GEOPHYSICS, VOL. 76, NO. 4 (JULY-AUGUST 2011); P. V59–V68, 11 FIGS.
10.1190/1.3587220

How reliable is statistical wavelet estimation?

Jonathan A. Edgar[1] and Mirko van der Baan[2]

ABSTRACT

Well logs often are used for the estimation of seismic wavelets. The phase is obtained by forcing a well-derived synthetic seismogram to match the seismic, thus assuming the well log provides ground truth. However, well logs are not always available and can predict different phase corrections at nearby locations. Thus, a wavelet-estimation method that reliably can predict phase from the seismic alone is required. Three statistical wavelet-estimation techniques were tested against the deterministic method of seismic-to-well ties. How the choice of method influences the estimated wavelet phase was explored, with the aim of finding a statistical method which consistently predicts a phase in agreement with well logs. It was shown that the statistical method of kurtosis maximization by constant phase rotation consistently is able to extract a phase in agreement with seismic-to-well ties. A statistical method based on a modified mutual-information-rate criterion was demonstrated to provide frequency-dependent phase wavelets where the deterministic method could not. Time-varying statistical wavelets also were estimated with good results — a challenge for deterministic approaches because of the short logging sequence. It was concluded that statistical techniques can be used as quality control tools for the deterministic methods, as a way of extrapolating phase away from wells, or to act as standalone tools in the absence of wells.

INTRODUCTION

Wavelet phase mismatches occur frequently between final processed seismic data and synthetic seismograms created from well logs, which lead to potential complications in stratigraphic and structural interpretation. Knowledge of the wavelet character and phase is important since any phase ambiguities might result in incorrect identification of low and high impedance contrasts in a seismic section, thereby creating unnecessary interpretation pitfalls (Brown, 2004). In a worst-case scenario with spatially and/or temporally nonstationary wavelets exhibiting phase changes of 90°, a positive reflection might correspond to a high impedance contrast in one part of a section and to a low impedance contrast in another. Likewise, unknown stationary phase mismatches pose an issue if not accounted for. For example, a 45° phase deviation from zero-phase seismic data results in impedance boundaries that cannot be attributed to peaks, troughs, or zero crossings in the recorded traces.

The introduction of controlled-phase acquisition and processing strategies has improved our control of seismic phase (Trantham, 1994); yet phase mismatches continue to exist between final processed data and synthetic seismograms created from well logs. During processing, deterministic zero-phase wavelet shaping corrections often are used to reshape the source impulse response from near minimum phase to zero phase. Further bulk adjustments to the phase can be made to account for attenuation and dispersion effects. Typically, such corrections are applied only in a global sense. Any remaining phase mismatches may be eliminated through additional phase corrections using well logs as ground truth. Thus a phase match between the data and synthetic seismograms is forced.

Irrespective of the validity of this phase-correction method, well logs are not always available and can predict different phase corrections at nearby locations. Thus, there is a need for a wavelet-estimation method that reliably can predict phase from the seismic data, without reliance on well-log control. Such a method could be used for phase extrapolation away from wells, serve as a quality control tool, or even act as a standalone wavelet-estimation technique.

We test three current statistical wavelet-estimation methods against the deterministic method of seismic-to-well ties. We consider three statistical techniques: a kurtosis-based approach

Manuscript received by the Editor 14 July 2010; revised manuscript received 28 October 2010; published online 3 June 2011.
[1]BG Group, Thames Valley Park, Reading, Berkshire, United Kingdom. E-mail: Jonathan.Edgar@bg-group.com.
[2]University of Alberta, Department of Physics, Edmonton, Alberta, Canada. E-mail: Mirko.VanderBaan@ualberta.ca.

of van der Baan (2008) producing a stationary, constant-phase wavelet, the modified mutual-information-rate criterion method of van der Baan and Pham (2008) yielding a stationary wavelet with a frequency-dependent phase, and finally a nonstationary extension of the kurtosis-based technique resulting in a time-varying, constant-phase wavelet. Specifically, we explore the extent to which the choice of method influences the estimated wavelet phase, with the aim of finding a statistical method which consistently predicts a phase in agreement with that obtained from well logs (Figure 1).

First, we describe the scientific rationale of each wavelet-estimation technique. We then apply the statistical and deterministic seismic-to-well-tie methods on three data sets from the North Sea, and compare the phase and amplitude spectra of the resulting wavelets. Finally, we question whether well logs always are the optimum source of wavelet phase information and advocate the use of statistical methods as a complementary tool or reliable alternative.

METHODOLOGY

The theory and practice of seismic-to-well tying is well established (Walden and White, 1984; White and Simm, 2003). Sonic logs are calibrated using well check-shot data to ensure that the time-depth relationship matches that of the seismic data. The calibrated sonic logs then are combined with the density logs to calculate impedance and reflectivity series for each well site.

An initial zero-phase statistical wavelet, with amplitude spectrum calculated from the square root of the amplitude spectrum of the autocorrelation of each trace, then is extracted from the seismic data. This wavelet is used to construct synthetic seismograms at each well location as per the convolutional model of the seismic trace.

Applying alterations to the wavelet amplitude and phase spectra, such that a maximum correlation is found between the synthetic seismograms and seismic traces, allows a deterministic wavelet to be estimated at each well location. This process can be modified to estimate either frequency-dependent or constant-phase wavelets. Our methodology followed that of White and Simm (2003), insomuch as "stretch and squeeze" was avoided and the check-shot calibration, plus small manual bulk time shifts, was relied upon to align the well log time-depth relationship to that of the seismic data.

For the three data sets tested in this study, this approach was sufficient to produce seismic-to-wells ties with high coefficients of correlation. For each data set tested, the time range used for deterministic wavelet estimation was at least twice the wavelet length (i.e., more than 0.5 s). Some important assumptions in the seismic-to-well tie technique are that the well logs provide ground truth, the convolutional model holds, and the wavelet is invariant in both time and space.

All of the statistical methods tested estimate phase from the data without appealing to well logs (van der Baan, 2008; van der Baan and Pham, 2008). This is done by using a consequence of the central limit theorem: that convolution of any filter with a white time series (with respect to all statistical orders) renders the amplitude distribution of the output more Gaussian. Thus, the optimum deconvolution filter will ensure that the amplitude distribution of the deconvolved output is maximally nonGaussian (Donoho, 1981). Well-log analyses have confirmed that the earth's reflectivity series is nonGaussian (Walden and Hosken, 1986) and, to first order, white (Walden and Hosken, 1985). Instead of deriving optimum deconvolution filters directly, one also can invoke Wiener filtering which is expressed in terms of the seismic wavelet (Berkhout, 1977). As a consequence, the seismic wavelet can be estimated by designing the optimum Wiener deconvolution filter yielding the maximally nonGaussian outcome when applied to the data (van der Baan, 2008).

The three statistical techniques we consider are the kurtosis-based approach of van der Baan (2008) producing a stationary, constant-phase wavelet, the modified mutual-information-rate criterion of van der Baan and Pham (2008) yielding a stationary wavelet with a frequency-dependent phase, and finally a nonstationary extension of the kurtosis-based technique resulting in a time-varying, constant-phase wavelet.

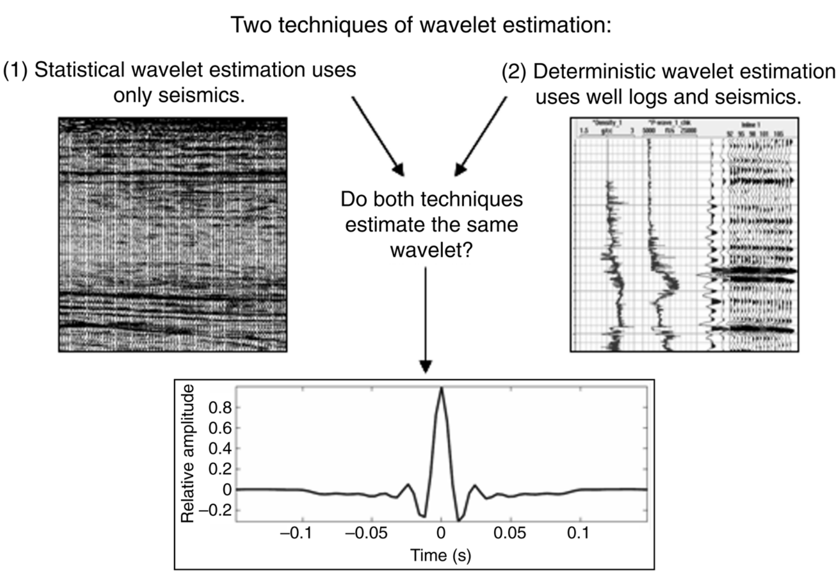

Figure 1. How reliable is statistical wavelet estimation? We evaluate the level of phase agreement among three current statistical wavelet-estimation methods and the deterministic method of seismic-to-well ties.

The first technique analyzes the nonGaussianity of the data when subjected to a series of constant phase rotations. The angle corresponding to the maximum kurtosis value determines the most likely wavelet phase (Levy and Oldenburg, 1987, Longbottom et al., 1988, White, 1988). In this approach, one initially ignores the amplitude spectrum of the wavelet, and the optimum Wiener filter becomes the phase rotation that maximizes the nonGaussianity of the data. The technique appeals to the kurtosis since this is a fourth-order statistic measuring deviation from Gaussianity (Mendel, 1991). The corresponding amplitude spectrum of the wavelet subsequently is obtained by spectral averaging of the analyzed data portion.

An assumption of this approach is that the seismic wavelet in the later stages of the processing sequence is approximately constant-phase. This approximation greatly reduces the number of degrees of freedom, thus creating a robust estimation technique. This method can derive a single, stationary, constant-phase wavelet from the entire data set, or a time-varying, constant-phase wavelet by dividing the data into partly overlapping sequences (van der Baan, 2008).

Longbottom et al. (1988) and White (1988) demonstrate that the method is stable if the peak frequency is smaller than the wavelet passband, or equivalently, when the bandwidth exceeds 1.585 octaves. This condition is unlikely to be problematic except for legacy data, where the bandwidth can be narrow and the signal-to-noise ratio poor. The impact of variation in the signal-to-noise ratio on statistical wavelet estimation is tested by van der Baan and Pham (2008) on a realistic synthetic data set.

The second statistical method tested can estimate wavelets with frequency-dependent phase using a modification of the mutual-information-rate criterion. This criterion measures the whiteness of a signal using statistics of all orders (Cover and Thomas, 1991), thereby also appealing to higher-order statistics. Unfortunately, whiteness-based deconvolution criteria have the disadvantage of boosting the noise level outside the passband of the wavelet because they enforce whiteness over the entire frequency range. This leads to problems if the actual wavelet is band limited.

Van der Baan and Pham (2008) present a modification of the mutual-information rate that takes the band limited nature of seismic wavelets into account, and whitens the deconvolution output only within the wavelet passband. Their approach estimates the frequency-dependent wavelet phase by maximizing the negentropy of the deconvolution outcome while ensuring that the wavelet amplitude spectrum remains close to that of the observations. The negentropy is a general-purpose nonGaussianity criterion appealing to statistics of all orders. The spectral regularization condition ensures that when Wiener filtering is invoked, whitening occurs only within the wavelet passband, thereby preventing noise amplification. This approach allows us to derive wavelets with frequency-dependent phase without appealing to well logs.

On the one hand, an inversion for wavelets with frequency-dependent phase involves a significantly larger number of degrees of freedom than for constant-phase wavelets, rendering an extension to the nonstationary case difficult in case of noisy observations. We therefore do not attempt to analyze the seismic data sets for the presence of nonstationary, frequency-dependent phase wavelets, contrary to the constant-phase case. On the other hand, van der Baan and Pham (2008) demonstrate that the method adequately can estimate seismic wavelets even when the peak frequency is larger than the bandwidth, contrary to the kurtosis-based approaches.

RESULTS

We use three data sets from different parts of the North Sea to extract and compare the results of statistical and deterministic wavelet estimation. We enforce that all seismic-to-well ties use a constant-phase wavelet as frequency-dependent wavelets were deemed to be unrealistic. This point will be addressed more fully in the discussion section.

All well ties have correlation coefficients above 70% over a time window at least twice the length of the estimated wavelets. For each data set we show the seismic-to-well tie and compare the shapes of the estimated deterministic and statistical wavelets and their amplitude spectra. We also provide extracted portions of some deconvolution results to highlight the importance of correct wavelet estimates for seismic deconvolution. Two data sets had known phase issues; the third data set is intended as a control set since it was anticipated to be zero phase.

The bandwidths, in octaves, for the three seismic data sets were 2.46, 2.70, and 3.50 respectively. This was calculated as the width in octaves at 5 dB below the peak frequency of the seismic data. Therefore, all three data sets meet the precondition of Longbottom et al. (1988) and White (1988) for stability of kurtosis-based phase estimation methods; that the seismic bandwidth must exceed 1.585 octaves. This is unsurprising as we are using modern 3D seismic data, but nevertheless it is important to check prior to using kurtosis-based phase estimation techniques.

Data set 1: Deterministic seismic-to-well-tie wavelet

Figure 2 shows the 2D seismic section, well location and associated seismic-to-well tie for data set 1. The seismic-to-well tie is reasonably high quality over the 600 ms interval where both sonic and density logs were available. The correlation coefficient for this tie is 81%. The time-domain wavelet estimated from this seismic-to-well tie is shown in Figure 3, and a 98° phase rotation is predicted. Unanticipated phase perturbations of this size can lead to erroneous interpretations. A 90° phase rotation implies

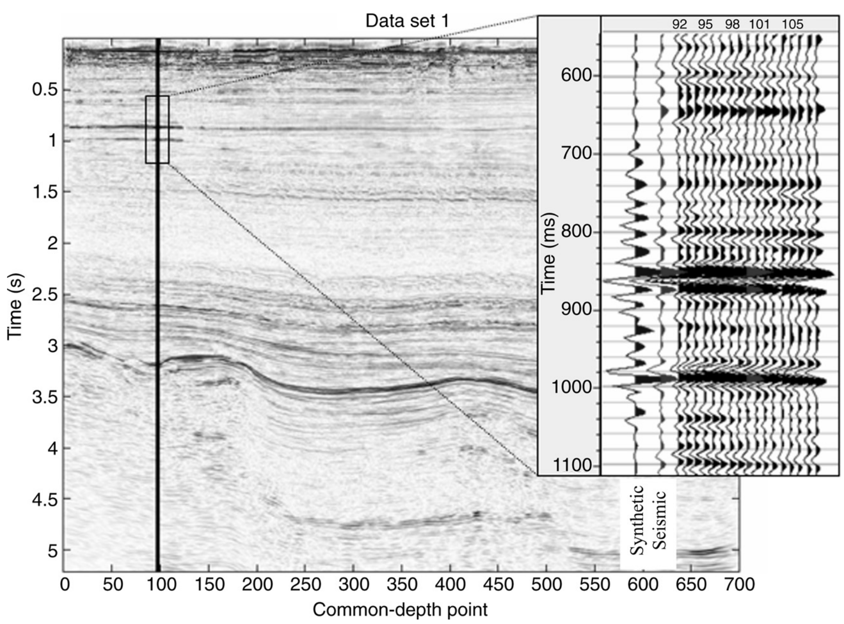

Figure 2. 2D seismic section with well location of data set 1. The location and quality of the seismic-to-well tie is shown in the inset: left, synthetic seismogram; right, seismic trace at the well location. The seismic-to-well tie correlation coefficient is 81%.

that the section is close to an impedance section, where the zero crossings relate to impedance boundaries and peak amplitudes occur within layers instead of at layer interfaces. Obviously such large perturbations from zero phase may lead to misleading interpretations if not correctly accounted for.

Data set 1: Statistical wavelets and phase comparisons

Figure 3 also shows the time-domain wavelets estimated using the three statistical methods. It is clear from visual inspections that there is good agreement between the statistical and deterministic methods in terms of estimated phase. For example, the statistical constant-phase wavelet estimated using the method of van der Baan (2008) has a phase rotation of 84°. This is 14° lower than the phase predicted by the deterministic seismic-to-well tie method, and the difference is hard to see with the naked eye.

The statistical frequency-dependent wavelet estimated by the method of van der Baan and Pham (2008) is similar to the deterministic seismic-to-well tie and the statistical constant-phase wavelet; it is almost asymmetric. The most noticeable difference between the deterministic and statistical wavelets occurs in the number of side lobes; an item we will address in the discussion section.

To make a quantitative comparison between the statistical frequency-dependent phase wavelet and all constant-phase wavelets, we approximated the former wavelet by a constant-phase rotation. Thus, a zero-phase wavelet with an amplitude spectrum matching that of the frequency-dependent wavelet is created and phase rotated until a maximum correlation is found between the two. This angle of rotation corresponds to the constant phase approximation of the frequency-dependent wavelet, and was found to be 83°. The value of the maximum cross-correlation coefficient is a measure of the validity of the constant-phase approximation. For data set 1, this value was 0.99, indicating that the constant phase approximation holds.

Figure 3 also shows the estimated time-varying constant-phase wavelets. The optimum wavelet required for deconvolution of data set 1 may be nonstationary with respect to time. This is displayed by the clear phase change with depth predicted by the method of van der Baan (2008). Each wavelet is obtained using a time-window of 3.3 s. The shallowest wavelet phase agrees with all other time-stationary phase estimates at 84°. The wavelet phase estimated from the middle section of data is lower, at 66°. The phase is estimated to rise slightly to 69° toward the end of the section. The possible origins of this time-variation are addressed in the discussion section.

Figure 3 demonstrates that the deterministic and all statistical wavelets visually are in close agreement in terms of estimated phase, with the statistical wavelets displaying less side lobe energy. In the next subsection we examine their amplitude spectra.

Data set 1: Amplitude spectra

Figure 4 displays the amplitude spectra of all wavelets estimated for data set 1 as shown in Figure 3. The amplitude spectra of the statistical wavelets are similar, with stronger low-frequency components than the deterministic estimate; yet the total passband is similar in all wavelets.

All statistical techniques involve spectral averaging of the recorded data and appear to produce smoother amplitude spectra than the auto-correlation method used in the deterministic seismic-to-well tie wavelet estimation. The deterministic method uses the square root of the amplitude spectrum of the autocorrelation of each trace, averaged over all traces, to estimate the wavelet amplitude spectrum. This estimate is confined to the time window used in wavelet phase estimation.

The statistical methods use the average power spectrum of each trace, averaged over all traces. However, as the statistical methods do not use a time window (apart from the time-varying method) the amount of data included in the spectrum calculation is greater, as is the amount of data being averaged. As a result, we would not expect the amplitude spectra to match perfectly across the statistic and deterministic methods. It would seem, though, that spectral averaging appears to produce wavelets with lower amplitude side lobes and less ringing than the auto-correlation method.

Time-varying statistical wavelet estimation produces an amplitude spectrum for each time window. Thus, the effect of attenuation and dispersion should be apparent. In this case, however, attenuation and dispersion corrections during processing have masked the expected fall in overall amplitude and loss of high frequencies with depth.

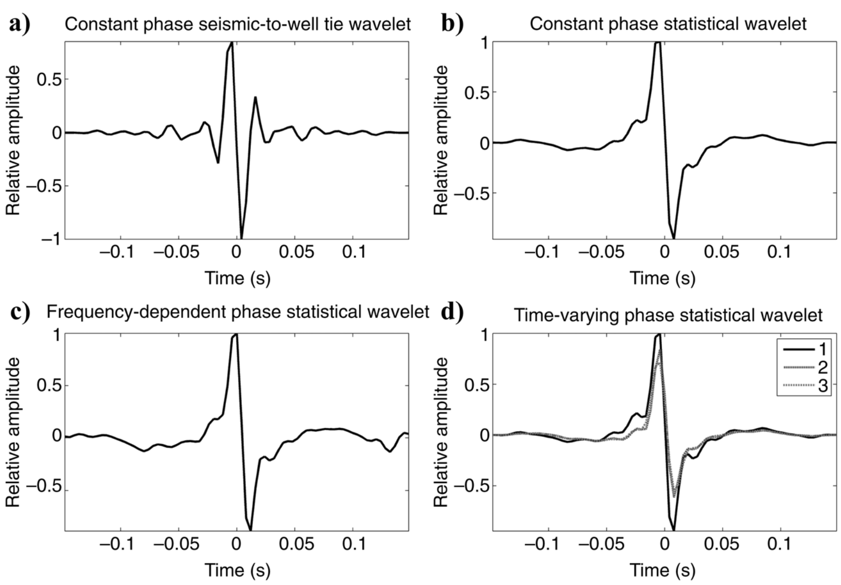

Figure 3. Wavelets estimated from data set 1 (a) deterministic seismic-to-well tie ($\phi = 98°$), (b) statistical constant phase ($\phi = 84°$), (c) statistical frequency-dependent phase ($\phi \approx 83°$), and (d) statistical time-varying constant phase ($\phi_{avg} = 73°$). Three time-varying wavelets have been extracted, numbered 1–3 with increasing time. All wavelets are similar in appearance with close constant-phase equivalents, yet the statistical wavelets contain less side lobe energy.

Data set 1: Deconvolution results

Wiener deconvolution is performed on the seismic section in Figure 2 to approximately remove the effects of the estimated wavelets. A separate Wiener filter is designed as per Equation 5 in van der Baan (2008) using the wavelets from each statistical method tested in this study. Since the deconvolution results are highly similar, we show the outcome using the statistical constant-phase wavelet only. The Wiener deconvolution filters designed using all statistical wavelets are able to zero phase the data to an accuracy of $\pm 10^\circ$.

Figure 5 displays a zoomed-in region of data set 1 before and after Wiener deconvolution, as well as the constant-phase wavelet used in the filter design and the estimated statistical wavelet after deconvolution. The region shown encompasses the data used to make the seismic-to-well tie in Figure 2. The strong events at approximately 0.8 and 1.0 seconds clearly have been phase rotated toward zero phase since the waveforms of the strongest reflectors now are more symmetric. Reapplication of the statistical constant-phase method on data set 1 after deconvolution confirms these visual observations (Figure 5c and 5d). The original 90° phase rotation estimated has been reduced successfully to zero via Wiener deconvolution.

Data set 2: Deterministic seismic-to-well-tie wavelet

Figure 6 shows a seismic section through data set 2, its well location, and associated seismic-to-well tie. The seismic-to-well tie again gives a correlation coefficient of 81% over the 600 ms logging interval. The time-domain wavelet estimated from this seismic-to-well tie is shown in Figure 7, and a 58° phase rotation is predicted.

It is unlikely that a phase rotation of this magnitude was planned for in the data acquisition and processing. Impedance boundaries in this case would not be attributable to the peak, trough, or zero crossing of the wavelet, and so phase deconvolution must be applied before conventional interpretation can be performed. The high correlation coefficient of 81% in the seismic-to-well tie gives us confidence in the estimated deterministic wavelet and its phase.

Data set 2: Statistical wavelets and phase comparisons

We estimate again a constant-phase, a frequency-dependent phase, and three time-varying wavelets directly from the data by means of the statistical techniques of van der Baan (2008) and van der Baan and Pham (2008). The resulting statistical wavelets are shown in Figure 7.

A visual comparison of the deterministic and statistical wavelets reveals that small phase discrepancies exist. The statistical constant-phase method predicts a phase rotation of 36°, which is a 22° lag with respect to the deterministic seismic-to-well tie wavelet. This phase rotation is near the limit of what the eye can notice and may not affect a structural interpretation. It would, however, influence the result of a quantitative interpretation technique.

The statistical frequency-dependent phase wavelet is estimated to have a constant-phase equivalent rotation of 31°, which is very close to the statistical constant-phase value; yet the frequency-dependent phase wavelet looks noisier. This may be caused by the significant increase in number of degrees of freedom when we allow for a different phase at each frequency, rendering the method more noise sensitive.

Figure 7 also shows the estimated time-varying constant-phase wavelets. Similar to data set 1, the optimum wavelet required for deconvolution of data set 2 may be nonstationary with respect to time. Each wavelet is obtained using a time-window of 2.4 s. Interestingly, at 69°, the shallowest wavelet phase is in close agreement with the deterministic seismic-to-well tie estimate of 58°, whereas the deeper two statistical phase estimates of 36° agree with the other statistical methods. Hence, the phase estimate from the seismic-to-well tie appears correct over the limited logging time range available, but is not representative of the entire section. The statistical methods also are sensitive to data in the deeper section, and thus estimate a smaller phase advance.

Similar to Figure 3, Figure 7 demonstrates that the deterministic and statistical wavelets differ only by a small phase discrepancy, just noticeable by eye. Contrary to data set 1 (Figure 3), there is no significant difference in the number of side lobes for the deterministic and statistical wavelet estimates, although the deterministic and frequency-dependent statistical wavelets come across as the more noisy estimates.

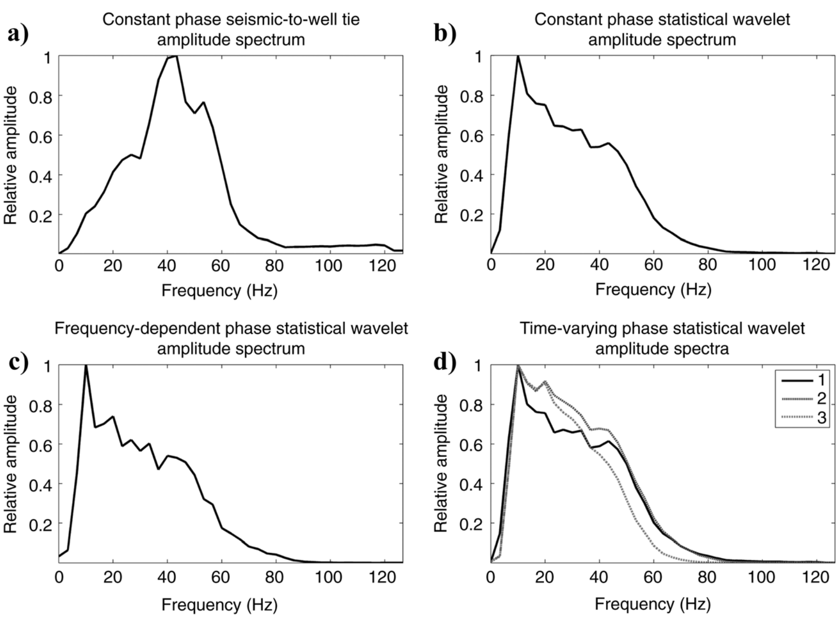

Figure 4. Amplitude spectra of wavelets shown in Figure 3 as estimated from data set 1 (a) deterministic seismic-to-well tie, (b) statistical constant phase, (c) statistical frequency-dependent phase, and (d) statistical time-varying constant phase. The deterministic amplitude spectrum is calculated over the same window of data as is used in the deterministic phase estimation, whereas the time-stationary statistical methods use the whole data section for both. Three time-varying wavelets have been extracted, numbered 1–3 with increasing time. The amplitude spectra of the statistical wavelets are similar, with stronger low-frequency components than the deterministic estimate.

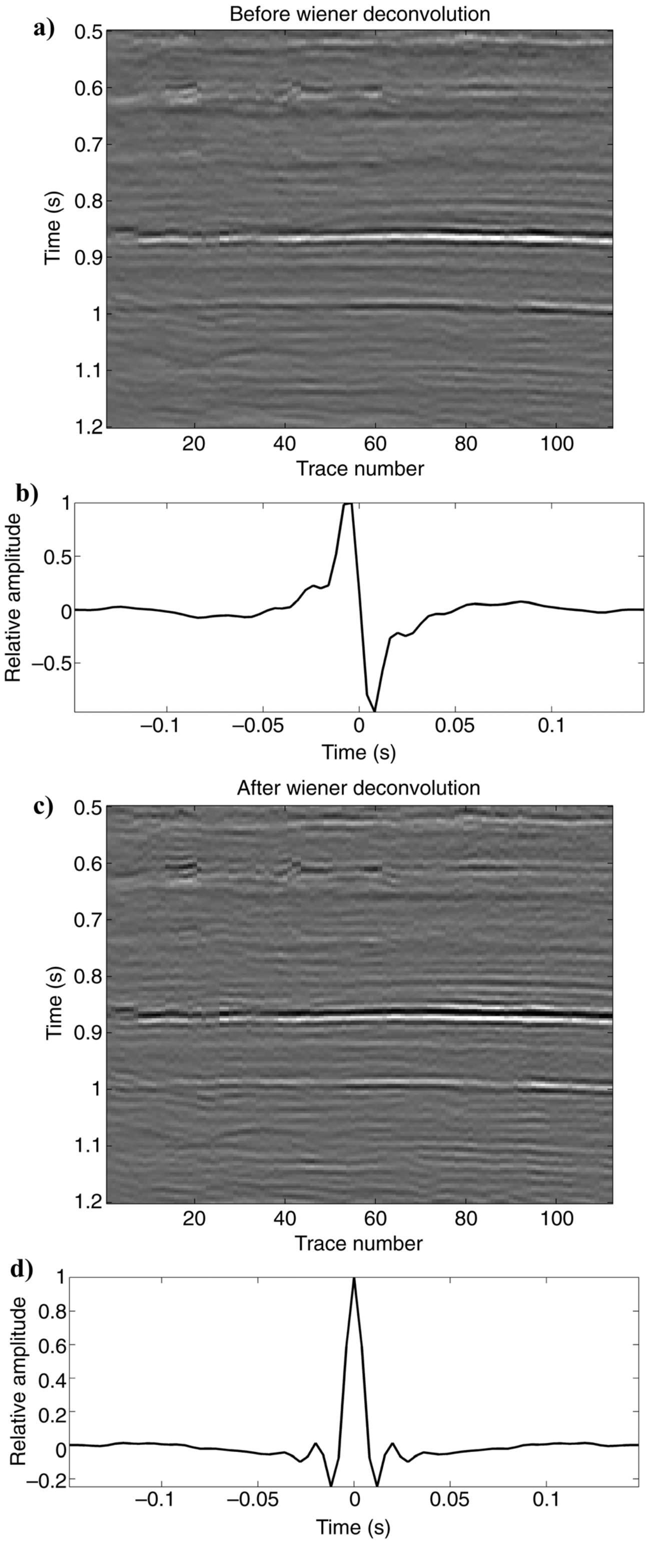

Figure 5. Wiener deconvolution results. (a) Section before deconvolution and (b) estimated constant-phase wavelet. (c) Section after deconvolution and (d) new constant-phase wavelet. The events at 0.8 and 1.0 seconds have been rotated toward zero phase after deconvolution, as evidenced by the more symmetric waveforms of the strongest reflectors.

Data set 2: Amplitude spectra

Figure 8 displays the amplitude spectra of all wavelets estimated for data set 2 as shown in Figure 7. The total passband again is similar for all wavelet estimates, with the statistical wavelet spectra containing slightly more energy at lower frequencies than the deterministic seismic-to-well tie wavelet.

The method of van der Baan and Pham (2008) to estimate the statistical frequency-dependent wavelet includes an amplitude whitening step constrained to the wavelet passband. In this instance the whitening appears to be too harsh, producing a boxcar shaped amplitude spectrum and hence increased ringing in the time domain. The constant-phase and time-varying statistical techniques use only spectral averaging and again have a simpler and "cleaner" appearance of the time-domain wavelets than the auto-correlation method used in the seismic-to-well tie.

As with data set 1, attenuation corrections during processing have hidden the expected fall in overall amplitude and loss of high frequencies with depth. This is evident since the amplitude-spectra of all three time-varying wavelets are similar.

All deterministic and statistical wavelets again can be used for phase-only or amplitude-and-phase deconvolution, e.g., by means of Wiener filtering (van der Baan, 2008). Analogous to Figure 5, phase-only deconvolution again can reveal subtle differences between the original and filtered seismic data, which, given the estimated constant-phase rotations in the range of 31° to 58°, could complicate an interpretation unnecessarily.

Data set 3: Deterministic seismic-to-well tie wavelet

The seismic-to-well tie made for data set 3 gave a correlation coefficient of 86% over the 500 ms window. The time-domain wavelet estimated from this seismic-to-well tie is shown in Figure 9, and a –2° phase rotation is predicted. The very high correlation coefficient indicates that the data is high quality and that the tie is sound. The resulting estimated wavelet is highly desirable from an interpretation perspective as impedance boundaries in this case would correspond to the dominant peaks and troughs in the seismic data.

Data set 3: Statistical wavelets and phase comparisons

Again, we estimate a constant-phase, a frequency-dependent phase, and three time-varying wavelets directly from the data by means of the statistical techniques. The resulting statistical wavelets are shown in Figure 9.

Of all three data sets tested, this data set 3 shows the closest visual agreement in wavelet estimates across all four techniques used. The statistical constant-phase method predicts a phase rotation of 3°, which is only a 5° advance with respect to the deterministic seismic-to-well tie wavelet. This phase rotation almost is below the limit of what the eye can notice, and would not make a visual difference to the seismic data.

The statistical frequency-dependent phase wavelet is estimated to have a constant-phase equivalent rotation of 5°, which is very close to both the statistical constant-phase value and the deterministic seismic-to-well tie estimate. Again, it is unlikely that such a small phase rotation would alter an interpretation.

Figure 9 also shows the estimated time-varying constant-phase wavelets. Unlike data sets 1 and 2, the wavelets estimated by this method appear nearly stationary with respect to time. Each wavelet is obtained using a time-window of 2.4 s. The most shallow wavelet phase is 9°, whereas the deeper two statistical phase estimates both are 3°.

Figures 3, 7, and now 9 demonstrate that the deterministic and statistical wavelets differ only by a small phase discrepancy, just noticeable to the eye. As with data set 1, the results from data set 3 indicate that the statistical methods produce cleaner looking wavelets with fewer side lobes than the deterministic seismic-to-well tie technique.

Data set 3: Amplitude spectra

Figure 10 displays the amplitude spectra of all wavelets estimated for data set 3, as shown in Figure 9. The total passband is similar for all statistical wavelet estimates, but the deterministic seismic-to-well tie wavelet passband is narrower. This, combined with the dual peaks displayed in the amplitude spectrum, manifests as noise and ringing in the time domain, apparent in Figure 9. The spectral averaging used by the statistical techniques makes for a simpler and "cleaner" appearance of the time-domain wavelets than the auto-correlation method used in the seismic-to-well tie process.

As with data sets 1 and 2, attenuation corrections during processing have hidden the expected fall in overall amplitude and loss of high frequencies with depth. This is evident since the amplitude-spectra of all three time-varying wavelets are similar.

All deterministic and statistical wavelets again can be used for phase-only or amplitude-and-phase deconvolution. However, in this case phase deconvolution is unlikely to be necessary, as the data already appear to be zero phase.

DISCUSSION

Numerous reasons exist why well logs may not represent ground truth — the fundamental assumption in any seismic-to-well tie. Significant well-log interpretation, calibration and corrections are required to produce the reflectivity series required for the seismic-to-well tie process.

This human element, combined with variable log quality and depth errors, makes wavelets estimated from seismic-to-well ties hard to reproduce accurately. It is unusual for any two persons to estimate precisely the same wavelet given identical suites of well logs. However, in this study the close correspondence of all wavelet estimates gives us confidence that both the statistical and deterministic methods have reproduced a close approximation of the true seismic wavelet over the logging interval.

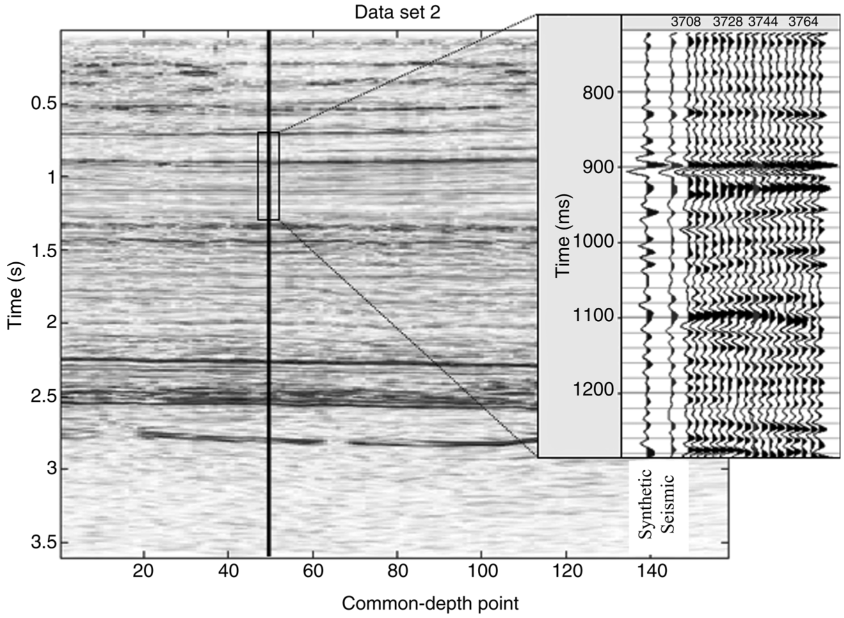

Figure 6. 2D seismic section with well location of data set 2. The location and quality of the seismic-to-well tie is shown in the inset: left, synthetic seismogram; right, seismic trace at the well location. The seismic-to-well tie correlation coefficient is 81%.

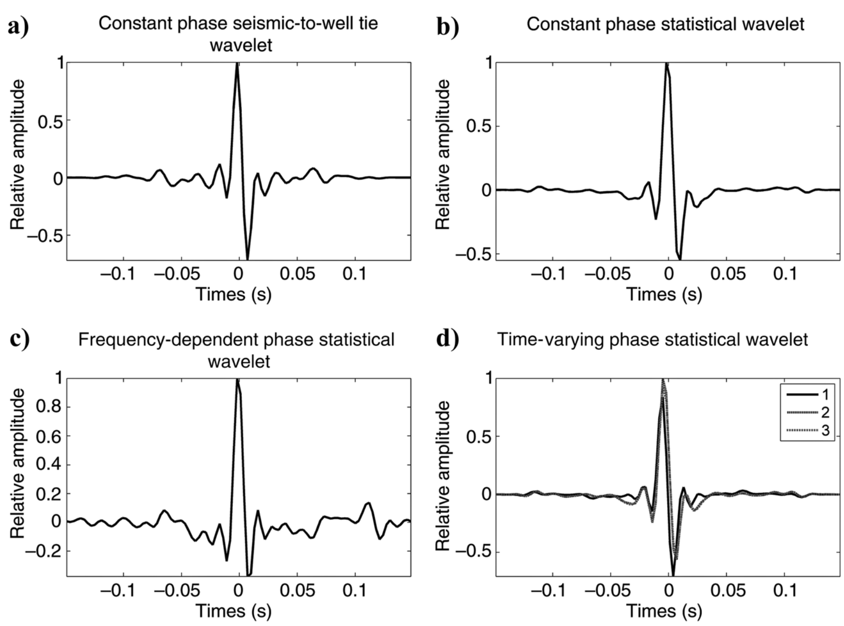

Figure 7. Wavelets estimated from data set 2 (a) deterministic seismic-to-well tie ($\phi = 58°$), (b) statistical constant phase ($\phi = 36°$), (c) statistical frequency-dependent phase ($\phi \approx 31°$), and (d) statistical time-varying constant phase ($\phi_{avg} = 47°$). Three time-varying wavelets have been extracted, numbered 1–3 with increasing time. A small phase discrepancy is visible between the deterministic and statistical methods. The time-varying wavelets indicate that the phase advance estimated by the deterministic seismic-to-well tie is true only of the shallow section.

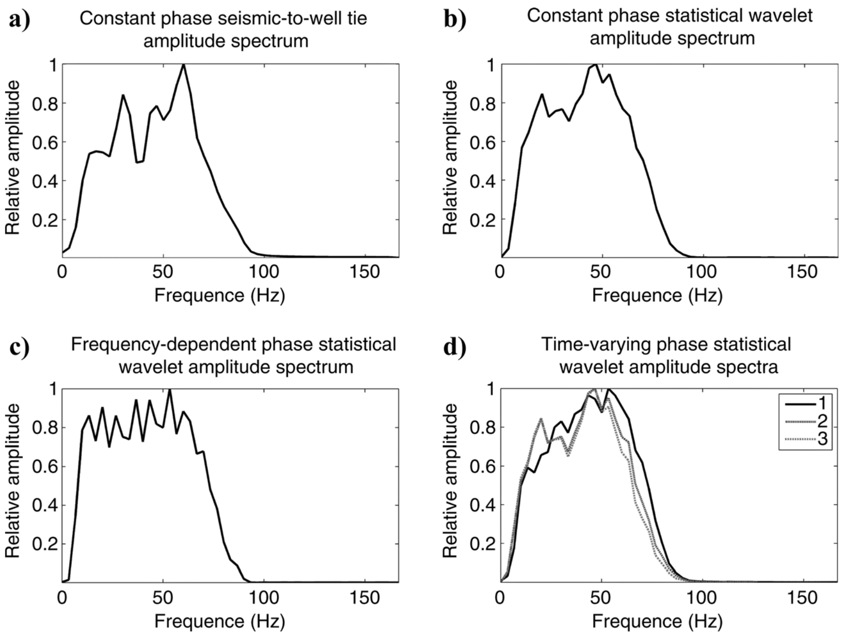

Figure 8. Amplitude spectra of wavelets estimated from data set 2 (a) deterministic seismic-to-well tie, (b) statistical constant phase, (c) statistical frequency-dependent phase, and (d) statistical time-varying constant phase. The deterministic amplitude spectrum is calculated over the same window of data as is used in the deterministic phase estimation, whereas the time-stationary statistical methods use the whole data section for both. Three time-varying wavelets have been extracted, numbered 1–3 with increasing time. The total passband of all wavelets is similar, but the statistical frequency-dependent phase technique has introduced some ringing in the time domain (Figure 7) through a slightly too-harsh whitening stage implicit within the method.

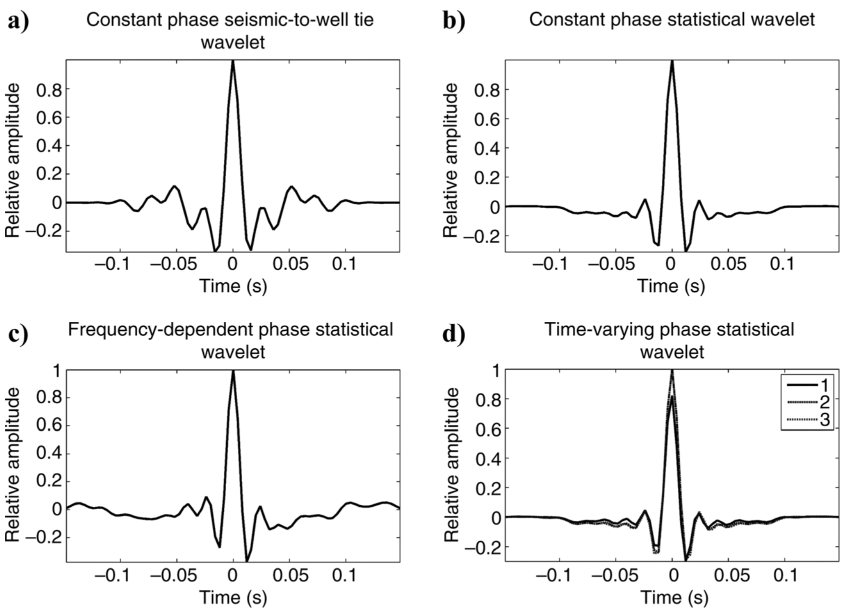

Figure 9. Wavelets estimated from data set 3 (a) deterministic seismic-to-well tie ($\phi = -2°$), (b) statistical constant phase ($\phi = 3°$), (c) statistical frequency-dependent phase ($\phi \approx 6°$) and (d) statistical time-varying constant phase ($\phi_{avg} = 5°$). Three time-varying wavelets have been extracted, numbered 1–3 with increasing time. All wavelets are visually and quantitatively in close agreement, with the deterministic method again providing the noisiest estimation.

The most noticeable difference between the deterministic and statistical wavelets occurs in the number of side lobes. As mentioned previously, this is a result of the difference in how the amplitude spectrum is calculated by the two methods. The statistical methods lead to much simpler wavelets without the side lobes of the seismic-to-well tie wavelets. We constrained the deterministic wavelets to have constant, frequency independent phase. Relaxing this constraint produces higher correlation coefficients between the synthetic seismogram and seismic trace (Figure 11), yet the resulting wavelets have increased side-lobe energy and look unrealistic.

This problem, noted by Ziolkowski (1991), may be a consequence of using synthetic seismogram to seismic correlation to estimate a wavelet; if the initial correlation is too low, the method may contaminate the true wavelet and merely output the filter required to remove the source time function and all remaining undesired components of the earth response. It is possible that the side lobes in the constant-phase seismic-to-well tie wavelets are artifacts that beautify the seismic-to-well tie, creating a statistical transfer function instead of retrieving the underlying seismic wavelet.

Statistical methods routinely are used to estimate wavelet amplitude spectra, whether by auto-correlation methods, spectral averaging, or another technique. Such methods are used widely and generally are considered reliable. As such, it was not the goal of this study to evaluate amplitude spectra estimation, but rather to address the issue of statistical estimation of wavelet phase.

The time-varying constant-phase statistical wavelet-estimation technique of van der Baan (2008) estimated at least some degree of nonstationary phase within each data set tested. This is not unexpected: attenuation and dispersion effects are frequency and time dependent, and thus will cause frequency and time variation of wavelet phase. Standard corrections at the data processing stage are unlikely to account fully for these effects. However, it is possible that geologic reasons exist for nonstationary wavelet phase, such as the presence of thin beds tuning the wavelet and producing an apparent 90° phase rotation (Edgar and Selvage, 2011).

Where nonstationary phase is estimated, without further information about the subsurface (such as a well log), it is not unambiguously possible to attribute the cause of time-dependent phase to any individual factor: It may be a remnant from acquisition and processing, it could be geologic, or it might be natural instability of the statistical method (Edgar and Selvage, 2010). However, a well-constrained, nonstationary

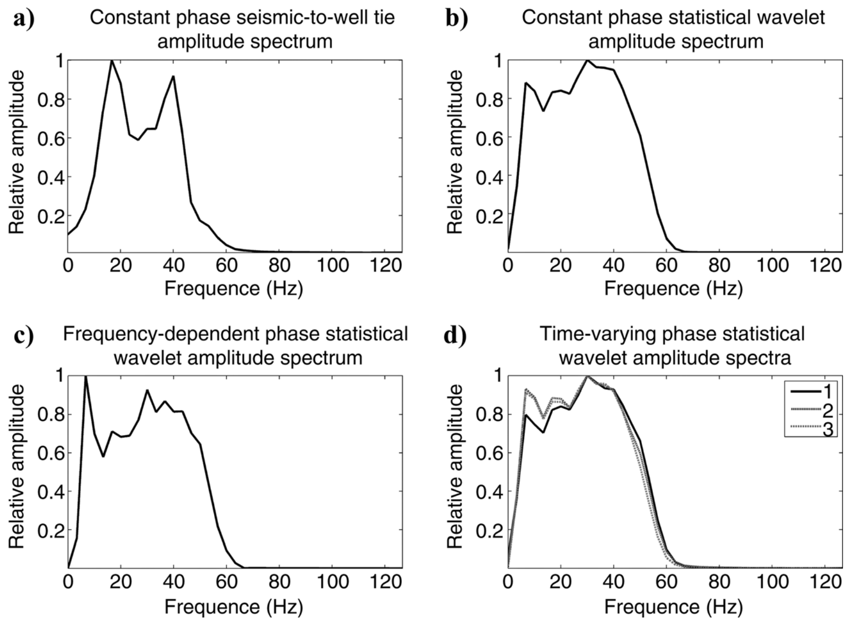

Figure 10. Amplitude spectra of wavelets estimated from data set 3 (a) deterministic seismic-to-well tie, (b) statistical constant phase, (c) statistical frequency-dependent phase, and (d) statistical time-varying constant phase. The deterministic amplitude spectrum is calculated over the same window of data as is used in the deterministic phase estimation, whereas the time-stationary statistical methods use the whole data section for both. Three time-varying wavelets have been extracted, numbered 1–3 with increasing time. The total passband of the deterministic wavelet is lower than that of the statistical wavelets, and also displays two peaks; this explains its more noisy appearance in the time domain (Figure 9).

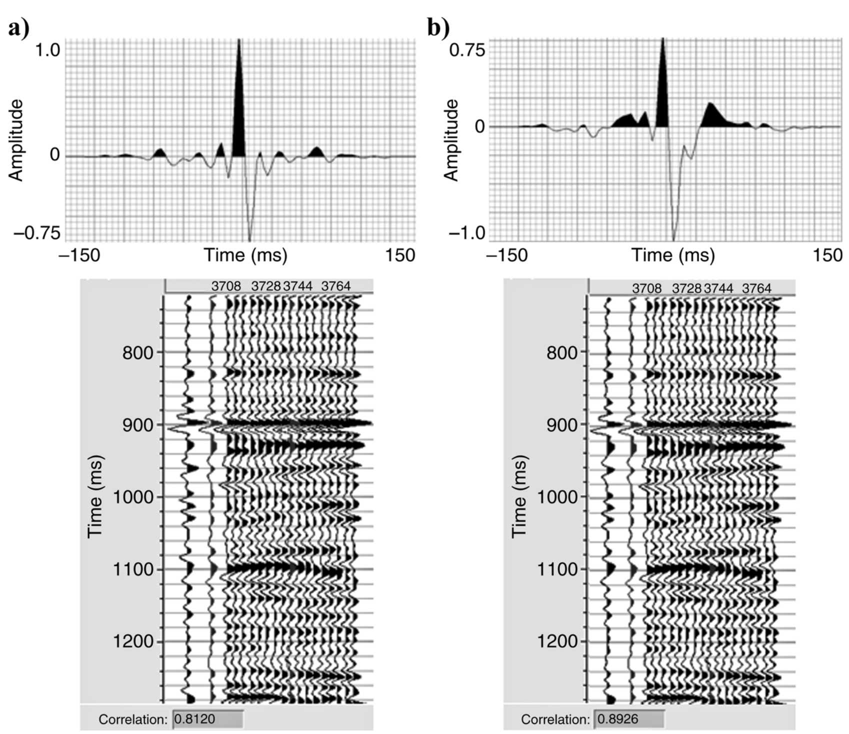

Figure 11. Comparison of deterministic seismic-to-well tie wavelets: (a) constant phase deterministic seismic-to-well tie wavelet above its corresponding well tie with correlation coefficient of 81%, (b) frequency-dependent phase deterministic seismic-to-well tie wavelet above its corresponding well tie with correlation coefficient of 89%. Comparison of (a and b) panels shows that relaxing the constant phase approximation increases the well-tie correlation coefficient, but introduces unrealistic and undesirable side lobes and noise to the wavelet.

phase analysis has potential as an interpretational tool. For instance, it has been shown to highlight subtle variations in the local geology such as thin beds, pinch outs, meandering channels, carbonate reefs and variations in coal sequences (van der Baan and Fomel, 2009; van der Baan et al., 2010; Edgar and Selvage 2011).

CONCLUSIONS

Deterministic corrections commonly are applied to rectify phase mismatches between final processed seismic data and synthetic seismograms created from well logs. These corrections force the synthetic seismograms to match the seismic data by assuming the well logs provide ground truth. However, different nearby wells often suggest different phase corrections, and well logs are not always available.

We have shown that statistical methods can be used to estimate wavelets from the seismic data alone, without the need for well control. Thanks to improvements in data quantity, bandwidth and noise suppression, allied with refining of the statistical techniques, these methods now can robustly estimate wavelet phase in close agreement with estimates obtained from well logs, directly from modern seismic data. The constant-phase method, in fact, is robust enough to allow the estimation of time-varying wavelets – a real challenge for deterministic approaches because of the generally short logging sequence. Frequency-dependent statistical wavelet estimation also is viable, leading to realistic looking wavelet estimates even when the seismic-to-well tie method cannot.

When applied to modern seismic data which meet the preconditions of kurtosis-based algorithms, the statistical methods can be used as a reliable quality control tool for the deterministic methods, a way of extrapolating phase away from wells, or as standalone tools in the absence of wells.

ACKNOWLEDGMENTS

The authors thank BG Group, BP, Chevron, the Department of Trade and Industry, Industry Technology Facilitator (ITF), and Shell for the financial support of the Blind Identification of Seismic Signals project, and Shell UK Ltd. for permission to use the data. We thank Jeroen Goudswaard for facilitating this project and his expert advice, as well as the anonymous reviewers for all their comments. Both authors were at the University of Leeds at the time this work was done.

REFERENCES

Berkhout, A. J., 1977, Least-squares inverse filtering and wavelet deconvolution: Geophysics, **42**, 1369–1383, doi:10.1190/1.1440798.
Brown, A. R., 2004, Interpretation of three-dimensional seismic data (sixth edition): SEG.
Cover, T. M., and J. A. Thomas, 1991, Elements of information theory: Wiley.
Donoho, D., 1981, On minimum entropy deconvolution, *in* D. F. Findley, ed., Applied time series analysis II: Academic Press Inc., 565–608.
Edgar, J. A., and J. I. Selvage, 2010, Estimating non-stationary wavelet phase and phase error: 72nd Annual International Conference and Exhibition, EAGE, Extended Abstracts, P394.
———, 2011, Can thin beds be identified using statistical phase estimation?: First Break, **29**, 55–65, doi: 10.3997/1365-2397.2011009.
Levy, S., and D. W. Oldenburg, 1987, Automatic phase correction of common-midpoint stacked data: Geophysics, **52**, 51–59, doi:10.1190/1.1442240.
Longbottom, J., A. T. Walden, and R. E. White, 1988, Principles and application of maximum kurtosis phase estimation: Geophysical Prospecting, **36**, 115–138, doi:10.1111/j.1365-2478.1988.tb02155.x.
Mendel, J. M., 1991, Tutorial on higher-order statistics (spectra) in signal processing and system theory: Theoretical results and some applications: Proceedings of the IEEE, **79**, 278–305, doi:10.1109/5.75086.
Trantham, E. C., 1994, Controlled-phase acquisition and processing: 64th Annual International Meeting, SEG, Expanded Abstracts, 890–894.
van der Baan, M., 2008, Time-varying wavelet estimation and deconvolution by kurtosis maximization: Geophysics, **73**, no. 2, V11–V18, doi:10.1190/1.2831936.
van der Baan, M., and S. Fomel, 2009, Nonstationary phase estimation using regularized local kurtosis maximization: Geophysics, **74**, no. 6, A75–A80, doi:10.1190/1.3213533.
van der Baan, M., and D-T. Pham, 2008, Robust wavelet estimation and blind deconvolution of noisy surface seismics: Geophysics, **73**, no. 5, V37–V46, doi:10.1190/1.2965028.
van der Baan, M., S. Fomel, and M. Perz, 2010, Nonstationary phase estimation: A tool for seismic interpretation?: The Leading Edge, **29**, 1020–1026, doi:10.1190/1.3485762.
Walden, A. T., and J. W. J. Hosken, 1985, An investigation of the spectral properties of primary reflection coefficients: Geophysical Prospecting, **33**, 400–435, doi:10.1111/j.1365-2478.1985.tb00443.x.
———, 1986, The nature of the non-Gaussianity of primary reflection coefficients and its significance for deconvolution: Geophysical Prospecting, **34**,1038–1066, doi:10.1111/j.1365-2478.1986.tb00512.x.
Walden, A. T., and R. E. White, 1984, On errors of fit and accuracy in matching synthetic seismograms and seismic traces: Geophysical Prospecting, **32**, 871–891, doi: 10.1111/j.1365-2478.1984.tb00744.x.
White, R. E., 1988, Maximum kurtosis phase correction: Geophysical Journal International, **95**, 371–389, doi:10.1111/j.1365-246X.1988.tb00475.x.
White, R. E., and R. Simm, 2003, Tutorial: Good practice in well ties: First Break, **21**, 75–83.
Ziolkowski, A., 1991, Why don't we measure seismic signatures?: Geophysics, **56**, 190–201, doi:10.1190/1.1443031.