Geologic lithofacies identification using seismic wavelet transformation

Moshe Strauss and Micha Sapir Nuclear Research Center, Negev, Beer Sheva, Israel; Michael E. Glinsky and Jesse J. Melick BHP Billiton Petroleum, Houston, Texas*

Summary

A forward acoustic model shows that geologic lithofacies groups can be identified by the character of the wavelet transform of their seismic response even for incident signals with wavelength much larger than the dominant bed thickness. The same model shows that multiple interbed reflections can be neglected. This allows the use of a simple analytical relation of the linear reflection response expressed as a convolution between the incident signal and the scaled derivative of the acoustic impedance. The relation is applied to solve the inverse problem for the acoustic impedance, using orthogonal discrete wavelet transform (DWT) and Fourier transform (FT) methods; good agreement is obtained between the well log wavelet spectrum and both the forward modeled seismic data and the real seismic data. It is found that the DWT approach is superior, having a better signal-to-noise ratio and more localized deconvolution artifacts. A population of well logs containing the lithofacies groupings is used to define the conditional probability of a wavelet transform response given a lithofacies group. These conditional probabilities are used to estimate the lithofacies probability given a seismic wavelet response via a Bayesian inversion.

Introduction

The multiscale character of geology and how it manifests itself in the seismic record has been studied by many authors. This has ranged from examining the frequency distribution of beds (Talling 2001, Rothman and Grotzinger 1996), to examining the theoretic reflection response of statistically generated bed sequences (Velzeboer, 1981), to statistical correlation of hyperspectral seismic attributes and log response using neural networks.

There has also been a recent body of research that has appeared in the image processing and target recognition literature that has used wavelet based techniques to analyze transient signals (Mallat, 1998). It has also been recognized that wavelet analysis is the best and most fundamental way to analyze a multiscale signal (Herrmann 1997).

This paper recognizes the multiscale character of geologic sedimentation that has been examined by many authors, and the efficacy of wavelet decompositions in analyzing multiscale signals. It establishes the fundamental relationship between the wavelet decomposition of the acoustic properties of the rocks and the wavelet decomposition of the seismic reflection response. This relationship is inverted so that the wavelet decomposition of the rocks can be determined from the wavelet decomposition of the seismic reflection response. It is found that even very low frequency seismic data (10 Hz) can distinguish multiscale geologic structure that has a dominant bed thickness that would require frequencies greater than 60 Hz to resolve. A population of well logs is analyzed to determine the characteristics of their wavelet transformations given their lithofacies. The inverse relationship along with the knowledge of the multiscale character of lithofacies, allows one to analytically determine the probability of a lithofacies given low frequency seismic data.

The difference between this approach and previous approaches lies in its rational, model based approach. Attempts at statistical correlation, that is assay, of seismic response to underlying geology suffer from (1) limited data where both a well log and good seismic exist, (2) biased data where high net pay sands are preferentially sampled and (3) an inability to extrapolate beyond the range of sampled physical situations. A rational, model based approach allows well logs to be used where there is no reliable seismic data, a compensation to be made for the biased sampling, and a reliable extrapolation to be made due to the constraints of the model.

The potential business value lies in the determination of the probability of the lithofacies. Each lithofacies can be characterized in terms of the range of its volumetric properties such as net-to-gross, and reservoir flow properties such as Kv/Kh. A more definitive determination of the probability of the lithofacies will reduce the uncertainty in the recoverable volumes, well count, and production rates. This will allow better business decisions to be made, creating fiscal value.

This paper will present the results of forward modeling using a hydrodynamic computer algorithm that does not allow for shear wave propagation. This is done for two very distinct lithofacies. It is shown that multiple interbed reflections are not important. This allows a linear approximation to be made and a relationship inverted to give the wavelet decomposition of the lithofacies given the wavelet decomposition of the seismic reflection response. It is shown that the DWT gives a superior inversion compared to the FT. This relationship is then used along with the conditional probability of a wavelet transform given a lithofacies (determined from well logs), to calculate the probability of a lithofacies given a seismic wavelet transform response.

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Method and Results

The seismic expression of two distinct lithofacies is examined using a hydrodynamic model. The model allows only compressional, that is, acoustic waves. It is valid for all internal reflections and accounts for full wave propagation. An incident wave is reflected off two localized 1D acoustic impedance perturbations taken from two real well logs. The length of the perturbations is approximately 200 m. The continuous wavelet transform (CWT) is taken of the derivative of the acoustic impedance. Figures 2a and 3a show the wavelet transform of the derivative of the acoustic impedance. Figures 2b and 3b show the wavelet transform of the reflected signal for incident signal (Mexican hat wavelet) with a 20 Hz central frequency. Figures 2c and 3c show the reflected signal for an incident signal with a 10Hz central frequency. Note that the central frequency for Fig. 3a is close to 60 Hz yet there are significant differences between 2b and 3b, and even between 2c and 3c.

The hydrodynamic model was modified to have a parameter that would amplify or attenuate the effects of multiple reflections. The forward model shown in Fig. 3b was done with the effects of multiple reflections reduced by a factor of 16. The result is shown in Fig. 1. No significant difference is seen (2.4% of the energy, and no significant change in the shape of the wavelet transform).

A linear scattering approximation is therefore made since the effect of multiple reflections can be neglected. The forward model reduces to convolution of the incident signal with the derivative of the acoustic impedance. A change of scale for the acoustic impedance is necessary to account for the two way travel time. The inverse model reduces to a deconvolution with the appropriate change of scale. This deconvolution can be done in the standard way via a Fourier transform (FT) or via a discrete wavelet transform (DWT). The results of the deconvolution done with both methods are shown in Figs. 4a and 4b. The signal-to-noise ratio for the FT is 13.8 dB compared to 22.1 dB for the DWT. The deconvolution artifacts are also more localized for the DWT. This would reduce the interference of multiple stacked packages. The DWT is therefore used to deconvolve the 20 Hz synthetic seismic shown in Figs. 2b and 3b. The results are shown in Figs. 2d and 3d. Notice the similarity to the original wavelet transform of the acoustic impedance shown in Figs. 2a and 3a.

The CWT of the actual seismic inversion is shown in Figs. 2e and 3e. The response is quite similar to the wavelet transform of the well log derivative acoustic impedance (Figs. 2a and 3a), even though the processing was not amplitude preserving and could have its bandwidth significantly improved.

The final component of this project is the collection of a population of well logs, classification of intervals of those well logs according to their lithofacies group, and calculation of the wavelet transforms of the derivatives of the acoustic impedance for the same intervals. After examining the wavelet transforms of each lithofacies population, a suitable parameter of the wavelet transform was chosen which discriminated the lithofacies. The chosen parameter was the log of the average scale, $< s >$. Histograms for each lithofacies were plotted and fit to a Gaussian. The result is shown in Fig. 5. Given these conditional probabilities, $P(< s >| \mathit{lithofacies})$, the prior probabilities of A and B, and the observed $< s >$; the probability of a lithofacies can be calculated via a Bayesian inversion

$$P(A |< s >) = \frac{P(< s >| A)}{P(< s >| A)+ P(< s >| B)}.$$

Given an observed average scale of 1.0 (lithofacies B, Fig. 3), the probability of A is 23%. An observed average scale of 1.6 (lithofacies A, Fig. 2), gives a 95% probability of A.

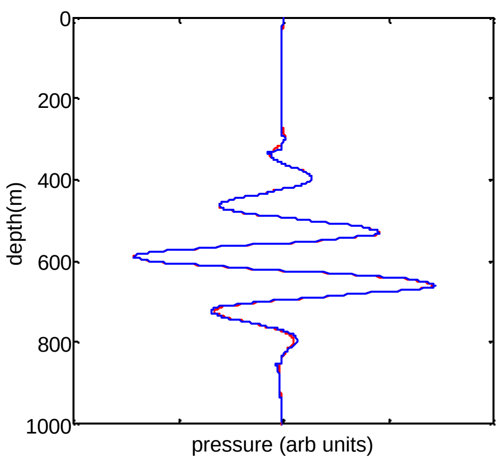

Figure 1. Reflected pressure profile. Reduced internal reflections (blue), full internal reflections (red).

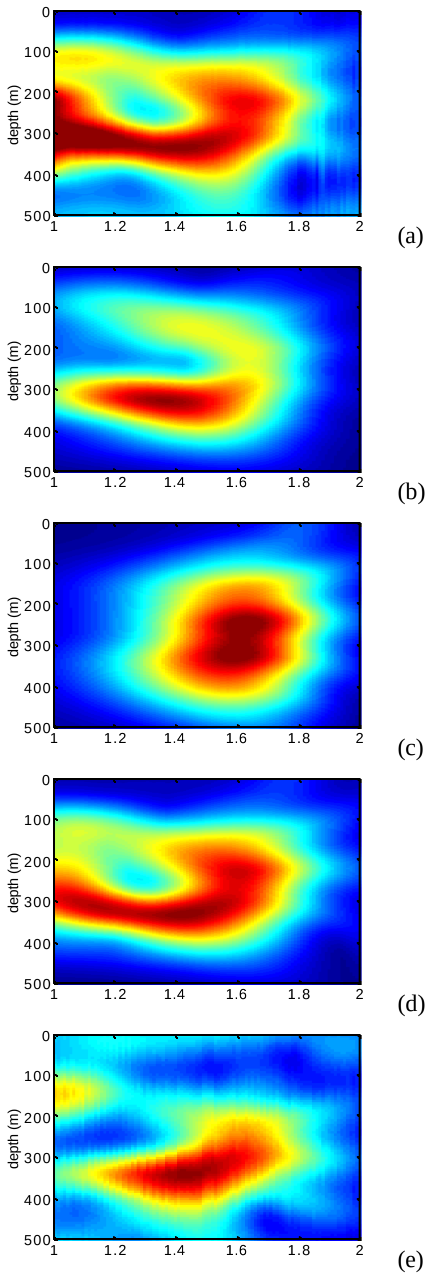

Figure 2. CWT for lithofacies A: (a) derivative of acoustic impedance of well log, (b) 20 Hz synthetic seismic, (c) 10 Hz synthetic seismic, (d) inverted 20 Hz synthetic seismic, (e) inverted real seismic. The x axis is the scale of the wavelet transform in $\log_{10}$ m. The color is determined by the smoothed (in depth, 30 m) absolute value of the CWT.

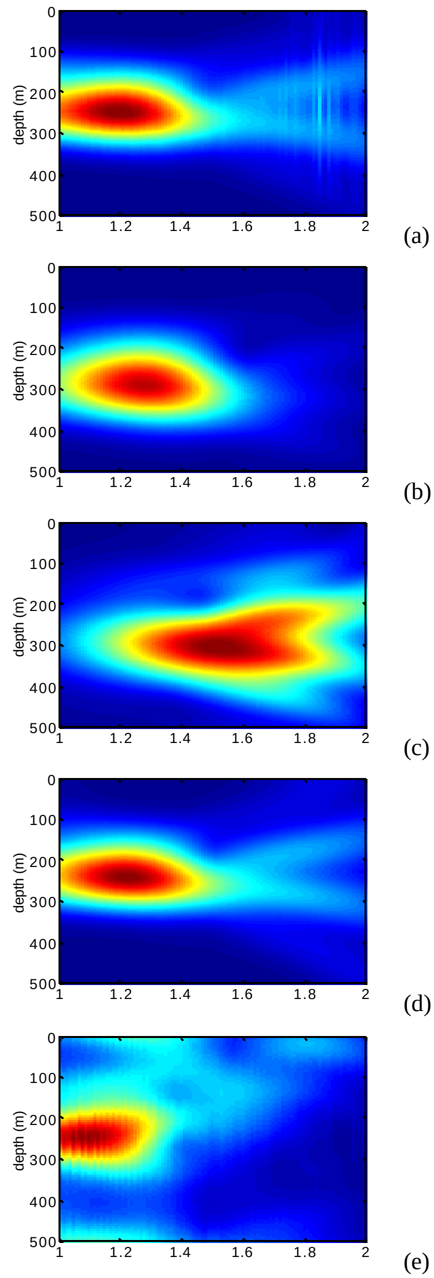

Figure 3. CWT for lithofacies B: (a) derivative of acoustic impedance of well log, (b) 20 Hz synthetic seismic, (c) 10 Hz synthetic seismic, (d) inverted 20 Hz synthetic seismic, (e) inverted real seismic. The x axis is the scale of the wavelet transform in $\log_{10}$ m. The color is determined by the smoothed (in depth, 30 m) absolute value of the CWT.

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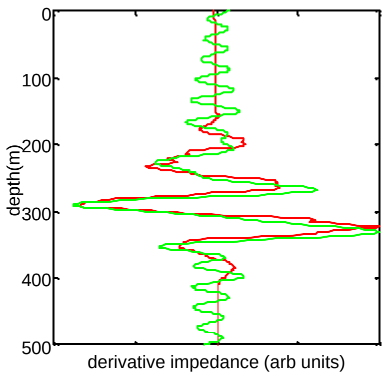
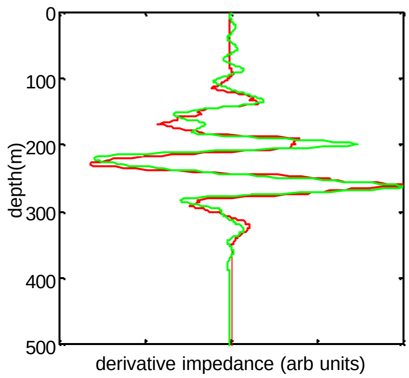


(a)



(b)

Figure 4. Inverted derivative impedance from synthetic 20 Hz data (green) and averaged well derivative impedance (red). This is shown for: (a) the FT inversion with a S/N=13.8 dB and (b) DWT inversion with a S/N=22.1 dB.

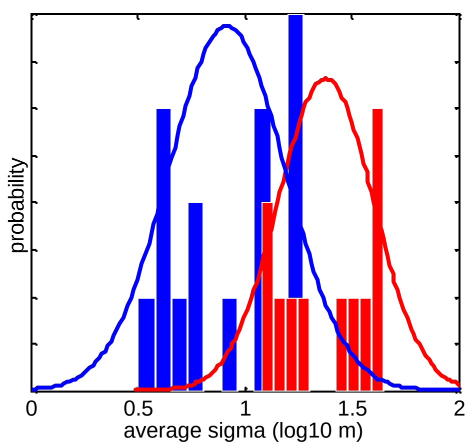


Figure 5. Conditional probability of average scale given the lithofacies. Lithofacies A (red), B (blue).

Conclusions

The analytic DWT inverse formula for the wavelet transform of the acoustic impedance given the seismic reflection response has been justified by the forward modeling and works well. Real seismic data shows the response predicted by the forward modeling. When this is combined by the conditional probabilities derived from a population of well logs, the probability of a lithofacies group can be reliably estimated. This can be done even if the bandwidth of the seismic data is not good enough to resolve the dominant bed thickness of the lithofacies group.

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