Calculation of spectral attribute based on the weak signal separation method

Yang Sannv, Qin Gangping, Deng Lin, Tang Jinbiao, and Wang Yutao,
LandOcean Energy Service Inc.

Abstract

Oil-gas reservoirs often respond with weak seismic amplitude enshrouded by strong background signals, making it difficult to extract critical reservoir information using traditional spectral analysis technology. This paper describes a method using sparse wavelet decomposition that separates the weak oil-gas signals from the strong background reflections. Spectral imaging of the separated components is then effective in extracting the information required for interpretation.

Introduction

Spectral imaging and spectral-related attributes play an important role in determining the thickness and distribution of target layers and detecting hydrocarbons directly in seismic exploration. Various methods have been developed for spectral technology such as the short window Fourier transform, continuous wavelet transform, S transform, wavelet matching decomposition, etc. Each method has its own advantages and disadvantages, and has different behaviors for different applications. In our experience it is common to encounter hidden reservoirs with weak seismic reflections enshrouded in strong background signals. We use sparse wavelet decomposition to separate the weak and strong signals, and then use spectral imaging to characterize the remaining (weak) signals in terms of reservoir parameters.

Methods

When seismic waves propagate through subsurface rock layers, elastic energy is partially absorbed and converted into heat. As a result, the energy and waveforms of received seismic signals may vary considerably. In the simple case, the reflected amplitude, A, decays according to the relation

$$A=A_0e^{-\eta x} \qquad (1)$$

where η, the absorption coefficient, is related to the quality factor, Q. As we know, the larger Q, the smaller the wave attenuation, and vice versa. As demonstrated experimentally, Q varies with lithology and pore fluid, with Q increasing in the order: gas-filled sandstone; fluid-filled sandstone; limestone, metamorphic rocks, and volcanics.

Other sources of attenuation include scattering and squirt-flow. Ignoring scattering, for a single constant lithology the change of Q in a reservoir due to squirt-flow is related only to the composition of the pore fluid. The presence of oil-gas in reservoir pores can substantially lower the seismic velocity, more for the P-wave than the S-wave, thus changing the Vp/Vs ratio of the oil-gas reservoir. Study of dispersion theory indicates that wave attenuation is the conjunct result of wave dispersion and fluid flowing. Permeable areas have specific wave attenuation characteristics. The attenuation attribute is usually used to detect rocks containing oil-gas or other fluids.

We use the method of spectral imaging to calculate the attenuation parameters of oil-gas reservoirs. However, sometimes target layers are enclosed in lithologies (like coal) that generate strong reflections, masking the reservoir response and making it difficult to extract the information needed for interpreting the reservoir characteristics. Here we describe a method that separates the weak and strong

signals, eliminating the strong ones from the data, and leaving the weak signals for interpretation..

Sparse Wavelet Decomposition

We use the Ricker wavelet as the basic wavelet

On the assumption that the seismic signal can be represented by Ricker wavelets with different

$$g(f)=\left(1-2p^2f^2t^2\right)\exp^{\left(-p^2f^2t^2\right)} \qquad (2)$$

amplitude and dominant frequency, according to the relation:

$$S=\sum_j a_j\, g\left(t-t_j, f_j, j_j\right) \quad +Noise \qquad (3)$$

The formula indicates that the seismic signal, S, is composed of a linear collection of wavelets and noise. We use the method of

sparse signal decomposition based on MP (Matching Pursuit) to calculate the coefficient a_j. Suppose the seismic signal is S and the signal length is L; if decomposing the seismic signal on a group of bases composed of Ricker wavelets with different dominant frequencies, the number of the base components should be the same as the number of layer reflection series. In order to obtain complete representation of the signals, bases have to be constructed in a compact way, which can no longer ensure their orthogonality. Therefore, the bases here are called wavelets. The collection of wavelets is over-complete, an over-complete dictionary of wavelets. Decomposition of seismic signals on an over-complete dictionary is surely sparse.

Let $D=\{g_f\}_{\gamma\in\Gamma}$, where D is an over-complete dictionary for sparse decomposition of the signals.

g_f is a wavelet determined by parameter f, its length equal to that of seismic signals and $\|g_f\|=1$.

Γ is the collection of parameters f. The process of decomposing signals by the MP method follows a series of steps

A wavelet g_{f_0} is selected from the over-complete dictionary that best matches the signals to be decomposed. It satisfies the condition:

$$\left|\langle S, g_{f_0}\rangle\right|=\sup_{\gamma\in\Gamma}\left|\langle S, g_f\rangle\right| \qquad (4)$$

Then signals can be decomposed into two parts, components of the best wavelet g_{f_0} and the residual, which can be expressed as:

$$S=\langle S, g_{f_0}\rangle g_{f_0}+R^1S \qquad (5)$$

where R^1S is the residual error after extracting the best matching part of the signals by the best wavelet. Repeat this step for the residual part, namely:

$$R^kS=\langle R^kS, g_{f_k}\rangle g_{f_k}+R^{k+1}S \qquad (6)$$

where g_{f_k} satisfies:

$$\left|\langle R^kS, g_{f_k}\rangle\right|=\sup_{f\in\Gamma}\left|\langle R^kS, g_f\rangle\right| \qquad (7)$$

From formulae（5）and（6）we know, after decomposing signals for n times, we have:

$$S=\sum_{k=0}^{n-1}\langle R^kS, g_{f_k}\rangle g_{f_k}+R^nS \qquad (8)$$

where R^nS is the residual error of decomposition for n times. For each step, the best selected

wavelet satisfies formula （7）.

Therefore, the error $R^n S$ decreases rapidly with the progress of decomposition. Mallat and Zhang (1993) proved that, when signal length is limited, $\|R^n S\|$ will attenuate and become zero with the infinite increase of n, thereby signals can be decomposed as:

$$S = \sum_{k=0}^{\infty} \langle R^k S, g_{f_k} \rangle g_{f_k} \qquad (9)$$

Furthermore, because of the attenuation characteristics of $\|R^n S\|$, it may be possible to use just a few wavelets to represent the main components of the signals, namely:

$$S \approx \sum_{k=0}^{n-1} \langle R^k S, g_{f_k} \rangle g_{f_k} \qquad (10)$$

where, $n << L$. Formula（10）and condition $n << L$ manifest the nature of sparse representation of signals.

Wavelet spectrum analysis

The frequency spectra for each wavelet is calculated for the seismic trace at a well location through wavelet decomposition. We can distinguish the useful wavelets by comparing their spectra with well log data. The wavelets related to target layers are marked by their temporal positions and sequences of spectral energy. Wavelets of strong events are also marked. The parameters at the well location are then extrapolated along the entire section.

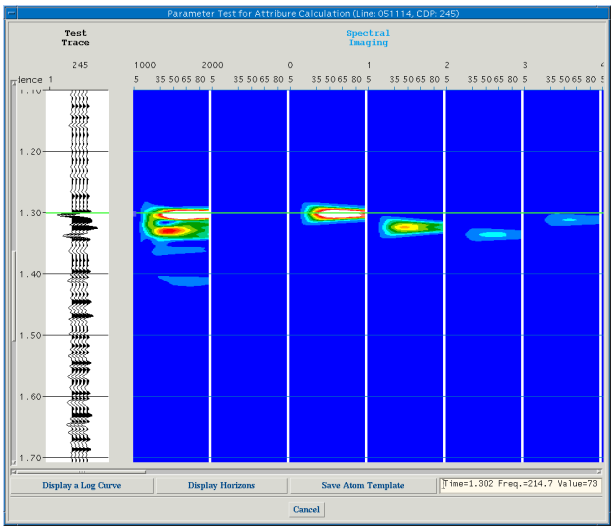

Figure 1. Frequency spectrum of wavelets (wavelets).

Eliminating strong reflection energy and calculating spectral attributes

（7）

Analyses of traces at the well locations are used to determine the (wavelet) groups related to strong reflected energy. With those groups eliminated, the spectra of the remaining wavelets are determined.

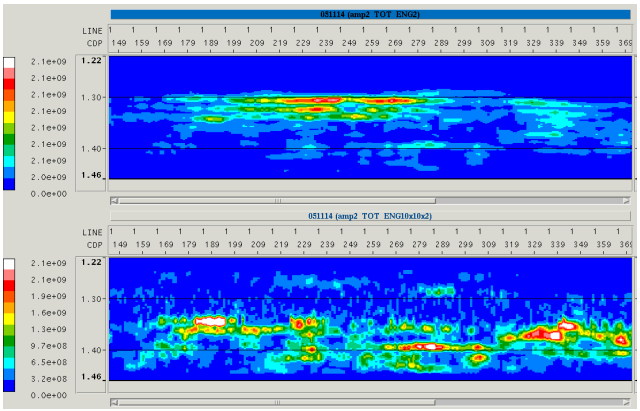

Figure 2. Energy attribute of a section before eliminating strong signals (upper window) and after (lower window).

The upper window of Figure 2 shows the energy (attribute) along a section. Strong coal reflections occur below 1.3 s. Beneath the coal layer is a gas reservoir, which is not very clear because of the strong coal reflected energy. The lower window of Figure 2 is the same section after eliminating the coal reflection; the gas reservoir is now easily distinguished.

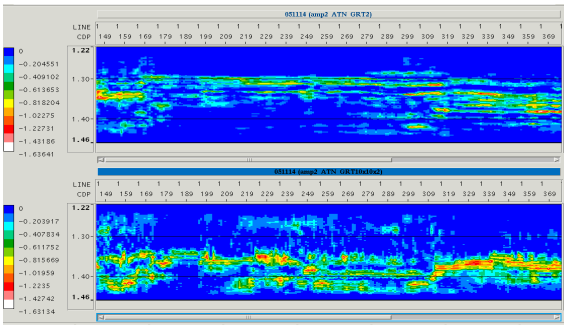

Figure 3. Attenuation gradient attributes of a section before eliminating strong energy (upper window) and after (lower window)

The upper window of Figure 3 shows an attenuation gradient attribute for the same section as in Figure 2. When the strong reflections from the coal are eliminated, the attribute related to the gas reservoir is easily distinguished.

Conclusion

In this paper, we use the method of sparse decomposition of the signals to transform seismic data into its sparse representation by a series of wavelets. By eliminating the strong signals, the weaker energy is more easily observed and the spectra determined. This technique is very useful in areas characterized by the reservoir target area beneath or contained within beds that give strong seismic reflections.

References

Gary Mavko,Tapan Mukerji,Jack Dvorkin.1998, The Rock Physics Handbook:Cambridge University Press.

Mallat S, Zhang Z. 1993, Matching pursuit with time-frequency dictionaries[J], IEEE Trans. On Signal Processing, 1993, 41(12):3397-3415.

Yin ZhongKe,Shao Zhun,Wang JianYin.2005, Signal Sparse Decomposition based on GA and Atom Property: Journal of the China railway Society,27,no.3,58-61

Sheriff,R.E.,1999,Encyclopedic dictionary of exploration geophysics,third ed.:SEG,52-53

Yu shouPeng.1996,Wide-band Ricker wavelet, Oil Geophysical Prospecting,31,no.5,605-615

Nicolas Martin,Armenio Azavache,Maria Donati, 1999,P-wave attenuation helps identify lithology and pore-fluid type – Statistical Data Included,World Oil,11,

T.Klimentos,C.McCann,1990,Relationships among Compressional___wave attenuation,porosity,clay content,and permeability in sandstones.Geophysics,55,998-1014.

Theodoros Klimentos,1995,Attenuation of P- and S-waves as a method of distinguishing gas and condensate from oil and water. Geophysics,60,447-458.

Sinha, S., Routh, P. S., Anno, P. D., and Castagna, J. P. [2005],Spectral decomposition of seismic data with continuous-wavelet transforms. Geophysics, 70, 19-25

Hua ZeXi，Yin ZhongKe，Fast Wavelet Construction Algorithm in Signal Decomposition in

Over-complete Dictionary，Transaction of Southwest Jiaotong University， 2005，6.
ShaoJun，Yin ZhongKe，Wang JianYing, Modification of MP Signal Sparse Decomposition Algorithm Based on FFT，Transaction of Southwest Jiaotong University ,2006, 8，Vol 41（4），ChengDu，pp：466-470

Key Words：spectral imaging, sparse decomposition, wavelet spectrum