero, is the best for interpretation (Simm and Bacon, 2014). Figure 1 shows a minimum-phase wavelet and a 100-degree phase wavelet in the both time and frequency domains. They share the same amplitude spectrum. In the time domain, the trough of the minimum-phase wavelet, where the absolute value of its amplitude is the maximum, is 10 samples away from the time zero while it is 3-sample-distance in the case of the constant-phase wavelet.

Two reflectivity series are created as $r(t)$. One is a synthetic of random time series. The other is calculated from the p-sonic and density logs of well 12-27 in the Hussar experiment after log editing and depth-time conversion. Time zero is assumed to start at the top of the logs, neglecting the overburdens. Figure 2 shows the synthetic and real reflectivities in the both time and frequency domains. From the amplitude spectrum in decibels in panel b), we can observe that the synthetic reflectivity has the constant power at all frequencies while the power of real reflectivity is relatively low at low and high frequencies. So the synthetic reflectivity has a white spectrum while the real reflectivity has a colored spectrum.

Convolving a reflectivity with a wavelet from above and adding random noise $n(t)$, a seismic trace is created as is shown in Figure 3. The signal to noise ratio is 3 in the time domain. Here we ignore the drift time caused by anelastic attenuation. We assume the reflectivity time is well calibrated to the seismic time (aligned) or there is only a static time shift between them (misaligned).

Next, the seismic wavelet $w(t)$ will be estimated using the seismic trace $s(t)$ only (the statistical method) or using both the seismic trace $s(t)$ and the reflectivity $r(t)$ (the full wavelet method, the constant phase method and the Roy White method). The influences of algorithm parameters (the data window length, desired wavelet length and data window type) and data types (noise-free or noisy, synthetic or real reflectivity, aligned or misaligned reflectivity) on the wavelet estimation in each method will also be tested and analyzed.

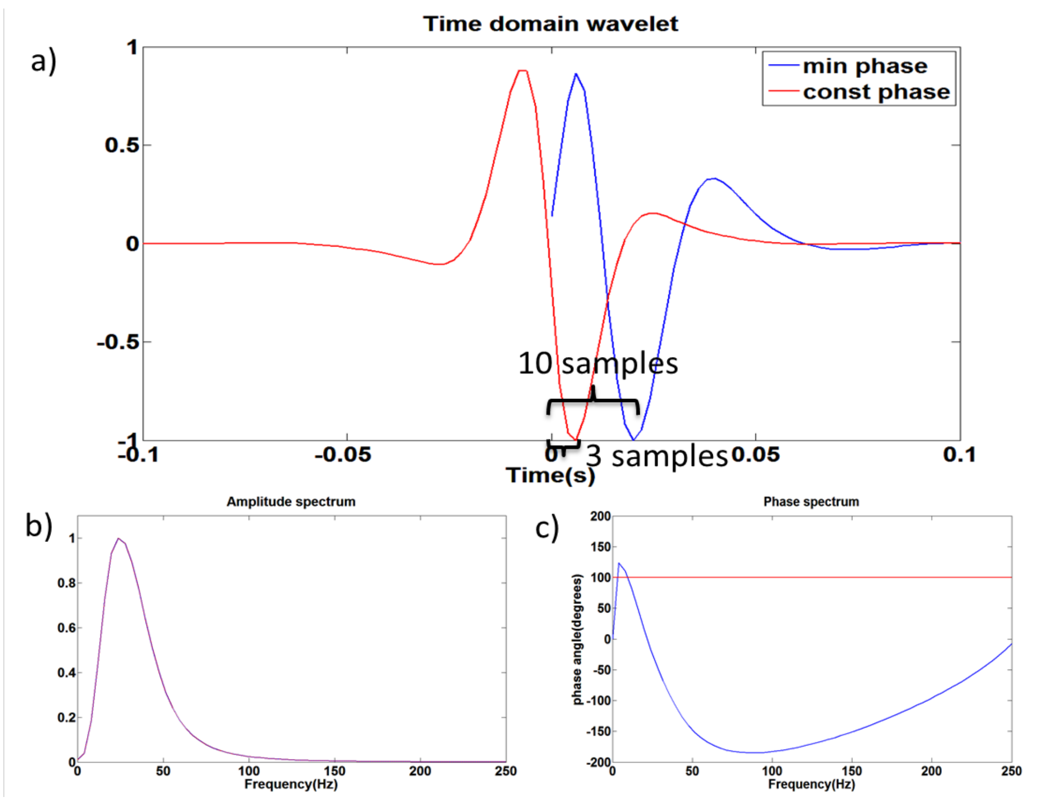

FIG 1: A minimum-phase wavelet and a constant-phase wavelet is shown as a) the time domain waveforms, b) the amplitude spectra and c) the phase spectra. In panel a), the trough of the minimum-phase wavelet is 10 samples away from the time zero while 3 samples for the constant-phase wavelet.

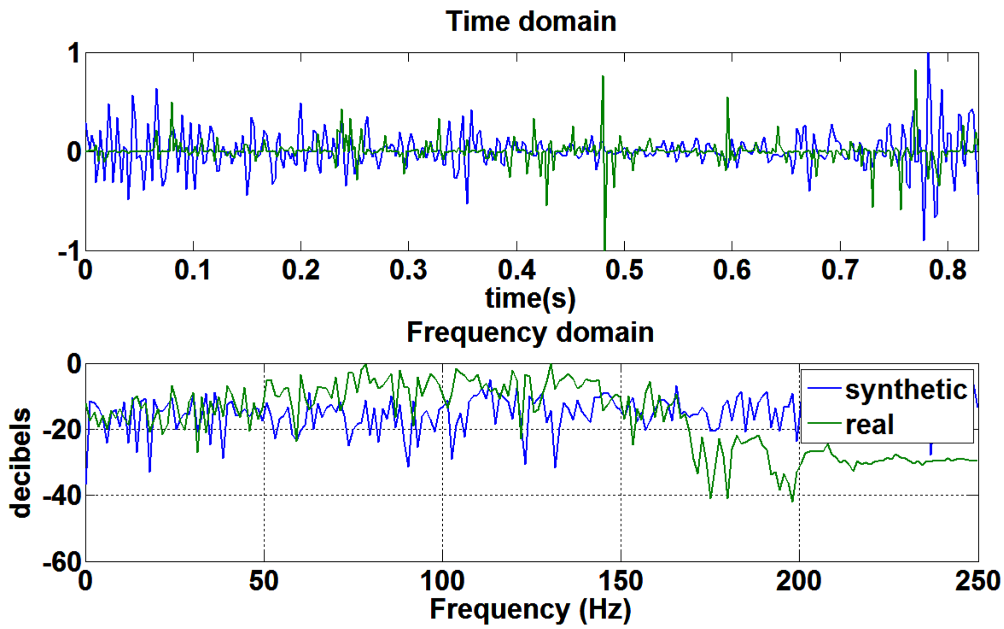

FIG 2: The synthetic and real reflectivities a) in the time domain and b) in the frequency domain.

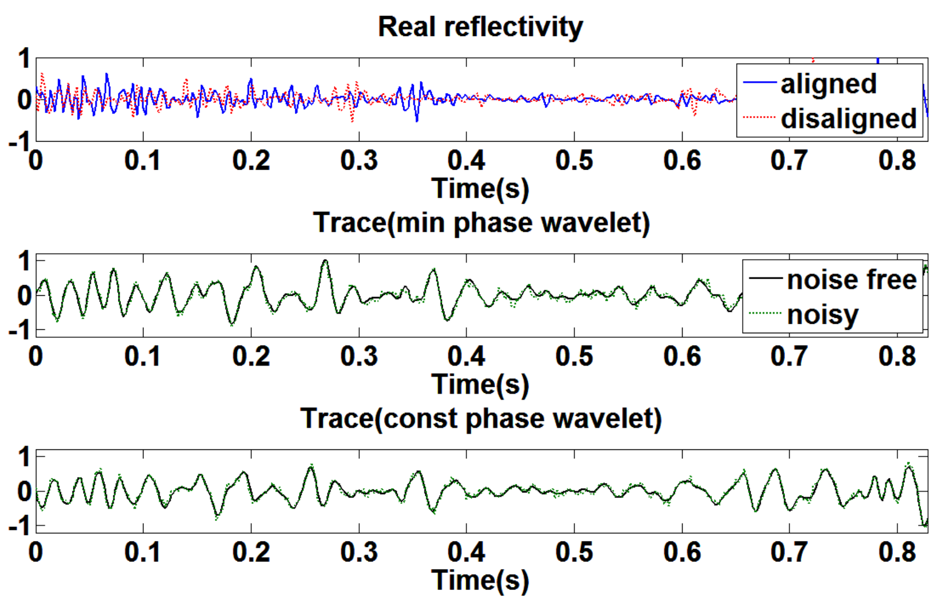

FIG 3: a) Reflectivities calculated from well 12-27. The red one is 30 samples (0.06 s) advanced relative to the blue one. b) Seismic traces from the convolution of the blue reflectivity in panel a) with the minimum-phase wavelet in Figure 1 without and with noise. c) Seismic traces from the convolution of the blue reflectivity in panel a) with the constant-phase wavelet in Figure 1 without and with noise. Thus, the blue reflectivity in panel a) is aligned with seismic traces in panels b) and c) while the red reflectivity not.

THE STATISTICAL METHOD

The statistical method estimates the wavelet from the seismic data alone. Take the seismic trace $s(t)$ and calculate its autocorrelation we get

$$
\begin{aligned}
\phi_s(t) &= \left[w(-t)\bullet r(-t)+n(-t)\right]\bullet\left[w(t)\bullet r(t)+n(t)\right] \\
&= w(-t)\bullet r(-t)\bullet w(t)\bullet r(t)+w(-t)\bullet r(-t)\bullet n(t) \\
&\quad + n(-t)\bullet w(t)\bullet r(t)+n(-t)\bullet n(t) \\
&= \phi_w(t)\bullet\phi_r(t)+w(-t)\bullet\phi_{rn}(t)+w(t)\bullet\phi_{nr}(t)+\phi_n(t)
\end{aligned}
\tag{2}
$$

(Margrave, 2013), where $\bullet$ indicates convolution; $\phi_s(t)$, $\phi_w(t)$, $\phi_r(t)$ and $\phi_n(t)$ is the autocorrelation of $s(t)$, $w(t)$, $r(t)$ and $n(t)$ respectively; $\phi_{rn}(t)$ and $\phi_{nr}(t)$ is the crosscorrelation of $r(t)$ and $n(t)$. Assume $r(t)$ and $n(t)$ are two different random series with infinite lengths

$$\phi_r(t) = \mathrm{P}_r\,\delta(t), \tag{3}$$

$$\phi_n(t) = \mathrm{P}_n\,\delta(t), \tag{4}$$

$$\phi_{rn}(t) = \phi_{nr}(t) = 0 \tag{5}$$

where P_r and P_n is the power of $r(t)$ and $n(t)$. Using equations 3, 4, and 5, equation 2 becomes

$$
\begin{aligned}
\phi_s(t) &= \mathrm{P}_r\,\phi_w(t)+\mathrm{P}_n\,\delta(t) \\
&\approx a\phi_w(t)
\end{aligned}
\tag{6}
$$

where a is a constant. In the frequency domain, equation 6 is

$$|S(f)|^2 \approx a|W(f)|^2 \tag{7}$$

where $S(f)$ and $W(f)$ is the Fourier transform of $s(t)$ and $w(t)$. Thus, the amplitude spectrum of the wavelet can be determined from the autocorrelation of the seismic trace. However, by taking autocorrelation, all the phase information is lost. So a minimum or constant phase has to be supplied.

The estimation procedure is:

1. Extract $s(t)$ of a window length. In the real case, the window is usually over the zone of interest. Since $s(t)$ is stationary here, the window location does not matter.

2. Calculate $\phi_s(t)$. The number of autocorrelation lags is equal to the number of the estimated wavelet samples. A longer autocorrelation will estimate a longer wavelet, whose amplitude spectrum is closer to the seismic and thus less smooth.

3. Apply a Gaussian or Bartlett window to $\phi_s(t)$ in order to get a smoothed amplitude spectrum.

4. Calculate the Fourier transform of $\phi_s(t)$ and take its square root to get $|W(f)|$.

5. Supply a minimum or constant phase $\varphi_w(f)$

$$W(f) = |W(f)| e^{i\varphi_w(f)} \tag{8}$$

where the minimum-phase $\varphi_m(f)$ is calculated by

$$\varphi_m(f) = H(\ln(|W(f)|)) \tag{9}$$

where H denotes the Hilbert Transform (Margrave, 2013).

6. Calculate the inverse Fourier transform of $W(f)$ to get $w(t)$.

Figure 4 shows the results of estimating the minimum-phase wavelet by the statistical method. The minimum-phase is supplied to get the time domain waveform. To analyse the influence of a certain parameter value or a data type on the result, only one variable changes at one time while others keep the same. Panels a) and b) show the estimated wavelets from the seismic trace for different window lengths. A longer window gives more accurate estimation. In panels c) and d), the desired wavelet lengths, or the maximum correlation lags, are different. The shorter one produces a smoother amplitude spectrum and a less oscillatory time-domain wavelet. Panels e), f), g) and h) exhibit different window types applied to the time-domain autocorrelation. After applying the Gaussian or Bartlett window, the amplitude spectrum becomes smoother and the time-domain wavelet is less oscillatory. The Gaussian window does a better job than the Bartlett window. In panels i) and j), wavelet estimation is done on a noise-free and noisy seismic trace respectively. Accurate estimation can be still got in the presence of noise. Panels k) and l) compare the wavelets estimated from seismic traces created by the synthetic and real reflectivities. The estimation in the real reflectivity case is a little distorted, the reason may be that the statistical algorithm assumes the reflectivity spectrum is white while the real one is colored. Thus, the algorithm assigns all the variations in the trace spectrum including the effect from colored spectrum to the wavelet.

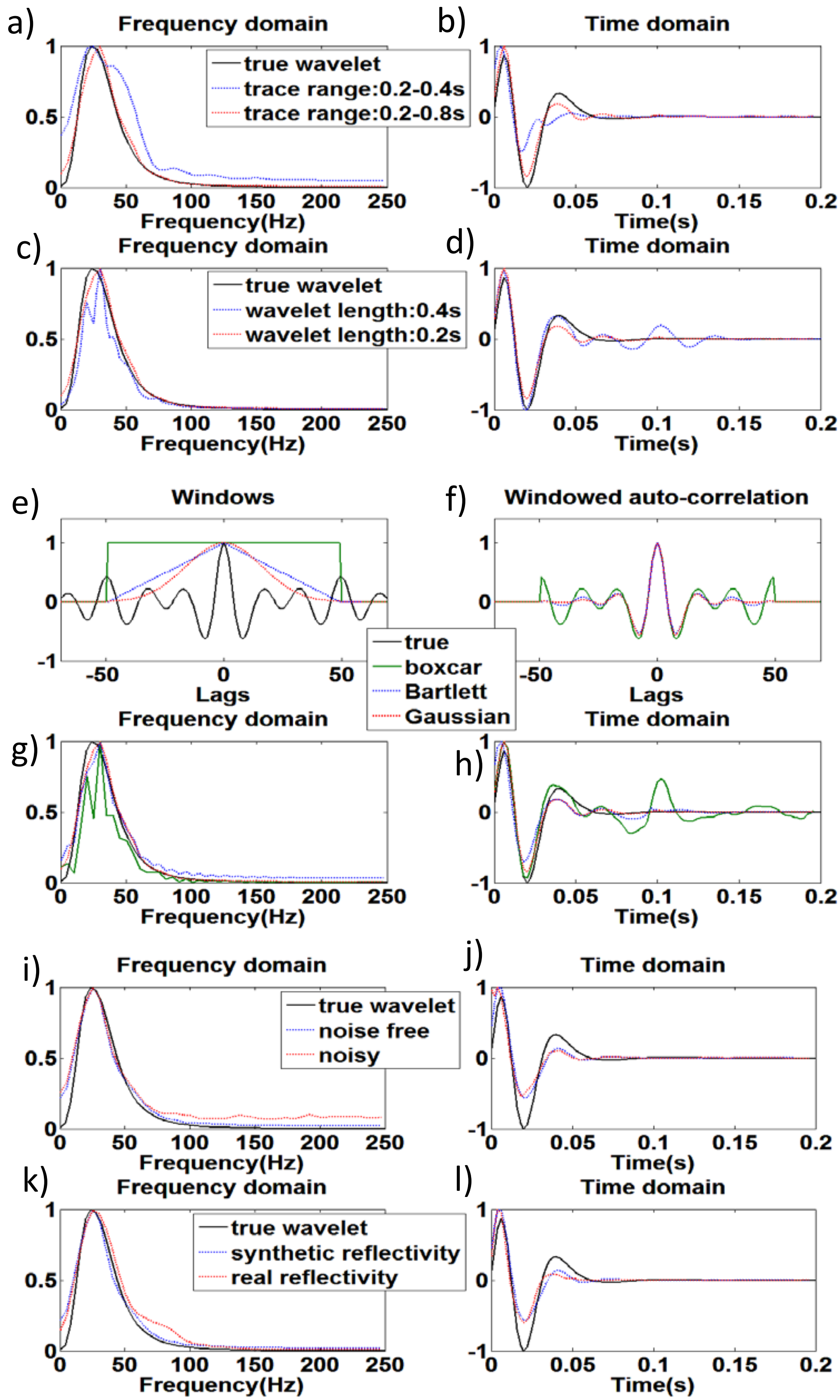

FIG 4: Minimum-phase wavelet estimation by the statistical method.

Similar results are obtained by estimating the constant-phase wavelet by the same method. Figure 5 shows the estimated constant-phase wavelet from the noisy seismic trace created by the real reflectivity choosing suitable parameter values.

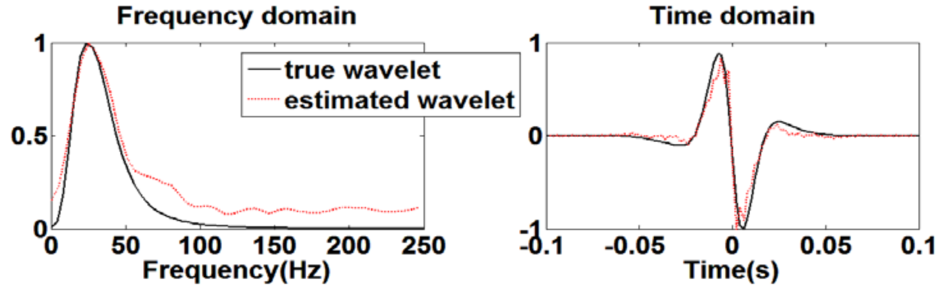

FIG 5: Constant-phase wavelet estimation by the statistical method.

THE FULL WAVELET METHOD

The full wavelet method uses both the seismic and reflectivity to determine the amplitude and phase spectra of the wavelet by applying a least-square filter which shapes the reflectivity to the seismic. An exact wavelet can be extracted without assumption about its amplitude or phase. However, this method is very sensitive to the quality of seismic-to-well ties (Hampson-Russell Software, 2013).

For simplicity, a five-sample seismic trace $s(t)=[s(0),s(1),s(2),s(3),s(4)]$ and a five-sample reflectivity $r(t)=[r(0),r(1),r(2),r(3),r(4)]$ are used to estimate a three-sample wavelet $w(t)=[w(-1),w(0),w(1)]$ to illustrate this algorithm. The wavelet is designed to have samples before time zero to make it more general. In other word, if the wavelet to be estimated is a causal one, the samples before time zero should be zero.

Equation 1 can be written as the following design equation neglecting the noise $n(t)$

$$\begin{pmatrix} r(1) & r(0) & 0 \\ r(2) & r(1) & r(0) \\ r(3) & r(2) & r(1) \\ r(4) & r(3) & r(2) \\ 0 & r(4) & r(3) \end{pmatrix} \begin{pmatrix} w(-1) \\ w(0) \\ w(1) \end{pmatrix} = \begin{pmatrix} s(0) \\ s(1) \\ s(2) \\ s(3) \\ s(4) \end{pmatrix}. \tag{10}$$

To find the least squares solution to equation 10, multiply it by the transpose of the leftmost matrix

$$\begin{pmatrix} r(1) & r(2) & r(3) & r(4) & 0 \\ r(0) & r(1) & r(2) & r(3) & r(4) \\ 0 & r(0) & r(1) & r(2) & r(3) \end{pmatrix} \begin{pmatrix} r(1) & r(0) & 0 \\ r(2) & r(1) & r(0) \\ r(3) & r(2) & r(1) \\ r(4) & r(3) & r(2) \\ 0 & r(4) & r(3) \end{pmatrix} \begin{pmatrix} w(-1) \\ w(0) \\ w(1) \end{pmatrix} = \begin{pmatrix} r(1) & r(2) & r(3) & r(4) & 0 \\ r(0) & r(1) & r(2) & r(3) & r(4) \\ 0 & r(0) & r(1) & r(2) & r(3) \end{pmatrix} \begin{pmatrix} s(0) \\ s(1) \\ s(2) \\ s(3) \\ s(4) \end{pmatrix}, \tag{11}$$

$$\begin{pmatrix} \phi_r(0) & \phi_r(1) & \phi_r(2) \\ \phi_r(1) & \phi_r(0) & \phi_r(1) \\ \phi_r(2) & \phi_r(1) & \phi_r(0) \end{pmatrix} \begin{pmatrix} w(-1) \\ w(0) \\ w(1) \end{pmatrix} = \begin{pmatrix} \phi_{rs}(-1) \\ \phi_{rs}(0) \\ \phi_{rs}(1) \end{pmatrix}. \tag{12}$$

A stability factor is added to $\phi_r(0)$ to make the solution stable. Solving equation 12 can get the estimated wavelet.

The estimation procedure is

1. Extract $s(t)$ and $r(t)$ of a window length.
2. Choose a certain wavelet length.
3. Build the normal equation 12 and calculate $\phi_r(t)$ and $\phi_{rs}(t)$ of the corresponding lags.
4. Solve equation 12 to get the estimated wavelet.

Figure 6 shows the time-domain results of estimating wavelets by the full wavelet method. Panel a) is the estimated wavelets from the seismic trace of different window lengths. Longer windows give more accurate estimation. The desired wavelet lengths in panel b) are different and it turns out they do not affect waveform. Panel c) exhibits wavelet estimation from noise-free and noisy seismic traces. The noisy one has unrealistic trembling compared to the noise-free one. As is shown in panel d), wavelets are estimated from the synthetic and real reflectivities and they appear quite similar. The wavelets in panel e) are estimated from the aligned and misaligned reflectivities shown in the Figure 3 panel a). The latter one seems to own a right waveform but an obvious time shift. The maximum crosscorrelation coefficient between it and the true wavelet is close to 1 at the -30 lags. The negative lag value means it is delayed relative to the true one. Convolve the misaligned reflectivity with this delayed wavelet to get a synthetic trace in panel f), which matches quite well with the true seismic trace in Figure 3 panel b). Thus, the advancement of the reflectivity relative to the seismic trace is compensated by the delay of the estimated wavelet and this can be proved by mathematics.

Based on equations 10-12, assume $r(t)$ is advanced by two samples relative to $s(t)$, namely $r(t) = [r(2), r(3), r(4), 0, 0]$ in this case. So equation 10 becomes

$$\begin{pmatrix} r(3) & r(2) & 0 \\ r(4) & r(3) & r(2) \\ 0 & r(4) & r(3) \\ 0 & 0 & r(4) \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} w(-1) \\ w(0) \\ w(1) \end{pmatrix} = \begin{pmatrix} s(0) \\ s(1) \\ s(2) \\ s(3) \\ s(4) \end{pmatrix}. \tag{13}$$

Equation 13 is essentially

$$\begin{pmatrix} r(3) & r(2) & 0 \\ r(4) & r(3) & r(2) \\ 0 & r(4) & r(3) \\ 0 & 0 & r(4) \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} w(-3) \\ w(-2) \\ w(-1) \end{pmatrix} = \begin{pmatrix} s(0) \\ s(1) \\ s(2) \\ s(3) \\ s(4) \end{pmatrix}. \tag{14}$$

We are actually calculating $w(t) = [w(-3), w(-2), w(-1)]$, which is delayed by two samples by regarding it as $w(t) = [w(-1), w(0), w(1)]$.

Panel g) and h) test the constant-phase wavelet estimation. The former one is estimated from the noise-free trace and synthetic reflectivity while the latter one is from the noisy trace and the real reflectivity which suffers from unrealistic trembling.

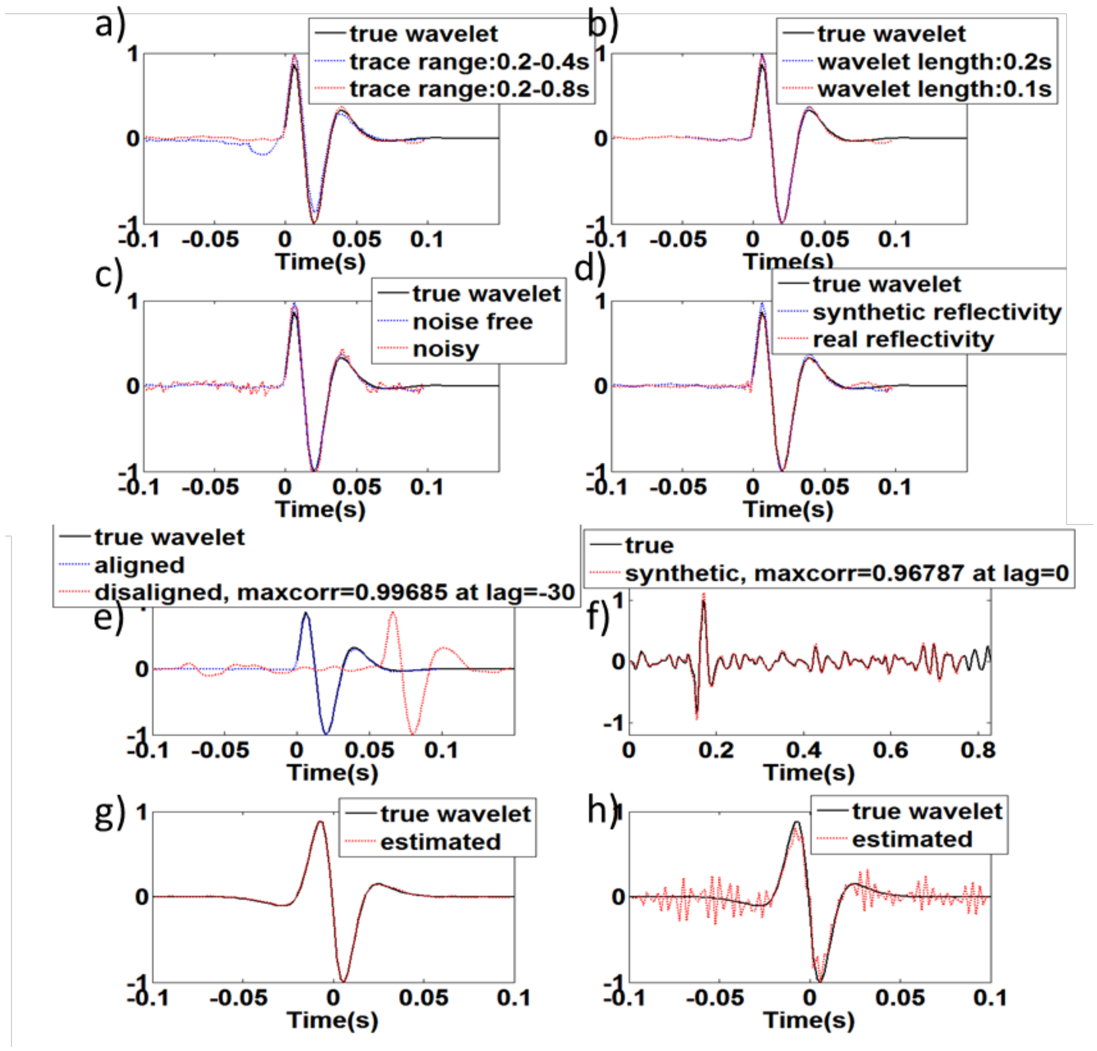

FIG 6: Wavelet estimation by the full wavelet method.

THE CONSTANT PHASE METHOD

The constant phase method uses the seismic data to determine the amplitude spectrum the same way as the statistical method. Then the reflectivity is used to determine the phase by constraining the wavelet phase to an approximate constant. The statistical wavelet, which is the starting solution, suffers from invalidity of the white reflectivity assumption. With the reflectivity available, the distortion can be corrected via dividing the statistical wavelet spectrum by the smoothed reflectivity spectrum (Hampson-Russell Software, 2013).

The procedure modified from Hampson-Russell Software manual is

1. Estimate the amplitude spectrum of the wavelet using the seismic data alone by the statistical method.

2. Calculate the amplitude spectrum of the reflectivity and smooth it. Divide the wavelet amplitude spectrum from 1 by this smoothed reflectivity amplitude spectrum.

3. Apply a series of constant-phase rotations ranging from -180 to 179 degrees with 1 degree interval to the wavelet amplitude spectrum after correction.

4. For each constant-phase rotation, calculate its time-domain wavelet. Convolve this wavelet with the reflectivity to get a synthetic trace. Calculate the maximum crosscorrelation coefficient between this synthetic trace and the seismic trace among a range of lags.

5. Choose the maximum coefficient among the 359 ones. The corresponding constant-phase is the estimated wavelet phase and the lag where to get this coefficient value indicates a time shift existing between the seismic trace and reflectivity.

Figure 7 shows the results of the constant phase method. Panel a) shows the amplitude spectra in decibels of the well log reflectivity, true wavelet, estimated wavelet by the statistical method and the estimated wavelet by the constant phase method, which is corrected after dividing by the reflectivity amplitude spectrum convolved with a 14 Hz width Gaussian window smoother. According to panel a), the red one is more consistent with the true one than green one from 0 to 125 Hz due to the correction while the high frequency components of the red one are unstable because the denominator is very small at high frequencies due to the anti-aliasing filter applied to the reflectivity. However, that should not be a problem since these high frequency components are not very useful for geophysics exploration and are always contaminated by noise. After filtering the 125-250 Hz components out and apply the correct constant-phase of 100 degrees, we get the time domain wavelets in panel b). Clearly, the estimated wavelet after amplitude spectrum correction by the constant phase method is more accurate than the one without correction. The wavelet estimation in panels c) and d) are all done with the real reflectivity. Panel c) compares the noise-free and noisy cases. They both give decent estimations about the constant-phase and the time shift. But the estimated wavelet is contaminated with noise. The wavelets in panel d) are obtained from the aligned and misaligned reflectivities. They both estimate decent phase. In the misaligned case, it detects the right time shift. The impacts of the data window length and the desired wavelet length are the same as the statistical method since they estimate the wavelet amplitude spectrum in the same way.

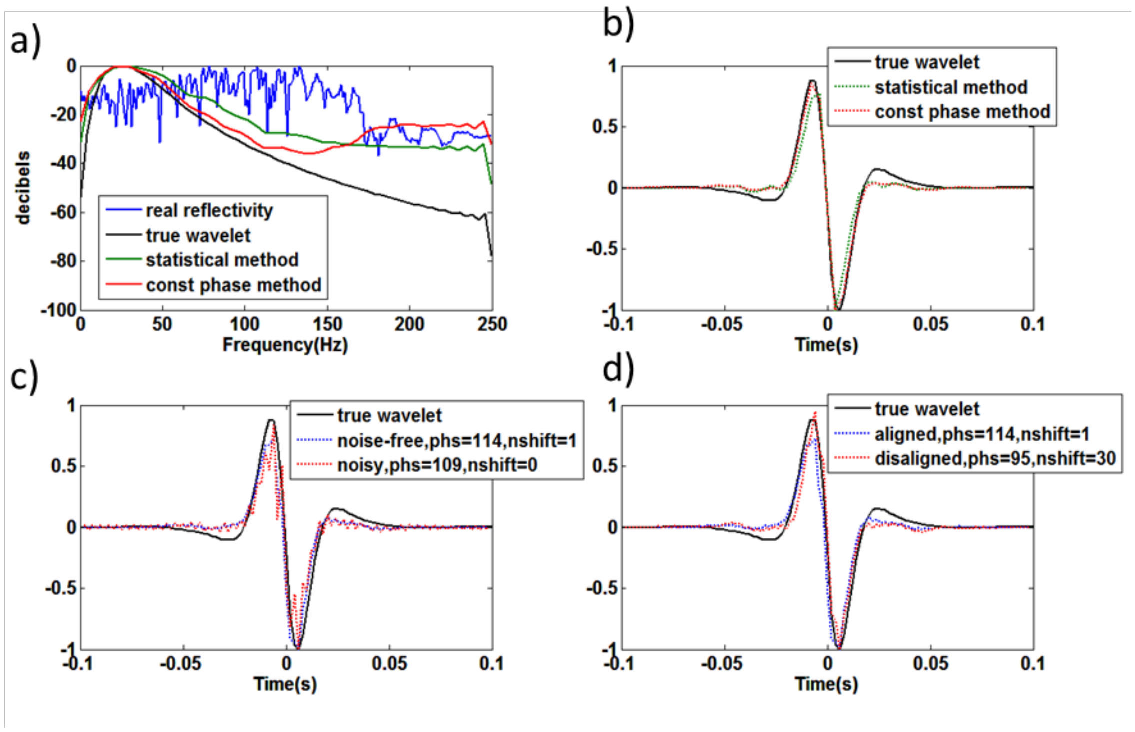

FIG 7: Wavelet estimation by the constant phase method.

THE ROY WHITE METHOD

The Roy White method estimates the wavelet by correlating the well log and seismic data. There are two steps modified from White and Simm (2003):

1. Search the best tie location using the coherence function assuming $r(t)$ is noise free

$$G(m) = \frac{\left[\sum_f R^*(m,f)S(f)\right]^2}{\sum_f [R^*(m,f)R(m,f) + stab]\sum_f S^*(f)S(f)} \tag{15}$$

where * denotes complex conjugate, $R(m,f)$ is $r(t)$ shifted by m samples relative to $s(t)$ in the time domain and then applied the forward Fourier transform. $r(t)$ is delayed when $m>0$ and delayed when $m<0$. $S(f)$ is the Fourier transform of $s(t)$. *stab* is a stability factor to make the division stable.

The coherence function $G(m)$ is essentially the crosscorrelation between $r(t)$ and $s(t)$ normalized by the autocorrelations of $r(t)$ and $s(t)$. It measures the proportion of energy in the seismic trace that can be predicted from the well-log reflectivity.

We search for N to maximize the coherence function

$$G(N) = \max[G(m)], -M \leqslant m \leqslant M \tag{16}$$

where $r(t)$ and $s(t)$ reaches the best alignment after $r(t)$ is shifted by the N.

2. Estimate the wavelet at the best tie location, where equation 1 in the frequency domain neglecting the noise is

$$S(f) = R(N, f)W(f). \tag{17}$$

Multiplying equation 17 by $R^*(N, f)$ on both sides we get

$$R^*(N, f)S(f) = R^*(N, f)R(N, f)W(f). \tag{18}$$

Divide equation 18 by $R(N, f)^* R(N, f)$ on both sides and add *stab* to the denominator to make the division stable

$$W(f) = \frac{R^*(N, f)S(f)}{R^*(N, f)R(N, f) + stab}. \tag{19}$$

Calculate the inverse Fourier transform of $W(f)$ to get the estimated wavelet

$$w(t) = IFT[W(f)]. \tag{20}$$

Thus, the length of seismic trace and reflectivity analysed is equal to the length of the estimated wavelet.

Figure 8 is the results of the Roy White method. Panels from a) to d) estimate wavelets from the noise-free synthetic reflectivities. In panel a), the seismic trace and reflectivity used are aligned and but the coherence function predicts some lags of the reflectivity relative to the seismic trace in both constant-phase and minimum-phase wavelet estimation. Similar to the full wavelet method, the predicted lags are compensated by the same lags of the estimated wavelet relative to the true wavelet in the opposite direction in panels c) and d). These unrealistic lags are caused by the embedded waveform since the coherence function curve looks very similar to the absolute value of the corresponding embedded wavelet and the number of samples between the wavelet trough (maximum absolute value) and time zero (Figure 1 panel a)) is equal to the corresponding unrealistic lag. Those demonstrate that the coherence function reaches the maximum value by matching the wavelet troughs. Panel b) shows the misaligned case where the detected lags are the sum of the real lags and the unrealistic lags. Panels c) and d) also compare impact of the trace and reflectivity lengths. It turns out that shorter length can avoid trembling side lobes. Panels from e) to g) work on the misaligned synthetic reflectivity case to test the influence of noise. The coherence function in panel e) still work well but the estimated wavelet is contaminated with noise. Panels from h) to j) work on the noise-free and the misaligned case to test the influence of real reflectivity. The coherence function in panel h) still works well and the estimated wavelets are quite similar from the synthetic and real reflectivities.

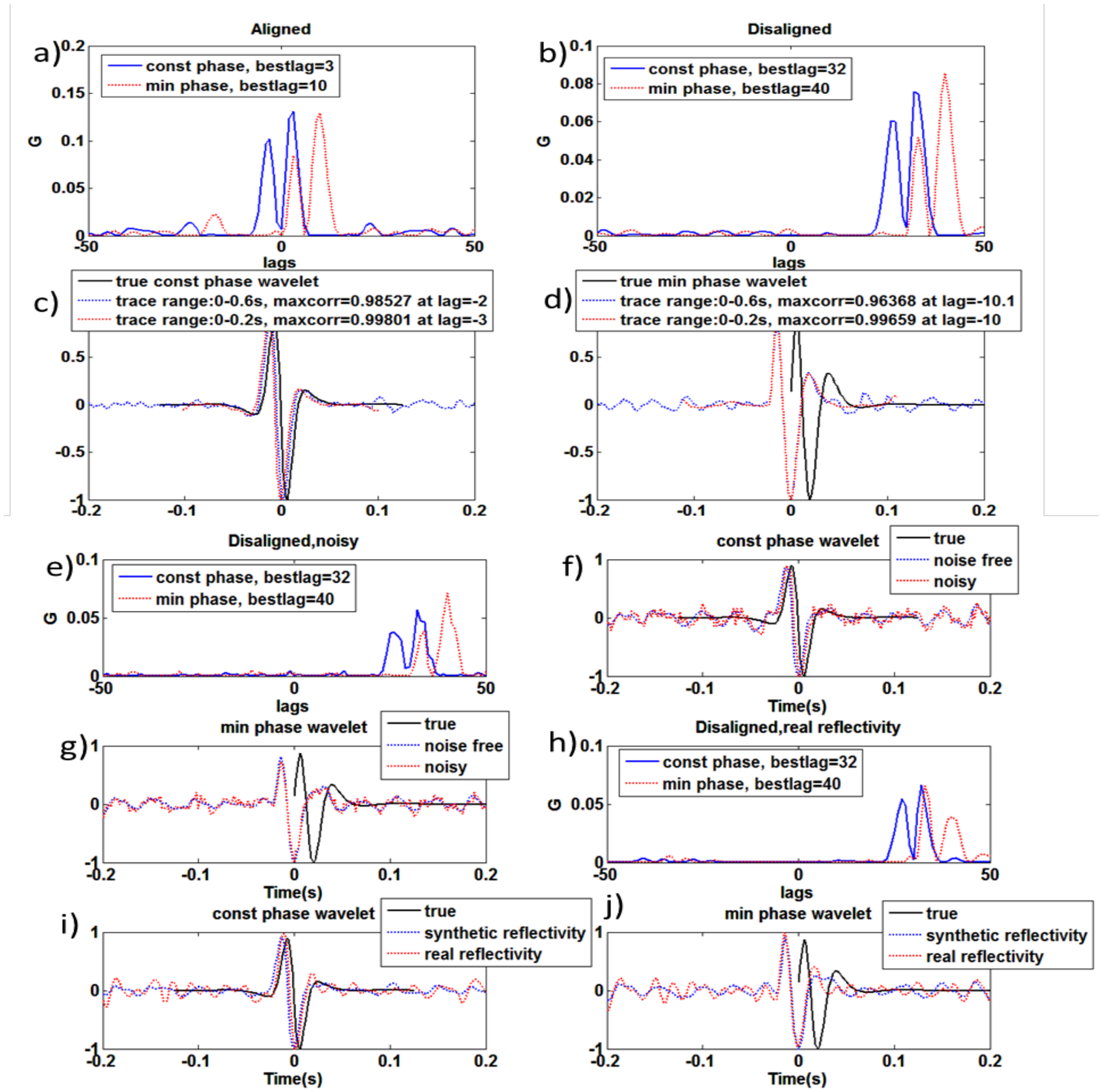

FIG 8: Wavelet estimation by the Roy White method.

MODELING THE MINIMUM-PHASE AS A LINEAR-PHASE

It is interesting to notice that the minimum-phase and constant-phase wavelets in Figure 1 panel a) have very similar waveforms and there is a time shift between the two. The similarity can be explained by modeling the minimum-phase wavelet as a linear-phase on most approximate to it. Figure 9 shows the procedure of modeling the minimum-phase wavelet (the same blue curves in panels a), c) and e)) as the linear-phase wavelet (the red curve in panel e). Panels b), d) and f) are the phase spectra of the wavelets in panels a), c) and e) respectively. First, take the amplitude spectrum of the minimum-phase wavelet and supply a zero-phase to get a zero-phase wavelet (red curve in panel a)). Then, apply a series of constant-phase rotations ranging from -180 to 179 degrees with 1 degree interval to the zero-phase wavelet. For each constant-phase rotation, calculate its time-domain wavelet and calculate the maximum crosscorrelation coefficient between this constant-phase wavelet and the minimum-phase wavelet. Choose the maximum coefficient among the 359 ones, which is about 0.97 at a time shift of 0.016 s (panel e)). The corresponding constant-phase to maximize the correlation is 125 degrees (panels c) and d)). Thus, the minimum-phase wavelet in this case can be modeled as a 125-degree constant-phase wavelet with a 0.016 s time shift, which is essentially a linear-phase wavelet shown in panel f), where the linear-phase line is nearly tangent to the minimum-phase curve.

This approximation is consistent with the procedure of seismic-to-well ties, in which the reflectivity calculated from the well log data is convolved with a zero-phase wavelet to create a synthetic seismogram. Then, the synthetic seismogram is stretched or squeezed, namely time shifted, as well as constant-phase rotated to match the seismic trace with minimum phase wavelets embedded. What is more, this approximation makes the minimum-phase wavelet estimation easier since the linear phase is more simple and more robust in the presence of noise.

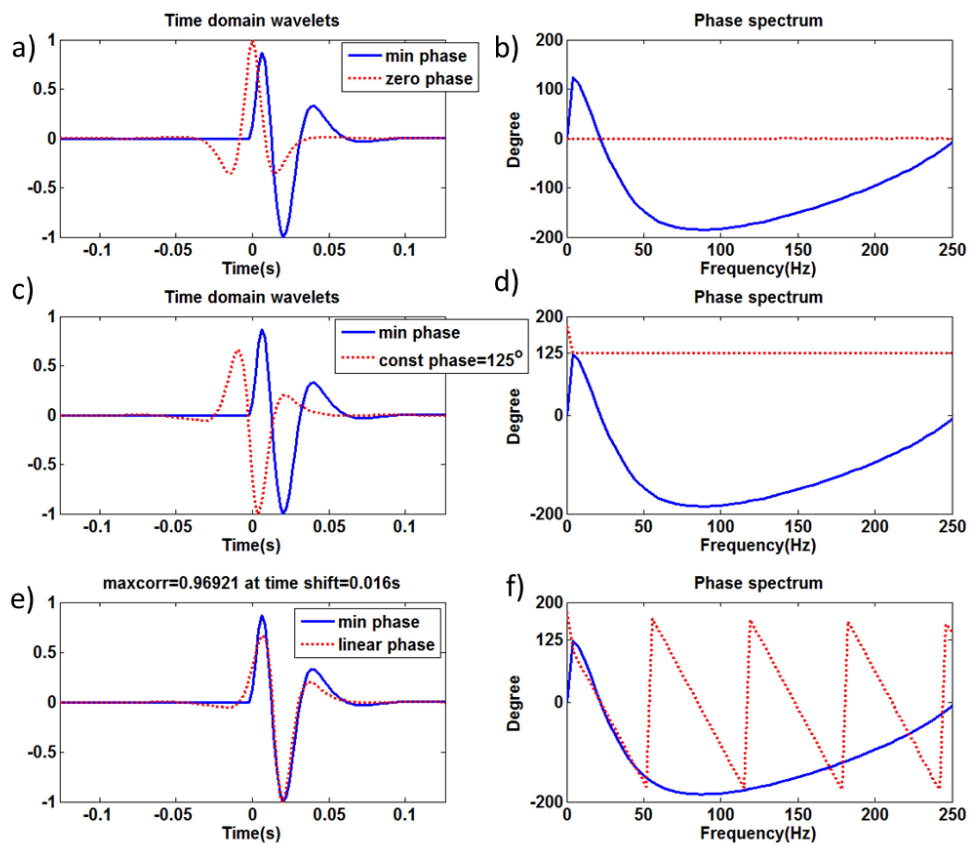

FIG 9: The procedure of modeling the minimum-phase wavelet as the most approximate linear-phase wavelet.

CONCLUSIONS

The characters of all the four wavelet estimation methods are summarize in Table 1.

<table>
<tr><th></th><th>Statistical method</th><th>Full wavelet method</th><th>Constant phase method</th><th>Roy White method</th></tr>
<tr><td>Data used</td><td>Seismic</td><td colspan="3">Seismic and well log</td></tr>
<tr><td>Wavelet estimated</td><td>Any wavelet with supplied phase</td><td>Any wavelet</td><td>Constant-phase wavelet</td><td>Any wavelet</td></tr>
<tr><td>Data window length</td><td colspan="3">Longer data length gets more accurate estimation</td><td rowspan="2">Data window length=desired wavelet length, longer length causes trembling side lobes</td></tr>
<tr><td>Desired wavelet length</td><td>Shorter length produces smoother amplitude spectrum and more stable waveform</td><td>No influence</td><td>Shorter length produces smoother amplitude spectrum and more stable waveform</td></tr>
<tr><td>Noise</td><td>Robust</td><td>unrealistic trembling waveform</td><td>Robust in estimating phase and lags, unrealistic trembling waveform</td><td>Robust in estimating lags, unrealistic trembling waveform</td></tr>
<tr><td>Real log reflectivity</td><td>Distorted</td><td>Robust</td><td>Robust</td><td>Robust</td></tr>
<tr><td>Misalignment</td><td>N/A</td><td>Robust</td><td>Robust</td><td>Robust</td></tr>
</table>

Table 1: Summary of wavelet estimation methods.

Different wavelet estimation methods have different characteristics. They are influenced differently by parameter values and data used so they may give different results. The best method needs to be determined for the dataset at hand and different parameter values should be tested by trial and error. Certain minimum-phase wavelets can be modeled as the linear-phase wavelets, which may make minimum-phase wavelet estimation more simple and robust.

ACKNOWLEDGEMENTS

We thank the sponsors of CREWES for their support. We also gratefully acknowledge support from NSERC (Natural Science and Engineering Research Council of Canada) through the grant CRDPJ 379744-08. We also thank Dr. Larry Lines and Dr. John Bancroft for suggestions on this topic.

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