A local f - x Cadzow method for noise reduction of seismic data obtained in complex formations

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Abstract: A noise-reduction method with sliding windows in the frequency-space (f - x) domain, called the local f - x Cadzow noise-reduction method, is presented in this paper. This method is based on the assumption that the signal in each window is linearly predictable in the spatial direction while the random noise is not. For each Toeplitz matrix constructed by constant frequency slice, a singular value decomposition (SVD) is applied to separate signal from noise. To avoid edge artifacts caused by zero percent overlap between windows and to remove more noise, an appropriate overlap is adopted. Besides flat and dipping events, this method can enhance curved and conflicting events. However, it is not suitable for seismic data that contains big spikes or null traces. It is also compared with the SVD, f - x deconvolution, and Cadzow method without windows. The comparison results show that the local Cadzow method performs well in removing random noise and preserving signal. In addition, a real data example proves that it is a potential noise-reduction technique for seismic data obtained in areas of complex formations.

Key words: Cadzow, sliding window, noise reduction, fidelity, complex formations, Toeplitz matrix, singular value decomposition

1 Introduction

In the past decades, the Cadzow filtering in the f - x domain, also called f - x eigenimage noise suppression, was proposed by Trickett (2002; 2003; 2008). Different from the conventional singular value decomposition (SVD) filtering in the time-space (t - x) domain, also called t - x eigenimage noise suppression (Ulrych et al, 1988), Cadzow filtering can reconstruct all linear coherent events with different slopes at the same time, while the conventional SVD filtering only can reconstruct the events with the same slope at one time.

In essence, f - x Cadzow filtering is based on an assumption that the signal is linearly predictable in the f - x domain, while the random noise is not. With this assumption, a theoretical standard that the rank of each Toeplitz matrix constructed by constant frequency slices is no more than the number of different slopes of linear events, can be obtained (Stephenson, 1988). Therefore, the SVD technique (Tyapkin et al, 2005) can be used to suppress noise in the f - x domain. It is worth noting that the f - x Cadzow method computes the SVD for the Toeplitz matrix constructed by constant frequency slices, different from the SVD filtering in the frequency domain (Shen and Li, 2010), which directly computes the SVD for two-dimensional (2D) data matrix in the f - x domain.

Like the f - x deconvolution (Canales, 1984; Bekara and van der Baan, 2009), the Cadzow method also adopts forward

or backward prediction. However, the difference between them is that the deconvolution method directly adopts an autoregressive (AR) model to suppress noise, while the Cadzow method just makes use of the AR model to derive a theoretical standard in the f - x domain so as to separate signal from noise using the SVD technique. For some cases, the f - x Cadzow and f - xy Cadzow methods are better for preserving signal than the f - x and f - xy deconvolution methods, especially for very noisy data (Trickett, 2002; 2008).

This method has been applied to relatively simple synthetic data and real seismic data examples. In this paper, we present a local f - x Cadzow method with sliding windows, which is suitable for complex data. There are mainly two purposes of using windows. One is to ensure the events are approximately linear and stationary. The other is to make sure there is a suitable number of different directions of events within the windows. That is because if the number of different directions of events is relatively large, we need to use more eigenimages to reconstruct the signal faithfully. In that case, more noise will probably be retained. If we select less eigenimages to reconstruct the signal, more noise will be removed, but the signal will be distorted. In order to avoid edge artifacts and remove more noise, we use an overlap between adjacent windows.

2 Theory

2.1 Principle

If we assume that seismic data $s(t, x)$ can be regarded as a weighted sum of linear events, nonlinear events and random

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noise, it can be expressed as the following equation in the frequency domain:

$$T(f, x) = \sum_{m=1}^{N_1} a_m(x)W(f) \exp(-i\omega(\tau_m + l_m x)) + \sum_{n=1}^{N_2} b_n(x)W(f) \exp(-i\omega\xi_n(x)) + N'(f, x) \quad (1)$$

where f is the frequency; $\omega=2\pi f$ is the angular frequency; x is the trace interval; $W(f)$ is the spectrum of the seismic wavelet; $i=\sqrt{-1}$ is the imaginary unit; N_1 and N_2 are the numbers of linear events and nonlinear events, respectively; $a_m(x)$ and $b_n(x)$ are the reflectivity; τ_m and l_m are the intercept and slope of the m th linear event, respectively; $\xi_n(x)$ denotes the n th nonlinear event variations versus x ; and $N'(f, x)$ is the spectrum of noise.

With sliding windows, $\xi_n(x)$ can be linearized. This means it can be approximately expressed as:

$$\xi_n(x) \approx \tau_n + l_n x \quad (2)$$

Substituting Eq. (2) into Eq. (1) gives

$$T(f, x) = \sum_{k=1}^K r_k(x)W(f) \exp(-i\omega\tau_k) \exp(-i\omega l_k x) + N'(f, x) + E(f, x) \quad (3)$$

where K is the total number of the linear and quasi-linear events; and $E(f, x)$ is the error caused by approximation of Eq. (2).

Letting $r_k(x)W(f) \exp(-i\omega\tau_k) = W_k(f)$ and $N(f, x) = N'(f, x) + E(f, x)$, Eq. (3) can be simplified as:

$$T(f, x) = \sum_{k=1}^K W_k(f) \exp(-i\omega l_k x) + N(f, x) = S(f, x) + N(f, x) \quad (4)$$

Extract a constant frequency slice $T(f_c, x)$ to construct a Toeplitz matrix:

$$\begin{aligned} \mathbf{T} &= \begin{bmatrix} T_{c,l} & T_{c,l-1} & \cdots & T_{c,1} \\ T_{c,l+1} & T_{c,l} & \cdots & T_{c,2} \\ \vdots & \vdots & \ddots & \vdots \\ T_{c,U} & T_{c,U-1} & \cdots & T_{c,U-l+1} \end{bmatrix} \\ &= \begin{bmatrix} S_{c,l} & S_{c,l-1} & \cdots & S_{c,1} \\ S_{c,l+1} & S_{c,l} & \cdots & S_{c,2} \\ \vdots & \vdots & \ddots & \vdots \\ S_{c,U} & S_{c,U-1} & \cdots & S_{c,U-l+1} \end{bmatrix} \\ &\quad + \begin{bmatrix} N_{c,l} & N_{c,l-1} & \cdots & N_{c,1} \\ N_{c,l+1} & N_{c,l} & \cdots & N_{c,2} \\ \vdots & \vdots & \ddots & \vdots \\ N_{c,U} & N_{c,U-1} & \cdots & N_{c,U-l+1} \end{bmatrix} \\ &= \mathbf{S} + \mathbf{N} \end{aligned} \quad (5)$$

where $\mathbf{S}$ is a $(U-l+1) \times l$ Toeplitz matrix constructed by signal; and $\mathbf{N}$ is a $(U-l+1) \times l$ matrix constructed by noise. Regularly, we choose $l = \lceil U/2 \rceil$ (Blu et al, 2008), to make the matrix as square as possible, where $\lceil \bullet \rceil$ denotes rounding up.

If the signal $\mathbf{S}$ contains linear events with L different slopes, the sample $S_{c,j}$ in the f - x domain can be written as (Naghizadeh and Sacchi, 2007):

$$S_{c,j} = \sum_{d=1}^L P_{c,d} S_{c,j-d} \quad (j = L+1, L+2, \dots, n) \quad (6)$$

where $P_{c,d}$ is the filter factor. Eq. (6) means that $S_{c,j}$ can be predicted by one step forward prediction in the spatial direction. Similarly, it also can be predicted by one step backward prediction.

According to Eq. (6) and the elementary operations of matrix, we have a key conclusion that the rank of $\mathbf{S}$ is no more than L , namely, $\text{rank}(\mathbf{S}) \leq L$. Usually, if $L < L$, $\text{rank}(\mathbf{S}) < L$. If $S_{c,l}=0$, $\text{rank}(\mathbf{S})=0$. With the influence of $\mathbf{N}$, the matrix $\mathbf{T}$ is always full-rank. Our final object is to reconstruct a rank- L Toeplitz matrix $\mathbf{S}^{app}$ which is closest to $\mathbf{S}$. To obtain this matrix, the SVD technique is adopted. The SVD of the matrix $\mathbf{T}$ leads to a linear orthogonal expansion as (Lu and Mou, 1996):

$$\mathbf{T} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^H = \sum_{k=1}^r \delta_k \mathbf{u}_k \mathbf{v}_k^H \quad (7)$$

where $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k, \dots, \mathbf{u}_r]$, and $\mathbf{u}_k$ is the left singular vector; $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k, \dots, \mathbf{v}_r]$, and $\mathbf{v}_k$ is the right singular vector; $\mathbf{\Sigma} = \text{diag}(\delta_1, \delta_2, \dots, \delta_k, \dots, \delta_r)$ is a diagonal matrix, and δ_k , sorted as $\delta_1 \geq \delta_2 \geq \dots \geq \delta_k \geq \dots \geq \delta_r \geq 0$, is the positive square root of the eigenvalue of the data covariance matrix $\mathbf{T} \mathbf{T}^H$; r is the rank of $\mathbf{T}$, and H denotes the complex conjugate.

In that case, $\mathbf{T}$ can be regarded as the sum of r weighted eigenimages and $\delta_k \mathbf{u}_k \mathbf{v}_k^H$ is the k th weighted eigenimage. Since the coherent events often correspond to large singular values and random noise corresponds to small singular values, we could use the sum of the first φ ($\varphi \geq L$) weighted eigenimages $\mathbf{S}^{app} = \sum_{k=1}^{\varphi} \delta_k \mathbf{u}_k \mathbf{v}_k^H$ to approximate the matrix $\mathbf{S}$. In theory, when there is no noise and setting $\varphi = L$, the signal can be totally recovered.

Generally, $\mathbf{S}^{app}$ is not a Toeplitz matrix any more. By averaging the entries of each diagonal of $\mathbf{S}^{app}$, a new Toeplitz matrix is obtained. Then for the new Toeplitz matrix, we decompose it, reconstruct a new matrix by the first φ weighted eigenimages again, and average the entries of each diagonal of the new reconstructed matrix. On repeating these steps a few times, the optimal denoised data of this constant-frequency slice can be achieved (Cadzow, 1988). After all frequency slices within this window have been processed, we take the inverse Fourier transform, then move to the next window until the whole data has been finished.

2.2 Window design

For the local Cadzow method, the window design is

a very important factor to achieve good noise reduction performance. How to set the parameters of the sliding window depends on the characteristics of the seismic data. Usually, the window width is neither too big nor too small. If it is too big, the local linearity and local stationarity can not be met, especially for complex formations. Moreover, the number of different directions of events will be relatively large. In that case, more eigenimages should be chosen to reconstruct the signal so as to keep the signal faithfully. However, more noise will probably be retained. If fewer eigenimages are selected to reconstruct the signal, more noise will be removed, but the signal will be distorted. If it is too small, the denoised signal may be distorted and noise can not be removed effectively. So a trade-off should be chosen according to the degree of complexity of the data. The more complex the data, the smaller the width. As for the window length in the time direction, it is dependent on the direction number of the

events, but less important than the window width. It should be appropriate to ensure the computing efficiency of the SVD and ensure a suitable number of different directions of events. To avoid edge artifacts of windows and to attenuate more noise, an appropriate overlap among adjacent windows is adopted. It is worth noting that when the formation structure changes greatly, adaptive windows could be adopted.

2.3 A comparison between the Cadzow and SVD methods

Both the Cadzow method and the conventional SVD noise attenuation method make use of singular value decomposition and reconstruction techniques. However, the conventional SVD method is based on the distribution difference between the singular values just corresponding to flat events and that corresponding to random noise in the time domain, while the Cadzow method is based on the distribution difference

Fig. 1 Comparisons between the Cadzow method and the conventional SVD method (a) Synthetic data without noise; (b) data reconstructed by the conventional SVD using the first weighted eigenimage; (c) difference data between (a) and (b); (d) singular value distribution for (a); (e) data reconstructed by the conventional SVD using the first two weighted eigenimages; (f) difference data between (a) and (e); (g) rank distribution of Toeplitz matrices constructed by each frequency slice; (h) data reconstructed by the Cadzow method; and (i) difference data between (a) and (h)

between the singular values corresponding to all linear events with different slopes and that corresponding to random noise in the frequency domain. In this section, noise-free data containing four events with two different slopes is used to make comparisons (Fig. 1). Fig. 1(a) is the synthetic data without noise, Fig. 1(b) is the data reconstructed by the conventional SVD using the first weighted eigenimage, Fig. 1(c) is the difference data between Fig. 1(a) and Fig. 1(b), Fig. 1(d) is the singular value distribution for Fig. 1(a), Fig. 1(e) is the data reconstructed by the conventional SVD using the first two weighted eigenimages, Fig. 1(f) is the difference data between Fig. 1(a) and Fig. 1(e), Fig. 1(g) is the rank distribution of Toeplitz matrices constructed by each frequency slice, Fig. 1(h) is the data reconstructed by the Cadzow method, and Fig. 1(i) is the difference data between Fig. 1(a) and Fig. 1(h). Note that the rank for each c is no more than the number of different slopes of events, and it is a key parameter for the Cadzow method. As these subfigures show, the Cadzow method can reconstruct the signal completely using the first two weighted eigenimages, while the conventional SVD can not if only the first one or the first two eigenimages are used. Moreover, the conventional SVD introduces additional disturbance. If more eigenimages are used, the dipping event can be better reconstructed. However,

when random noise is added to Fig. 1(a), more noise will also be retained in the filtered data (The results are not displayed here).

The local SVD (Lu, 2006; Bekara and van der Baan, 2007; Yuan and Wang, 2010) uses dip steering to flatten dipping events, then applies the SVD to enhance flattened coherent events and shifts them back to their original positions. Fig. 2(a) is the synthetic data without noise, and Fig. 2(b) is the data reconstructed by the local SVD. Here, every event is reconstructed only using the first weighted eigenimage. Fig. 2(c) is the difference data between Fig. 2(a) and Fig. 2(b), Fig. 2(d) is the rank distribution of Toeplitz matrices constructed by each frequency slice, Fig. 2(e) is the data reconstructed by the Cadzow method, and Fig. 2(f) is the difference data between Fig. 2(a) and Fig. 2(e). As these subfigures show, although the local SVD also can enhance dipping events, we need to obtain slopes of all events before dip steering. When the data contains events with a few more directions, the local SVD method is a little complicated. In addition, the conflicting events are distorted and additional disturbance is introduced after local SVD filtering. However, the local Cadzow method can cope with dipping events without dip steering and has higher fidelity than the local SVD for enhancing conflicting events.

Fig. 2 Comparisons between the Cadzow method and the local SVD method (a) Synthetic data without noise; (b) data reconstructed by the local SVD; (c) difference data between (a) and (b); (d) rank distribution of Toeplitz matrices constructed by each frequency slice; (e) data reconstructed by the Cadzow method; and (f) difference data between (a) and (e)

2.4 Limitations

The Cadzow method has its own limitations. We discuss its two limitations in this section. Fig. 3(a) is the synthetic data which contains a dipping event and a big spike. Fig. 3(b) is the reconstructed data just using the first weighted

eigenimage, and Fig. 3(c) is the difference data between Fig. 3(a) and Fig. 3(b). From these three subfigures, we can see that the big spike has a negative impact on the final result. Not only is disturbance introduced, but also an artifact that looks like a linear event is caused. This artifact will mislead

the following processing, inversion and interpretation. Therefore, this big spike should be eliminated before filtering. By setting a threshold, the spike is removed (Fig. 3(d)), and the reconstructed data using the same parameter is shown in Fig. 3(e). Fig. 3(f) is the difference data between Fig. 3(d) and Fig. 3(e). The linear event can be reconstructed perfectly without the influence of the big spike. Moreover, no additional disturbance is introduced.

Fig. 4(a) is another synthetic data set containing a flat event and a dipping event, where trace 8 and trace 9 are missed or null. Fig. 4(b) is the reconstructed data using the

first two weighted eigenimages, and Fig. 4(c) is the difference data. As Fig. 4(c) shows, not only are the missed traces interpolated, but also other traces are distorted. This is partly because the Cadzow method is based on the assumption that the signal is predictable. If we interpolate the missed traces or null traces (Zwartjes and Sacchi, 2007) before reconstruction (Fig. 4(d) is the interpolated data), the two events can be reconstructed perfectly without distortion (Fig. 4e is the reconstructed data for Fig. 4(d), and Fig. 4(f) is the difference data between Fig. 4(d) and Fig. 4(e)). Therefore, we should pay attention to this problem while using the Cadzow method.

Fig. 3 Influence of a big spike (a) Synthetic data with a big spike; (b) reconstructed data for (a); (c) difference data between (a) and (b); (d) the data after eliminating the big spike; (e) reconstructed data for (d); and (f) difference data between (d) and (e)

3 Numerical examples

We use two synthetic examples to compare the local Cadzow filtering with the f - x deconvolution and the Cadzow filtering without windows. Fig. 5(a) is the noise-free synthetic data containing conflicting events (A), pinching (B), a lateral amplitude changing event (C), fault (D), and an isolated event (E). Fig. 5(b) is the noisy data with SNR 2/3 (defining the ratio of signal energy to noise energy as SNR).

Comparison results between the local Cadzow method, f - x deconvolution and the Cadzow method without windows are shown in Fig. 6. Fig. 6(a) is the result of local Cadzow filtering and the difference section. Fig. 6(b) is the result of the f - x deconvolution, and Fig. 6(c) is that of the Cadzow filtering without windows. The sliding window for the local Cadzow method and the f - x deconvolution is simply set to be 100×20 . To avoid edge artifacts and to reduce more noise, we use a 50% overlap. For the f - x deconvolution, the average of forward and backward prediction is the final

result, with the filter operator length 2. For the local Cadzow filtering and Cadzow filtering without windows, φ is set to be 2. As these subfigures show, the local Cadzow method has good performance of attenuating noise and high fidelity simultaneously. The performance of noise attenuation of the f - x deconvolution is as good as the local Cadzow filtering, but its fidelity is inferior, especially for the conflicting events. The Cadzow filtering without windows has the worst fidelity. In addition, extrapolation phenomena appear at two terminals of the isolated event and the breakpoints of the fault. Certainly, if φ for the Cadzow filtering without windows is more than 4, a better result will be obtained, but less noise will be reduced.

Fig. 7(a) is another noise-free synthetic data set containing a flat event (A), five curved events with different curvatures (B), and a “^” shaped event (C). Fig. 7(b) is the noisy data with the SNR of 1.

Fig. 8(a)-(c) have the same meaning and parameters as Fig. 6(a)-(c), respectively. Fig. 8(d) is noise reduction result of the Cadzow filtering without windows when φ is 8.

Fig. 4 Influence of missed traces or null traces (a) Synthetic data without noise; (b) reconstructed data for (a); (c) difference data between (a) and (b); (d) the data after interpolation; (e) reconstructed data for (d); and (f) difference data between (d) and (e)

Fig. 5 Synthetic data (a) Noise-free data and (b) noisy data (SNR = 2/3)

For this example, the local Cadzow method still performs well to reduce noise and preserve signal simultaneously. With the curvature becoming bigger, the fidelity of the f - x deconvolution becomes worse than the local Cadzow method. No matter what φ is, the Cadzow method without windows has the worst fidelity.

4 Real data examples

To test its application potential, the local Cadzow method is applied to a real seismic data set (Fig. 9) from China. The left panel of Fig. 9 is the real data, which mainly includes curved events, discontinuous events, and nonstationary events. The middle panel is the filtered data, and the right

panel is difference data between the middle panel and the left panel. For this example, a 100×20 slipping window and 50% overlap are used. In all windows, $\varphi = 2$. As Fig. 9 shows, the signal after filtering is clearly visible without obvious distortion.

5 Conclusions and discussion

The local Cadzow method can not only suppress random noise effectively, but also performs well to preserve complex signals. Compared with the conventional SVD technique, it can enhance dipping linear events directly, while the conventional SVD method can not; compared with the local SVD, it does not need dip steering and is better at enhancing

Fig. 6 Results of different methods (a) Local Cadzow; (b) f - x deconvolution; and (c) Cadzow without windows. In (a)-(c), the left panel is the filtered data and the right panel is difference data between the left one and Fig. 5(a)

Fig. 7 Synthetic data (a) Noise-free data and (b) noisy data (SNR: 1)

Fig. 8 Results of different methods (a) Local Cadzow; (b) f - x deconvolution; (c) Cadzow without windows, with $\phi=2$; and (d) Cadzow without windows, with $\phi=8$. In (a)-(d), the left panel is the filtered data and the right panel is difference data between the left one and Fig. 7(a)

Fig. 9 Real seismic data example

conflicting events; compared with the f - x deconvolution, it has better fidelity for conflicting events, curved events, and isolated events in our examples; compared with the Cadzow method without windows, besides higher fidelity for curved events, the parameter ϕ is easy to set. For the local Cadzow, if the sliding windows are selected appropriately, ϕ is relatively small. The smaller the ϕ , the higher the SNR.

However, if the seismic data contain big spikes or null traces, the local Cadzow method may cause artifacts and mislead interpretation. Therefore, a pre-process step is necessary to resolve these problems. As for discontinuous events and isolated events, it is hard to eliminate interpolation and extrapolation artifacts when using the local Cadzow method, as well as the f - x deconvolution and the Cadzow method without windows. Fortunately, artifacts are not very obvious, probably owing to the use of the SVD. The local SVD can avoid this problem, but it is hard to determine how many eigenimages should be chosen in each window.

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