THE ACCURACY OF DIPOLE SONIC LOGS AND ITS IMPLICATIONS FOR SEISMIC INTERPRETATION

L.R. LINES, P.F. DALEY and L. IBNA-HAMID

Department of Geoscience, University of Calgary, Calgary, Alberta, Canada T2N 1N4.
lrlines@ucalgary.ca

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ABSTRACT

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Sonic logs contain errors due to mud invasion and cycle skipping, and repeat logs may be recorded to validate measurements. For repeated dipole sonic logs, it is interesting to note differences in the (compressional) P-wave and (shear) S-wave velocities, as well as the resulting differences in reflectivity sequences and synthetic seismograms. For synthetic seismograms with low-frequency wavelets, the differences are often barely perceptible, especially for P-wave synthetic traces. When correlating these different synthetic traces with reflected events on real seismic data, our interpretations would often not be affected. However, for the purposes of deconvolution, seismic wavelets are often estimated by using both sonic logs and real seismic data. In some cases, where there are noticeable differences in estimated log-based wavelets, it is advisable to check log-based wavelet estimates using statistical methods, such as minimum phase wavelet estimation. Also in these comparisons of dipole sonic logs, synthetic seismograms and wavelet estimates, we have generally found the repeatability of P-wave logs to be superior to that of the shear-wave logs. This is not surprising due to the difficulty of picking shear-wave arrivals compared to P-wave first break picks. In comparing the maps of V_P/V_S ratios obtained by kriging of many dipole sonic logs, we find that the map trends are similar, but the details may differ, especially for thin bed targets. In general, repeat measures of dipole sonic logs will be worthwhile for insuring that the P-wave synthetic seismograms, shear-wave synthetic seismograms, wavelet estimates and V_P/V_S maps are accurate.

KEYWORDS: dipole sonic logs, V_P/V_S, wavelets.

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INTRODUCTION

It is well known that, like all geophysical measurements, sonic logs contain inaccuracies. Such inaccuracies may be caused by mud invasion, cycle skipping, hole conditions such as caving, instrument problems or noisy recording conditions. Inaccuracies with sonic logs may cause the sonic logging experiment to be repeated. Repeated logging runs are done routinely over zones of interest since the costs for repeat logs are minimal compared to the setup time for a rig. Repeat logs are a useful quality control measure. In this short note, we investigate discrepancies in repeat logs. Through this analysis, we specifically examine:

1. Differences in reflectivity functions for repeat logs.

2. Resulting differences in synthetic seismograms.

3. Resulting differences in log-based wavelet estimations due to reflectivity errors.

4. Comparisons of log-based wavelet estimations with statistically based methods.

5. Comparisons of the above attributes for P-wave and shear-wave logs.

6. Comparisons of the V_P/V_S maps resulting from kriging (least squares prediction of velocities for P-wave and shear-wave logs).

In this analysis of sonic log errors and repeatability, we examine a series of sonic logs from Nexen's Long Lake heavy oil field. From a set of 42 dipole sonic logs, we examined some repeated logs and looked at the differences and similarities of these data. In this note, we show some typical examples of P-wave and shear-wave logs from this field.

Fig. 1 shows two P-wave sonic logs from a well between depths of 153.5 and 292.1 m, sampled at intervals of 0.1 m. We note that the logs are quite similar except at depths of 155, 172, 192, 252 and 290 m. We plot a "discrepancy" log as the third trace in this display to show the difference between the velocities. In other words, the repeat log (log B) looks similar to the log of well A except for a few locations, specifically at about 1 m (10 sample intervals) at depths of 2, 35, 40, 96, 120 and 137 m from the top of the log.

Our sonic log gives slowness (reciprocal velocity) measurements at regular depths (10 cm intervals) through the subsurface. The seismic data are recorded in time. In order to compare the sonic log data to seismic data, we convert the reciprocal velocity versus depth readings to readings of velocity versus time. We can then compute reflection coefficients, r_j, as a function of time by the simple formula at a time sample at an interface between the layers j and j + 1 as

$$r_j = (v_{j+1} - v_j)/(v_{j+1} + v_j) \quad . \tag{1}$$

More correctly if we convert density versus depth to density versus time, we compute the reflectivity as the contrast in acoustic impedances, $I_k = \rho_k v_k$ as:

$$r_j = (\rho_{j+1}v_{j+1} - \rho_j v_j)/(\rho_{j+1}v_{j+1} + \rho_j v_j) = (I_{j+1} - I_j)/(I_{j+1} + I_j) \quad . \tag{2}$$

As expected by the velocity differences versus depth in Fig. 1, there will be differences between the reflectivities of logs A and B. In Fig. 2 we compare the computations for logs A and B as a function of time. Also shown is a third trace that is the difference in the reflectivities, showing that the comparisons, as one would expect, are similar to Fig. 1.

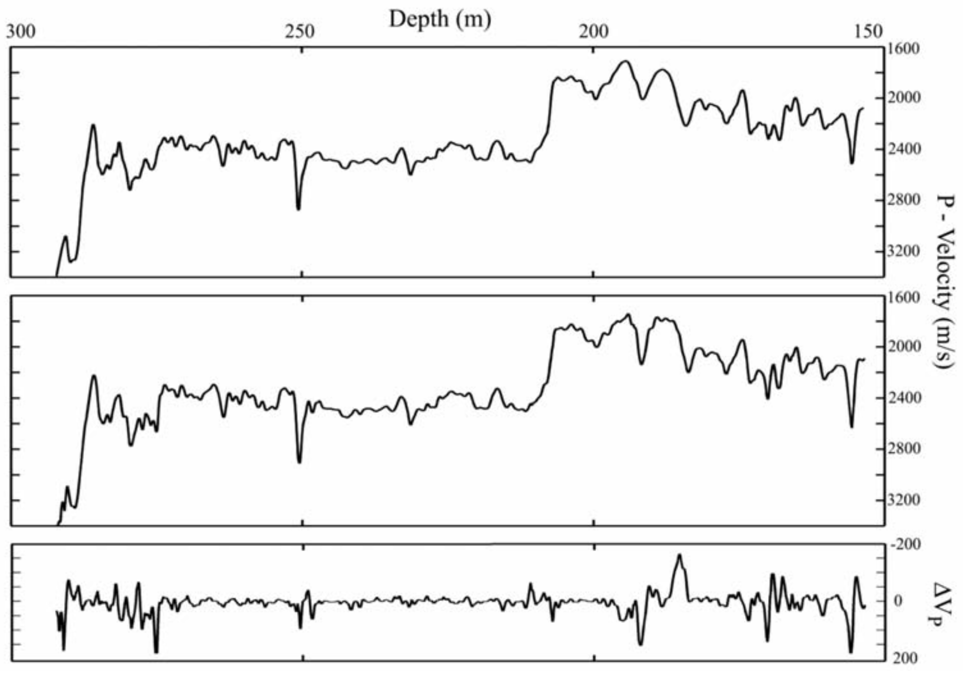


Fig. 1. A comparison of sonic logs from two wells (denoted in the text as log A and log B) spanning a depth range from 153.5 - 292.1 m. Maximum trace deflection is 3480 m/s. The third trace in the plot is a discrepancy log giving the difference in velocities between wells A and B (log B − log A velocities). Note that the biggest differences are at depths of about 155, 172, 192, 252 and 290 m.

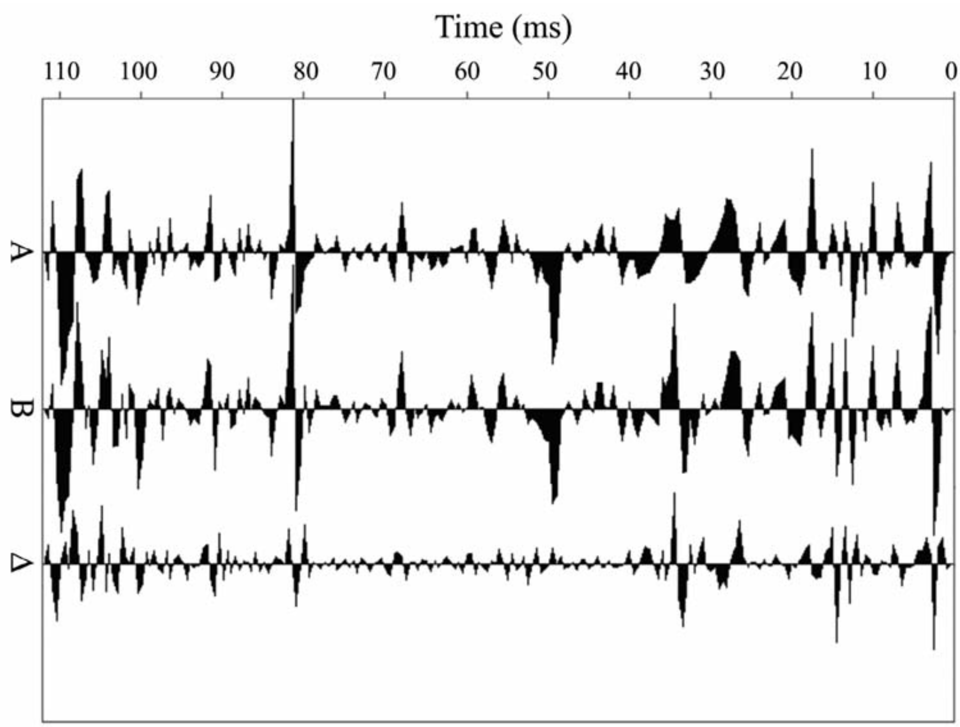


Fig. 2. The P-wave reflectivity on the left is for log A, and the reflectivity in the middle is for log B. The third trace represents the difference between reflectivities given by reflectivity B-A. The two logs span 223 samples at a sample rate of 0.5 ms for a total time of 111.5 ms.

In Fig. 2, there are differences between the reflectivities at the times expected from the velocities in Fig. 1. Note that these areas of difference are now in time rather than in depth and that we are looking essentially at trace amplitudes which are proportional to derivatives of the velocity values in Fig. 1. Despite the differences between reflectivities, the semblance between the traces 1 and 2 in Fig. 2 is still fairly high with a value of 0.93.

COMPARISON OF P-WAVE SYNTHETIC SEISMOGRAMS

For our initial calculations, we shall focus on the P-wave interpretation, which is still the main application of synthetic seismograms in interpretation. One of the primary purposes for acquiring sonic logs is to compute synthetic seismograms in order to initiate the interpretation of reflections in seismic data. To do this, we convolve the reflectivities derived from the sonic log with a seismic wavelet believed to be representative of source wavelets in our seismic data. Ideally, we would want these seismic wavelets to have a broad band of frequencies extending to the Nyquist frequency in our recording. In typical seismic data, these wavelets will have spectra in the range 5 - 80 Hz for land recording. In exceptional cases of shallow reflectors, we can have useful frequencies that extend as high as 150 - 200 Hz. For this particular example, we are dealing with shallow reflectors with depths less than 400 m. Hence, we use a wavelet with peak frequency of 150 Hz.

Fig. 3 shows synthetic seismograms wherein the reflectivities of Fig. 2 have been convolved with the minimum phase equivalent of 150 Hz Ricker wavelet. (We choose the minimum-phase equivalent of the Ricker wavelet rather than the symmetric Ricker in order to conduct the wavelet estimation tests in a later section.) The traces in Fig. 3 are essentially smoothed versions of the reflectivities of Fig. 2. The third trace represents the difference between the synthetic traces of logs B and A. Interestingly (but perhaps not surprisingly), the traces show greater similarity than the reflectivities with a semblance of 0.985. Considering these small discrepancies between traces and the high similarity (semblance), the question that naturally arises from this comparison is the following. Would the interpretation of seismic data be likely to change if we used the synthetic trace in B rather than the synthetic trace in A? The answer for these particular synthetic seismograms is "probably not".

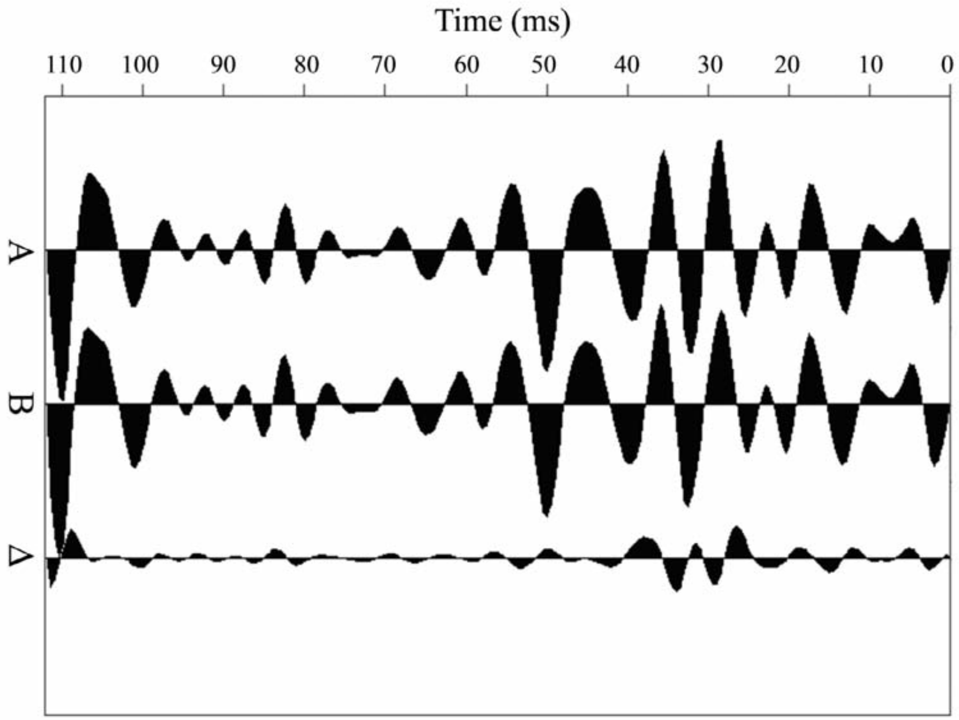


Fig. 3. The synthetic trace on the left is for log A, and the trace in the middle is for log B. The third trace represents the difference between the seismic traces by trace B-A. The two traces span 223 samples at a sample rate of 0.5 ms or a total time of 111.5 ms accuracy of log-derived wavelets.

At this point, we may be questioning whether the repeat log may have been worthwhile or not - at least for P-waves. Did the second log simply verify the validity first log without any significant change to interpreted arrivals? However, before dismissing the repeated log as unnecessary or merely as a confirmation of our original log, we may wish to examine other uses of dipole sonic logs such as the interpretation of shear-wave reflections as well as the process of wavelet estimation.

For the process of wavelet estimation, we use a method described by Danielson and Karlsson (1984), and later by Lines and Treitel (1985). In these wavelet estimation methods, we consider the convolutional model of the seismic trace in the frequency domain in which the Fourier transform of the trace, Y(f), is given by the product of the wavelet's Fourier transform, W(f) and the reflectivity's Fourier transform, R(f)

$$Y(f) = W(f)R(f) \quad . \quad [Y(\omega) = W(\omega)R(\omega)] \tag{3}$$

Generally speaking the seismic trace is known and we hope to estimate the reflectivity. We often do not explicitly know the wavelet either, but use statistical properties of the reflectivity and wavelet to estimate W(f). If we assume that the reflectivity is random, we can obtain the wavelet's spectrum to be given by the trace's amplitude spectrum. If we use a minimum phase assumption, the wavelet's phase spectrum is often obtained by computing the Hilbert transform of the log amplitude spectrum (as originally described by Robinson, 1967). The minimum phase assumption is generally believed to be reasonably accurate for impulsive sources such as dynamite or air guns. If sources do not have an impulsive nature, we may wish to use other statistical methods that do not make these assumptions (but different assumptions) such as homomorphic deconvolution, (Ulrych, 1971).

However, if we have reliable sonic logs, we may not need to invoke minimum phase or random reflectivity assumptions. We can compute the wavelet by using the seismic data and the reflectivity computed from the sonic log. We essentially compute the reflectivity and take its Fourier transform to give R(f) and then divide the trace's Fourier transform, Y(f), by this value. That is, the wavelet's Fourier Transform is given by computing:

$$W(f) = Y(f)/R(f) \quad . \quad [W(\omega) = Y(\omega)/R(\omega)] \tag{4}$$

Lines and Treitel (1985) gave computational reasons for computing this result in the time domain using Wiener filters, but the results are mathematically equivalent to eq. (4). Once the wavelet is estimated by this process, a digital filter designed to deconvolve the wavelet, can then be applied to the entire seismic line. This wavelet deconvolution process makes two fundamental assumptions:

1. The wavelet estimated at the well is basically consistent for the entire seismic line.

2. The reflectivity used in wavelet estimation can be reliably estimated from the well log.

The first assumption is essentially one of source repeatability in the field experiments. The second assumption of reflectivity reliability is one that we can evaluate using repeated logs. The repetition of logs gives us some representation of the log's accuracy.

For the logs in our example, let us test the accuracy of log-based wavelet estimation by assuming that the second sonic log, log B, is accurate, and that log A has errors. How will this situation affect the wavelet estimate? In order to compare with minimum phase statistical measures, we use traces in Fig. 3 which contain the minimum phase equivalent of the 150 Hz Ricker.

Since we are assuming log B to be accurate, we use the second trace in Fig. 3b as our data. We then apply eq. (4) to estimate W(f) using reflectivities from the two sonic logs. The wavelet estimate derived with the reflectivity from log B should be correct while the estimate with the erroneous log A will show variability. This is exactly the result shown in Fig. 4, which compares the correct wavelet, the wavelet derived from log A, and the one derived from B. As expected, there is slight difference using log A for trace B, but the wavelet estimate using the incorrect log is still a good estimate of the correct wavelet, with a deviation from the true wavelet being 3.58%. The wavelet estimate using the correct log (third wavelet in Fig. 4) is virtually identical to the true wavelet, as expected.

A simple mathematical error analysis of this situation could be viewed as an alteration of eq. (4) in which R(f) is replaced by $R(f) + \epsilon(f)$, where $\epsilon(f)$ represents the reflectivity errors in the frequency domain. Hence the wavelet estimate for an erroneous reflectivity would require that eq. (4) be revised to give:

$$\hat{W}(f) = Y(f)/\{R(f) + \epsilon(f)\} \quad . \quad [\hat{W}(\omega) = Y(\omega)/\{R(\omega) + \epsilon(\omega)\}] \tag{5}$$

For the case where reflectivity errors are small, $\epsilon(f)$ is much less than R(f) in amplitude, and we can write:

$$\begin{aligned} \hat{W}(f) &\cong \{Y(f)/R(f)\}\{1 - \epsilon(f)/R(f)\} \\ \hat{W}(\omega) &= \{Y(\omega)/R(\omega)\}\{1 - \epsilon(\omega)/R(\omega)\} \end{aligned} \quad . \tag{6}$$

Hence the accuracy of the wavelet estimate is essentially controlled by the "noise to signal ratio" for the estimated reflectivity. An estimate of this noise-to-signal ratio, $\epsilon(f)/R(f)$, can be gauged by examining the repeated log measurements.

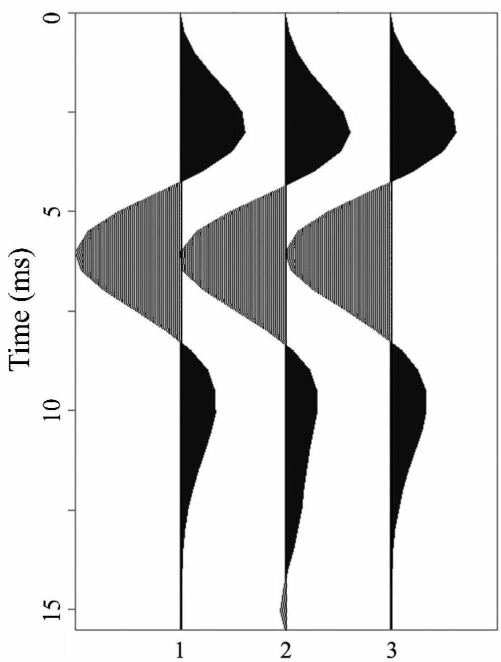


Fig. 4. A comparison of actual wavelet and the wavelet estimates using different reflectivity functions in the log-based wavelet estimation. The first is the actual wavelet, which is the minimum phase equivalent of 150 Hz Ricker. Sample interval = 0.5 ms. The data trace is the convolution of this wavelet with the reflectivity of log B. The second wavelet is the estimate obtained using log A. The third wavelet is obtained using correct reflectivity from log B and as expected, is virtually identical to the correct wavelet. Although the second wavelet has used the incorrect log values, it is still accurate to within 3.58%.

COMPARISONS WITH STATISTICAL WAVELET ESTIMATION

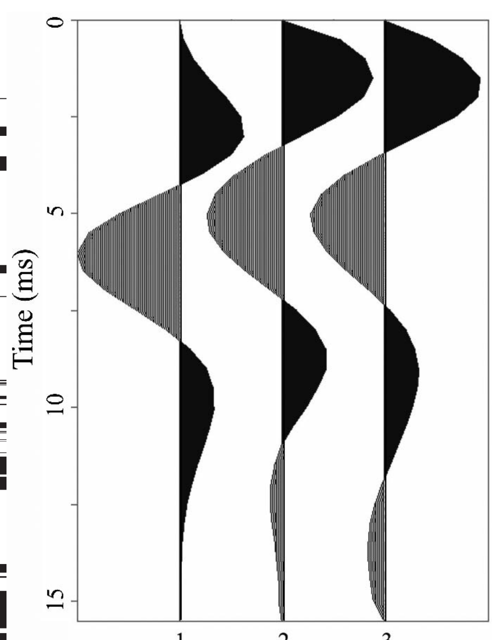
As previously mentioned, a competitor in wavelet estimation for the log-derived wavelet is the minimum phase wavelet, which does not rely on the same assumptions as the log-derived wavelet, but rather depends on two other assumptions:

1. The reflectivity function is uncorrelated. (That is, its autocorrelation is a delta function and the wavelet's spectrum equals the trace spectrum multiplied by a constant).

2. The wavelet is minimum phase.

The minimum-phase wavelet estimates do not require well logs, and can be effective even when used on traces that are somewhat noisy (Kelly and Lines, 1995). In fact, a small amount of white noise can stabilize the estimation process. Fig. 5 illustrates the minimum phase estimates derived from the traces' amplitude spectra. We see that these estimated wavelets are similar to the actual wavelet, but are slightly shifted in time. (Since the reflectivity is not perfectly random, the trace amplitude spectra are not identical to the wavelet spectra and the minimum-phase wavelets are not ideal.) Statistical tests of reflectivity randomness have been given by Dey and Lines (1999), among others.

Nevertheless, the deviation of the minimum-phase wavelet estimates from the correct wavelet estimates is about 3.5%, almost the same as using the log-based wavelet estimate. It is interesting that although both the log-based wavelet estimate and the minimum-phase wavelet estimates have made different assumptions, they have both provided very acceptable estimates that deviate



REPEATABILITY OF SHEAR-WAVE LOGS

From our present calculations, the repeatability tests for P-wave logs have shown generally encouraging results. For the P-wave logs, the reflectivities and the synthetic seismogram results are similar with very high semblance values. The log-based wavelet estimates are very similar to minimum-phase wavelet estimates, both appearing to be reliable.

However, an important characteristic of dipole sonic log information is the shear-wave information. This is important information since the shear-wave velocities allow for important lithology discrimination between sandstones and shales that would not be found from P-wave velocity information alone. The use of V_P/V_S ratios for lithology discrimination have been shown to be useful in at least two heavy oil fields in Western Canada including Plover Lake Field (Lines et al., 2005) and Long Lake Field (Dumitrescu et al., 2009).

As explained in the lucid review article by Close et al. (2009), the estimation of shear-wave velocities from dipole sonic logs is expected to be

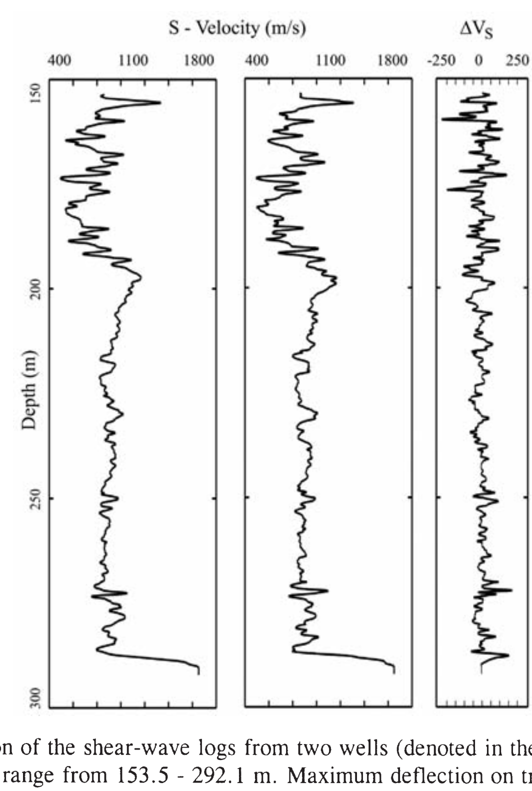


Fig. 6. A comparison of the shear-wave logs from two wells (denoted in the text as log A and log B) spanning a depth range from 153.5 - 292.1 m. Maximum deflection on traces is 1600 m/s. The third trace in the plot is a discrepancy log giving the difference in velocities between wells A and B. The difference trace in this case represents an average absolute amplitude difference of 5.14%, which is about 3.5 times greater than for the P-wave logs.

much more challenging than the estimation of P-wave velocities due to the problem of picking shear-wave arrivals. The P-wave arrival is obtained from the first break in the seismic wave arrivals in the borehole while the shear-wave arrival is imbedded in the coda of earlier arrivals. The repeatability of shear-wave velocity values is generally much more challenging.

As anticipated, the results for shear-wave repeatability for this area do not look quite as good for P-wave repeatability. If we examine the shear-wave results for logs A and B in Fig. 6, we note that the shear-wave velocities are similar but less so than the P-wave velocity logs, shown in Fig. 1. The figure shows that the shear-wave logs for A and B similar, with a difference trace that shows 5.14% discrepancy, compared to the P-wave velocities in Fig. 1 which show a discrepancy of 1.42 %.

If the synthetic traces are computed using minimum phase wavelet for the reflectivities of the logs in Fig. 6, we obtain shear-wave synthetic traces for the logs as shown in Fig. 7. The semblance for the traces in Fig. 7 is 0.884 which is somewhat less than the semblance for P-wave synthetic traces which is 0.985.

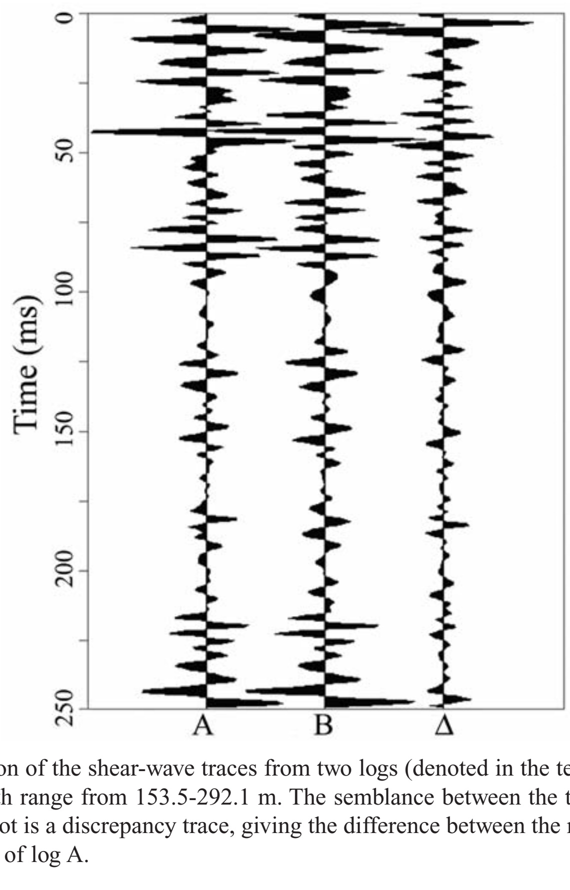


Fig. 7. A comparison of the shear-wave traces from two logs (denoted in the text as log A and log B) spanning a depth range from 153.5-292.1 m. The semblance between the traces is 0.884. The third trace in the plot is a discrepancy trace, giving the difference between the reflectivity of log B and the reflectivity of log A.

We do notice that there are definite phase shifts between the shear-wave synthetic traces that would give rise to a lower semblance value than for the P-wave synthetic traces. We notice these phase shifts in the log-based wavelet estimates as well when we repeat the wavelet estimation procedure used to produce the wavelet We employ the same wavelet estimation procedure used to produce Fig. 4. Fig. 8 shows the actual minimum phase wavelet as well as the wavelet estimates from logs A and B. The wavelet for trace A has a noticeable delay when compared to the actual wavelet and the wavelet for log B. The average fractional difference between the actual wavelet (first wavelet in Fig. 8) and the log-based estimate (second wavelet in Fig. 8) is 5.14%, which is slightly worse than the estimates for the P-wave synthetic seismic trace.

The repeatability for the shear-wave logs is not as reliable as for the P-wave logs. This is not unexpected since the detection of P-wave arrivals essentially involves picking the first arrivals of waves in a borehole, whereas the shear-wave arrival is immersed in a coda of arrivals. The detection of the shear-wave is more problematic since critically refracted shear waves do not occur if the shear-wave velocity is less than the P-wave velocity in the borehole

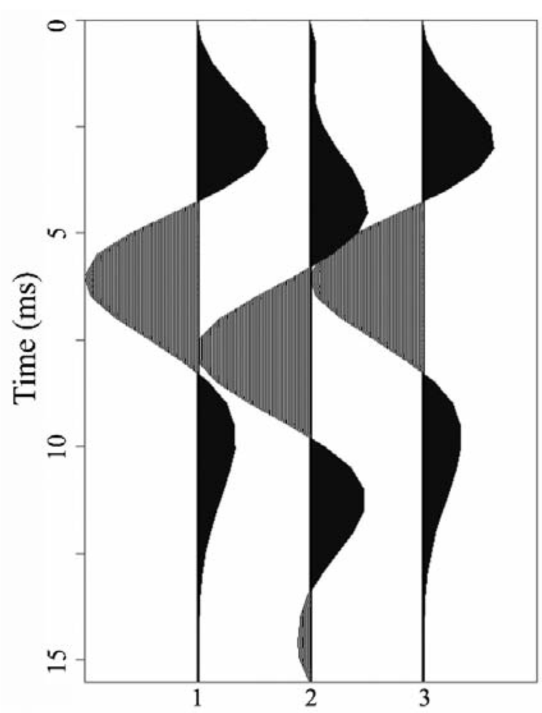


Fig. 8. A comparison of actual wavelet and the wavelet estimates using different reflectivity functions in the log-based wavelet estimation for shear waves. The first is the actual wavelet, with a minimum phase equivalent of a 150 Hz Ricker. The actual trace is the convolution of this wavelet with the reflectivity of log B. The second wavelet is the estimate obtained using log A. The third wavelet is obtained using correct reflectivity and as expected, is virtually identical to the correct wavelet.

fluid. The shear-wave arrival arises from a flexural wave created by a dipole source. Since the shear-wave arrivals are imbedded in a coda of events following the P-wave, its detection and timing is generally more difficult than the timing of the P-wave. Therefore it is not surprising that we may see more inconsistencies in the shear-wave arrivals than the P-waves. For a detailed explanation of these sonic log phenomena, the reader is referred to the paper by Close et al. (2009).

PROPOSED STRATEGY FOR WAVELET ESTIMATION AND ANALYSIS OF REPEATED DIPOLE SONIC LOGS

It is interesting in these computational experiments to notice that both the log-based and minimum-phase wavelet estimates were similar and accurate. Both methods use different sets of assumptions, and in these cases, both sets of assumptions were valid. Similarity of wavelet estimates would lead one to have confidence in the well logs and the wavelet estimates.

However, one can imagine a strategy that could be used if the log-based wavelet estimates for the repeated logs were radically different. Then one would suspect that at least one of the sonic logs would be erroneous. In such cases, which one of the log-based estimates would be the optimal choice?

In such cases, one could compare the log-based wavelets to minimum phase wavelet estimates for the seismic data. This data-derived estimate does not depend upon the reliability of the log, but on the validity of a minimum phase source wavelet and a random reflectivity. One could question the validity of those assumptions, but it has been our general experience that these assumptions are reasonably valid for dynamite and air gun sources. Otherwise, the process of spiking deconvolution, which uses these assumptions, would not have enjoyed decades of applications in seismic data processing (Robinson and Treitel, 1980). If a wavelet from the logs more closely resembles the minimum phase wavelet, this wavelet and its corresponding sonic log would tend to have more credibility.

EFFECT OF REPEAT DIPOLE LOGS ON V_P/V_S MAPS

One of the most important uses of dipole sonic logs has been their use in the construction of maps of the V_P/V_S ratio for lithology discrimination. An example of such an application was given by Lines et al. (2005) for the delineation of lithologies in the Bakken formation at Plover Lake, Saskatchewan. This map was based on multicomponent seismic data and a couple of dipole sonic logs. Since that study, we have seen dipole sonic logs being gathered much more routinely for heavy oil sands prospects in Western Canada. At Long Lake in Alberta, Nexen Inc. has recorded 41 dipole sonic logs for a field of dimensions 6.2 km by 4.8 km. Fig. 9 is a map of the average V_P/V_S ratio for the producing McMurray formation, as obtained from the original dipole sonic logs. Fig. 10 gives the same type of map, obtained from repeated dipole sonic logs from the same wells. In these maps, the yellow-green zones show V_P/V_S ratios of 2.0-2.2 which shows sand domination. The blue zones indicate V_P/V_S values of 2.2-2.6 which shows mostly sand with some shale. The blue zone which bends from NE trending to SE trending is likely indicative of an abandoned channel. The purple zone along the North side of the map generally indicates a shale dominated zone. These V_P/V_S maps and the lithology interpretations agree well with the kriged maps of gamma ray logs. In essence, the maps representing average V_P/V_S values over the entire McMurray formation do not differ significantly from each other. The trends are similar, although there appears to be more detail in the variation of V_P/V_S for the maps of the repeat logs. As we look at subintervals of the McMurray formation, the comparisons of maps between logs and repeat logs show considerable differences. As expected, these comparisons indicate that repeat logs will not

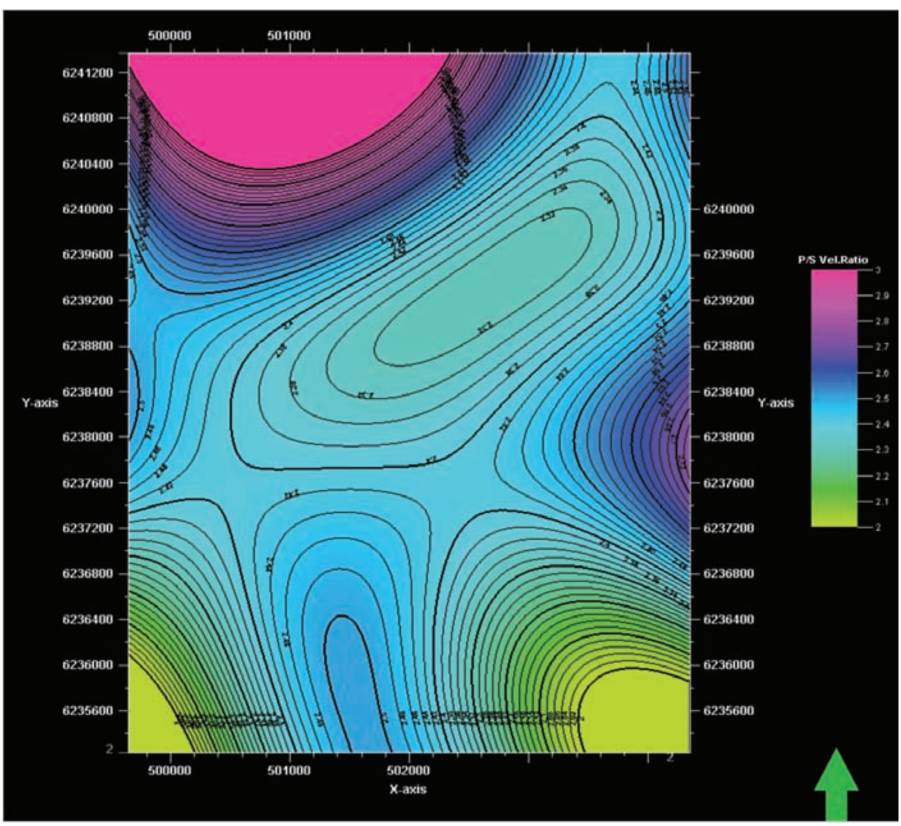


Fig. 9. A map of the V_P/V_S ratio for the McMurray formation in a heavy oil field at Long Lake, Alberta. The map was obtained by kriging the average V_P/V_S values from the original dipole sonic logs at 41 wells. Dimensions of the field are 6.2 by 4.8 km.

greatly change the general trend of thick intervals on the map, but could significantly change maps for thinner intervals. In other words, large thickness averages of logs generally do not show appreciable differences between logging runs since the differences between logs tends to be averaged out.

CONCLUSIONS

Sonic logs involve errors in measurements. Hence, the well log experiments are repeated to evaluate their reliability. The resulting logs and computed reflectivities will show differences. Due to the smoothing effect of seismic wavelets, the difference in synthetic seismograms for repeated logs is often less evident than for reflectivities. The sonic log differences will also affect the log-based wavelet estimations for deconvolution. The decision of whether to use log-based wavelet estimation or minimum phase wavelet estimation will depend on the accuracy of the sonic logs and on the wavelet phase. In our experience, we have found the P-wave logs to be slightly more

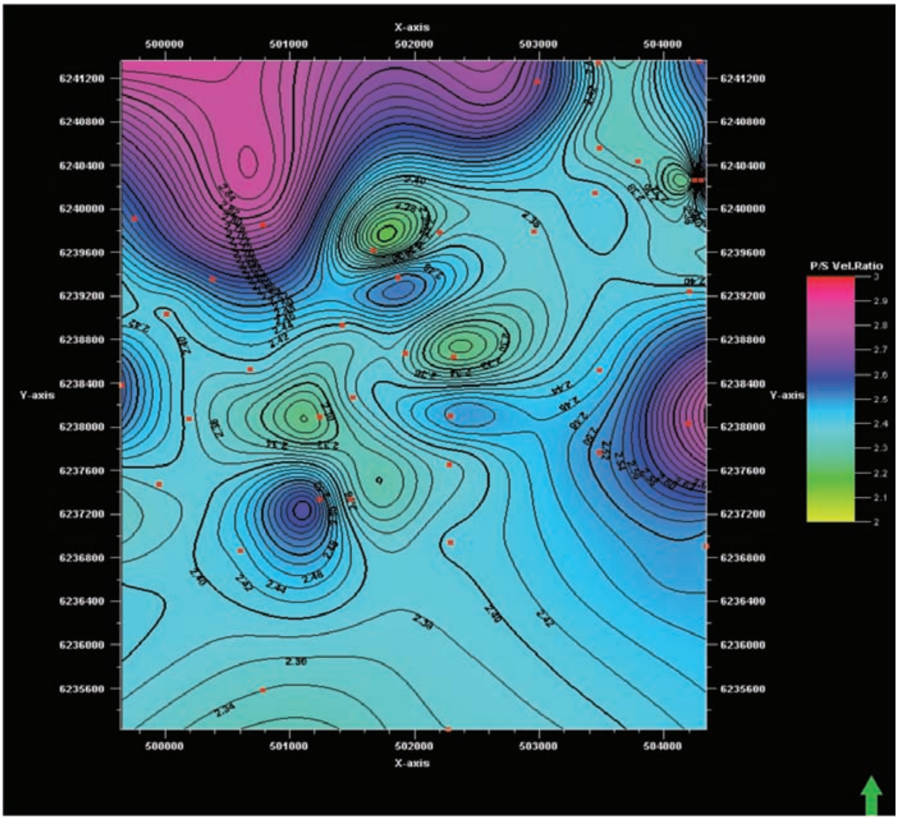


Fig. 10. A map of the V_P/V_S ratio for the McMurray formation in a heavy oil field at Long Lake, Alberta. The map was obtained by kriging the average V_P/V_S values from the repeated dipole sonic logs in the same wells as Fig. 9. Dimensions of the field are 6.2 by 4.8 km.

repeatable and reliable than the shear-wave information. This is due to the nature of the dipole logging measurements and the ease of timing P-wave arrivals compared to shear-wave arrivals. In this paper, we offer some guidelines on how to judge the validity of log-based wavelets compared to those derived entirely from seismic data. In terms of V_P/V_S mapping, we note that the estimates derived over thicker layer intervals will show less difference between the original and repeat logs due to the averaging effects over greater depth. On the other hand, the difference between V_P/V_S layers for repeat logs and original logs can vary considerably over thinner layers (less than 10 m). In such cases, it is instructive to examine caliper logs and hole conditions to judge which of the maps have the most credibility. In general, after judging the reliability and variation of dipole sonic logs, synthetic seismograms and V_P/V_S maps, it is generally believed that the repeat measures of dipole sonic logs are worthwhile in the interpretation of lithology variations in the subsurface.

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