Enhancing the resolution of seismic data using improved time-frequency spectral modeling
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Summary
Maximizing vertical resolution is a key objective in seismic data processing. In this study, we propose an improved time-frequency spectral modeling deconvolution method, which firstly uses a generalized S-transform (GST) to decompose each seismic trace, then models smoothly varying spectra of the seismic wavelet using nonstationary polynomial fitting (NPF) from the seismic trace, and finally performs deconvolution and the inverse GST to obtain the seismic data with enhanced resolution. Application to a synthetic and a large 3D survey from onshore China shows the proposed method is superior to conventional spectral modeling method in improving vertical resolution, and confirms that the proposed method is stable in practice and robust in the presence of noise.

Introduction
The need to properly “land” horizontal wells in resource plays has reinvigorated the need to improve the vertical resolution of 3D surface seismic surveys. Conventional enhancing resolution methods are based on a stationary convolutional model (Robinson and Treitel, 1967) that assumes the propagating wavelet does not evolve with travel time. In reality, seismic energy spreads geometrically through a heterogeneous, anelastic subsurface which gives rise to both attenuation and dispersion effects, deforming the seismic wavelet with travel time, and giving rise to a nonstationary signal (Ziolkowski, 1991; Margrave and Lamoureux, 2001). The problem of wavefront divergence is commonly addressed by applying a simple geometric spreading correction (Yilmaz, 1987, 2001). The more challenging frequency-dependent attenuation is usually referred to as the “Q-effect”. While many authors, including Futtermann (1962), Kjartansson (1979), Hale (1982), Hargreaves and Calvert (1991), Hargreaves (1992), Zhang et al. (2007) and Wang (2010), have proposed the design of inverse Q-filters to deal with the attenuation component of nonstationarity, however, the estimation of an accurate Q-model is difficult in practice. Margrave et al. (2011) presented a time-varying deconvolutional method that estimates the (attenuating) wavelet spectrum and reflectivity spectrum directly from the Gabor transform spectrum of the measured seismic data. Wang et al. (2013) developed a nonstationary spectral-broadening method to improve the resolution of seismic data, based on the assumption that the seismic data can be split into approximately stationary segments.

Seismic interpreters routinely use the spectral response of seismic reflections to detect subtle changes in stratigraphy. Such nonstationary changes in the spectral response are quantitatively estimated using a series of nonstationary time-frequency analysis techniques including Gabor transform (Gabor, 1946), the short-time Fourier transform (STFT) (Partyka et al., 1999), wavelet transform (Rioul and Vetterli, 1991), empirical mode decomposition (Huang et al., 1998), and seislet transform (Fomel and Liu, 2010). One of the more popular techniques is the S-transform (Stockwell et al., 1996) which avoids many of the shortcomings of the short-time Fourier transform. While the original S-transform used a fixed mother wavelet, McFadden et al. (1999), Pinnegar and Mansinha (2003) and Gao et al. (2003) chose the decomposition parameters based on the demands of the seismic data, giving rise to the generalized S-transform (GST). Liu et al. (2011) proposed a local attribute analysis method for nonstationary signals using an iterative inversion framework, which calculates time-varying Fourier coefficients by solving a least-squares problem based on regularized nonstationary regression (Fomel, 2007, 2009, 2013).

We begin this study with a review of the expanded generalized S-transform used to compute the time-frequency components of the seismic trace. Next, we use the improved spectral modeling method using NPF (Fomel, 2009) to estimate time-varying wavelet spectra from seismic trace and perform the deconvolution for seismic data. Finally, we apply this workflow to a synthetic and a 3D land survey acquired in China to illustrate the adaptability and effectiveness in improving vertical resolution.

Methodology
The generalized S-transform
Time-frequency analysis is powerful to characterize the nonstationarity of seismic signal using the generalized S-transform (GST), which is defined as

\[
\hat{x}(\tau, f)_{\text{GST}} = \int_{-\infty}^{\infty} x(t) \frac{j\tau}{2\pi(\sigma)} e^{-\frac{j\tau f}{2\sigma}} e^{j\sigma \beta t} dt, \tag{1}
\]

DOI http://dx.doi.org/10.1190/segam2014-0353.1
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SEG Denver 2014 Annual Meeting
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where $x(t)$ is the original seismic signal, $\tau$ is the time shift parameter, $\hat{x}(\tau, f)$ is the expression of a two-dimensional time-frequency variable with regard to $f$ and $\tau$, $\sigma'$ and $r$ are adjustable parameters. Examining equation (1), we see that the Gabor transform (Gabor, 1946) is a special case of the GST when $r=0$. Similarly one obtains the S-transform (Stockwell et al., 1996) by setting $\sigma'=1$, and $r=1$.

Deconvolution using the improved spectral modeling

Based on the assumption of statistically white reflectivity, Rosa and Ulrych (1991) represented to model the amplitude spectra of the wavelet from seismic trace using a smooth polynomial, in time-frequency domain (or generalize S-domain), which can be defined as

$$W_a(\tau, f_m) = \left| f_m \right| \exp \left[ \sum_{n=0}^{N} a_n(\tau) f_m^n \right], \quad (2)$$

where $W_a(\tau, f_m)$ denotes a smooth amplitude spectrum of a time-varying wavelet, $a_n(\tau)$ is the $n^{th}$ polynomial coefficient independent on frequency at time $\tau$, $N$ is the polynomial order, and $f_m$ is the $m^{th}$ frequency. The conventional method is to use equation (2) to model the amplitude spectrum of a wavelet. In our study, we think that the polynomial coefficients varying with time and frequency represent the nonstationarity of seismic data more precisely than conventional fitting method. Hence, we can redefine the equation (2) as

$$W_a(\tau, f_m) = \left| f_m \right| \exp \left[ \sum_{n=0}^{N} a_n(\tau, f_m) f_m^n \right], \quad (3)$$

As illustrated in the context, we can estimate the polynomial coefficients by solving the following least-squares problem:

$$\min_{a_n(\tau, f_m)} \sum_{k=1}^{Q} \left| A(\tau, f_{m_k}) - k \ln |f_{m_k}| \right|^2 + R(a_n(\tau, f_m)), \quad (4)$$

where $\| \cdot \|$ denotes the squared $L$-2 norm of a function, $A(\tau, f_m)$ denotes the time-frequency amplitude spectra of seismic trace, $a_n(\tau, f_m)$ expresses the polynomial coefficients varying with time and frequency, $R$ denotes the regularization operator, and $\varepsilon_m$ is the misfit error to be minimized. Here we use Fomel’s (2007) “shaping regularization” which uses an adjustable radius Gaussian smoothing operator to control the smoothness of the coefficients $a_n(\tau, f_m)$. We note that time-frequency amplitude spectra $W_a(\tau, f_m)$ of a wavelet, can be estimated by iterating the procedure of equation (3) and (4) over all the frequencies at every time-sample $\tau$. As discussed above, once getting the nonstationary polynomial coefficients $a_n(\tau, f_m)$, we can model wavelet spectra between equation (3) and the amplitude of seismic trace, and then design the deconvolution operator to complete the processing of resolution enhancement.

Application

In this section, we demonstrate the effectiveness and advantage of the improved spectral modeling deconvolution method proposed in this study on synthetic data, a 2D seismic line, and a large 3D data volume acquired from onshore China.

Synthetic data example

In order to verify the effects of the improved spectra modeling method based on the nonstationary polynomial fitting (NPF) in resolution enhancement for seismic data, we use the nonstationary convolution model (Margrave and Lamoureux, 2001) to produce a synthetic for testing purpose. Figure 1 shows the comparison results using respectively stationary polynomial fitting (SPF) and nonstationary polynomial fitting (NPF) deconvolution (improved spectra modeling method) to process the stationary (Figure 1b) and nonstationary synthetic (Figure 1b). Comparing Figure 1d, 1e, 1f and 1g in the red dashed-line boxes, we find that the adjacent reflection events centered about 200ms and 250ms cannot be distinguished in Figure 1d and 1e processed by SPF deconvolution method, but resolved in Figure 1f and 1g applied by NPF deconvolution method. In comparison of these results with the reflectivity (Figure 1a) we again confirm that the improved spectra modeling deconvolution is superior to conventional method based on the SPF.
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**Field data examples**

The previous synthetic example is noise free. In order to compare the effectiveness and stability of the SPF (Figure 2b) vs the NPF (Figure 2c) deconvolution algorithm we apply them to a vertical slice (Figure 2a) from a large 3D poststack seismic volume acquired from an area in Western China. Comparing the events within yellow ovals of Figures 2a and 2b, we see an improvement in vertical resolution that brings out more detailed reflections. The thin beds indicated by the red arrow in Figure 2c are unresolved in Figure 2b. While both SPF and NPF improve the spectral content of the signal, NPF method which more accurately accounts for the nonstationarity of the seismic wavelet is significantly better. In addition, the NPF deconvolution algorithm avoids increasing the spectral content of the noise.

![Figure 2: A vertical slice through a 3D seismic amplitude volume (a) before and after deconvolution using the (b) SPF and (c) NPF algorithms. Location of the vertical slice is shown in Figure 4. Yellow ovals and red arrows indicate areas of improved vertical resolution using the NPF algorithm.](image)

In Figure 3 we illustrate the comparison of the average amplitude spectra for the three images shown in Figure 2. As expected from our previous inspection of Figure 2, the spectrum of the NPF deconvolution data (red dot-dashed curve) is broader than that of the SPF deconvolution data (green dot-dashed curve), and broader still than the original data (black curve).

Seismic coherence is a measure of lateral changes in the seismic response caused by variation in structure, stratigraphy, lithology, porosity and the presence of hydrocarbons (Marfurt et al., 1998). To see if we have improved the lateral delineation of any thin stratigraphic features, we calculate coherence for the three seismic volumes shown in Figure 2. Figure 4 shows representative time slices at \(t=2920\) ms through the amplitude and coherence volumes before and after SPF as well as NPF deconvolution. Figures 4b and 4c show amplitude time slices applying the conventional method and improved method for input data (Figure 4a). We find that the improved method (NPF deconvolution) provides higher temporal and spatial resolution. Time slices from the coherence attribute volumes shown respectively in Figures 4d, 4e and 4f manifest that the high resolution volume generated from the improved NPF deconvolution serves to show the increased details and more subtle structure characters.

![Figure 3: Comparison of average amplitude spectra of three images shown in Figure 2 for the original data (black dot-dashed curve), data after SPF deconvolution (green dot-dashed curve) and data after NPF deconvolution (red dot-dashed curve). Note that the dominant frequency is higher and bandwidth is broader for the seismic section processed by NPF algorithm compared to the original and SPF deconvolution data.](image)
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Figure 4: Time slices at t=2920ms through the (a) original data volume and data volumes after (b) application of SPF deconvolution, and (c) NPF deconvolution. (d)-(f) Time slices through the corresponding coherence volumes. Black line indicates location of the vertical slice shown in Figure 2. Notice the enhancement in reflection detail on the time slice of amplitude and coherence attribute data after applying the improved method.

Figure 5: Stratal slices through the (a) original data volume, and after (b) application of SPF deconvolution and, (c) NPF deconvolution. (d)-(e) Stratal slices through the corresponding coherence volumes. Note that the stratal slices from the amplitude and coherence volumes show much more stratigraphic features (green arrows and red ovals) and subtle faults (red arrows) with improved method than the other two.

In Figure 5, we show stratal slices of amplitude volumes from the original seismic data (Figure 5a) as well as resolution-enhanced data generated using the SPF algorithm (Figure 5b) and NPF deconvolution method (Figure 5c). The stratal slices through the corresponding coherence volumes are shown in Figures 5d-f. In comparison areas (indicated by red ovals and green arrows), we observe that the two methods can greatly improve the seismic resolution and efficiently identify the faults. Note that the result using the improved NPF deconvolution is superior in delineating stratigraphic features and subtle faults (show in red arrow) than SPF deconvolution method. This example manifests that the enhanced resolution data using the improved method is helpful to extract the better seismic attribute and facilitate interpreters to accurately depict the structural and stratigraphic features. Notice that the amplitude and coherence slices show improved resolution in the order stated above, with the highest lateral resolution observed from slices computed on improved spectral modeling algorithm.

Conclusions

Time-frequency analysis using the generalize S-transform provides a basis for more precise and adaptive deconvolution (or spectral modeling) algorithms. Previous algorithms based on stationary polynomial fitting of the spectrum assumed fitting coefficients to be invariable over all the frequencies. By using nonstationary polynomial fitting concepts described by Fomel (2009) we develop a deconvolution algorithm that adjusts adaptively according to nonstationary seismic wavelets. Unlike earlier algorithms, our nonstationary polynomial fitting (NPF) deconvolution algorithm circumvents the need to explicitly choose spectral modeling parameters $k$ and $N$ and avoids an explicit parameterization of $Q$. Application to synthetic and field data show that the improved method not only enhances the seismic resolution without boosting the noise more effectively and also performs better compensation for attenuation than conventional spectra modeling. Furthermore, application to a large 3D survey from onshore China shows an improvement in vertical resolution that significantly facilitates stratigraphic interpretation, and also confirms that the proposed method in practice is stable and robust in the presence of noise.

Acknowledgement

This work is financially supported by the National Natural Science Foundation of China (Grant No. 41204091), and Science and Technology Support Program (Grant No. 2011GZ0244) from Science and Technology Department of Sichuan Province of China. The first author appreciates the Chinese Scholarship Council for financial support. We also thank Puguang Branch of Zhongyuan Oilfield of SINOPEC for permission to present these results and want to honestly thank Ph.D. students Shiguang Guo, Fangyu Li and Tao Zhao in the University of Oklahoma for their inspiring discussions.
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