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T-x frequency filtering of high resolution seismic reflection data using singular spectral analysis

Rajesh Rekapalli [a,*], R.K. Tiwari [a,b], K. Dhanam [b], T. Seshunarayana [b]

[a] AcSIR-NGRI, Hyderabad, Andhra Pradesh, India
[b] CSIR-NGRI, Hyderabad, Andhra Pradesh, India

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ABSTRACT

We develop here an efficient approach using singular spectral analysis (SSA) for frequency filtering of seismic reflection data in t-x domain. The abrupt change in geophysical records creates ringing artifacts in the Fourier based filtering operations. We use here complete data adaptive basis functions in SSA filtering, which enables the self-similarity of the data in reconstruction of such sudden changes. We first tested the SSA based filtering algorithm on synthetic seismic data and then applied to real seismic reflection data from Singareni coalfields, Andhra Pradesh, India. The individual trace from each channel in the shot gathers is processed and compared with Fourier and multichannel SSA filtered output. Our analysis demonstrates that SSA filtering attenuated the low frequency ground role and high frequency noise embedded in the seismic record in a more efficient way than the other two methods. The coal formations and faults identified in the stack section of filtered data match quite well with the geological information available in the study region.

1. Introduction

Frequency domain filtering is a common practice in seismic data processing (Canales, 1984; Yilmaz, 1987; Abma and Claerbout, 1995; Yilmaz, 2001; Karsli, 2006). For this, researchers have used Fourier (Bracewell, 1986; Yilmaz, 1987, Foufoula-Georgiou and Kumar, 1994), and Curvlet (Hennenfent and Herrmann, 2006) methods extensively. The underlying methods involve decomposition of signal into the basis functions (like sines and cosines) of different frequencies and then zeroing/shrinking the coefficients corresponding to the frequencies to be filtered (Claerbout, 1976; Sheriff and Geldhart, 1983). However, for analyzing/filtering the signals with sudden changes/discontinuities the Fourier based methods (sinusoidal) are not appropriate (Bansal and Dimri, 2001, 2005; Bath, 1974; Dimri, 1992). Such abrupt jumps/discontinuous signal are generally represented by the boxcar function or seesaw-shapes and could be better reconstructed by a single pair of eigen modes using SSA rather than involving many harmonics with fixed basis functions (Ghil and Taricco, 1997). In essence, the SSA technique uses the complete data adaptive eigenvectors as basis function which enable to differentiate signal more precisely from noise. The coherent and correlated noise produce systematic eigenvector pattern facilitating to identify them in the eigen spectrum as they map on to the tail of the spectrum. If we analyze the different eigen components of geophysical data sets, the shape and frequency content of each component differs significantly. Hence, a more appropriate and accurate signal reconstruction is possible in SSA (Yiou et al., 2000). Recently the SSA method has been applied for filtering the geophysical data and astronomical images (Zotov, 2012) and also for frequency filtering (Golyandina and Zhigljavsky, 2013; Harris and Yan, 2010). Bozzo et al (2010) has carried out comparative study of spectral components employing the SSA and Fourier methods on synthetic data. Their analysis suggested that for the systematic and non-noisy periodic data the results of both the methods agree well. However, if noise is present in the data, the data-adaptive basis functions or the eigen modes of the trajectory matrix provide a better way of signal filtering and reconstruction in the time domain than in the classical Fourier method.

Trickett (2003) has used SSA for seismic image processing. In a more recent study Oropeza and Sacchi (2011) employed the f-x domain Multichannel SSA (MSSA) method for de-noising multi channel seismic data. In both the methods, the data was initially converted into the frequency domain using Fourier transform and then it was subjected to the SSA/MSSA. It may, however, be noted that domain conversion of data may allow artifacts in the data, which would further be enhanced in the SSA reconstruction. We can suppress the effect of such artifacts, by applying SSA algorithm directly on the time domain seismic data. The purpose of the present research work is therefore to (i) develop a SSA based t-x frequency filtering algorithm (ii) test the algorithm on synthetic and real time seismic reflection data in comparison with Fourier and MSSA methods and (iii) apply the method on the seismic refection data from a zone of coal reserves.

* Corresponding author. Tel.: +91 9912545974.
E-mail address: rekapalli@gmail.com (R. Rekapalli).

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2. Methodology

The singular spectral analysis (SSA) is known since a decade (Broomhead and King, 1986a, b; Fraedrich, 1986; Golyandina et al, 2001; Vautard et al, 1992) and is an efficient method to identify the unknown/partially known dynamics of data series (Ghil et al, 2002) from noise background. The brief methodology of SSA is presented in the following four systematic steps:

I). Embedding: We begin with embedding the data of each trace $Y(t) = \{y_1, y_2, \ldots, y_N\}$ in the form of trajectory matrix $T_{(L \times K)}$ using an appropriate window length L ($2 < L \le N/2$, $K = N - L + 1$), where N is the number of data points. Here trajectory matrix $T_{L \times K} = [Y_1 : \ldots\ldots : Y_K]$, where $Y_i = \{y_i, y_{i+1}, y_{i+2}, \ldots, y_{i+L-1}\}$ is a vector of length L and $1 \le i \le K$. The selection of optimal window length is crucial in the SSA method. In general, one has to choose the window length at least equal to the highest period that is present in the data within the classical limit $2 < L \le N/2$. For the present analysis, we have chosen the window length twice the time corresponding to the lowest frequency present in the data.

II). Decomposition: In the second step, the trajectory matrix was subjected to Singular Value Decomposition (SVD) to obtain eigenvectors (U_i, V_i) and eigenvalues (λ_i). The decomposition of trajectory matrix T in terms U_i, V_i and λ_i is given by $T = \sum_{i=1}^{d} \sqrt{\lambda_i}\, U_i V_i^T$. The group ($\sqrt{\lambda_i}$, U_i, V_i) is called the ith eigentriplet.

III). Grouping and Reconstruction: After obtaining the eigentriplets, periodicities of eigenvectors calculated to perform frequency filtering. For low pass filtering with a cut off frequency f_L, the eigentriplets corresponding to eigenvectors with periodicity less than $1/f_L$ were dropped in the grouping process. A similar approach used for high and band pass filtering. By doing so, the trajectory matrix (X) is reconstructed from the selected group of eigentriplets using $X = \sum_i \sqrt{\lambda_i U_i V_i^T}$, where 'i' represents the group of selected eigentriplets (Golyandina and Zhigljavsky, 2013). The reconstructed trajectory matrix looks as follows.

$$X = \begin{bmatrix} y_{(1,1)} & \cdots & y_{(1,K)} \\ \vdots & \ddots & \vdots \\ y_{(L,1)} & \cdots & y_{(L,K)} \end{bmatrix}.$$

IV). Diagonal Averaging: Finally, the reconstructed trajectory matrix diagonally averaged to get the filtered data series. The elements of reconstructed series $Y_r = \{g_1, g_2 \ldots g_k \ldots \ldots g_N\}$ are computed from the reconstructed trajectory matrix X as follows. Let X be an $L \times K$ matrix with elements y_{ij} ($1 \le i \le L$, $1 \le j \le K$). Let $L^* = \min(L, K)$, $K^* = \max(L, K)$, $N = L + K - 1$ and $y^*_{ij} = y_{ij}$ if $L < K$ $y^*_{ij} = y_{ji}$ otherwise.

$$g_k = \frac{1}{k+1} \sum_{m=1}^{k+1} y^*_{m,k-m+2} \text{ for } 1 \le k < L^*$$

$$\frac{1}{L^*} \sum_{m=1}^{L^*} y^*_{m,k-m+2} \text{ for } L^* \le k < K^* + 1$$

$$\frac{1}{N-k} \sum_{m=k-K^* \mp 2}^{N-K^*+1} y^*_{m,k-m+2} \text{ for } K^* + 1 \le k \le N.$$

For the above procedure, a parallel MATLAB code was developed and the results are discussed and demonstrated in the next section.

3. Data analysis and discussion

We generated a pure synthetic trace (Fig. 1.a) by convolving the Ricker wavelet with reflection coefficient and then added 30% correlated noise using the equation $\boldsymbol{x_n} = \boldsymbol{\sigma}.\,\boldsymbol{x_{n-1}} + \boldsymbol{\varepsilon}$ (σ is chosen between 0 and 1 and ε is white noise) (Fig. 1.b). The SSA and Fourier filtered outputs of noisy trace (Fig. 1.b) are shown respectively in Fig. 1c and d. One can see that the reflectors reproduced in the Fourier filtered data (1d) contain many pseudo events than the pure due to the presence of noise. On the other hand the noisy data processed using the SSA filtering technique is clean and the events are almost matching with the pure data. Hence, it is clear from this synthetic example that the proposed SSA filtering method is efficient in reducing the effects of artifacts/noise arising from the correlated noise in comparison to the Fourier based filtering method.

The seismic data used in the present study was taken from the Singareni coalfields, Ramagundam, situated in the Pranhita–Godavari (PG) graben of the Andhra Pradesh, India. PG graben is bounded by the major tectonic units of Bastar and Dharwar cratons that contained the Archaean gneisses and granites overlain by Proterozoic sedimentary basins. In this region, the eastern tilting generated by complex system of faulting followed by erosion affected the Lower Gondwana rock formations leading to the gradual east ward exposure of successive younger rocks. The overall strike is ~NNW–SSE and dips gently towards ENE and WSW. There are two sets of probable faults likewise NW–SE faults parallel to the PG basin boundary faults, and NE–SW oriented faults. These faults are largely dip-slip faults (normal-sense) and appear to cut across all the Lower Gondwana formations, although there is possible minor left-lateral strike-slip component (Murthy and Rao, 1994). In general, the fault systems observed, may be related to either the Permian or Mesozoic fault systems (Biswas, 2003). The area is traversed by a major NW–SE trending faults that runs through the middle of the Ramagundam coalfield, (Chaudhuri and Deb, 2004; Das et al., 2003).

The seismic reflection data was acquired using 60 channels at 0.25 mS sampling interval and with dynamic range of 144 dB. The shot gather data was corrected for NMO and then processed using the SSA filtering algorithm. Following the method as discussed above, trajectory matrix was formed using individual channel data and decomposed into eigenvectors and values. In the present study, optimum window length of 70 mS was selected, which correspond to 280 data points ($t = 0.25 \times 280 = 70$ mS). In order to reconstruct trajectory matrix, we grouped a band of 5 to 17 eigenvectors corresponding to frequencies range from 30 to 140 Hz. Accordingly the first four eigenvectors with high period (frequency less than 30 Hz) corresponding to ground roll and other low frequency noise and the higher order vectors from 18 onwards corresponding to high frequency (more than 140 Hz) were discarded. Finally the filtered seismic data is obtained by the diagonal averaging of the reconstructed trajectory matrix.

Initially, the result of SSA filtering was compared with the results of MSSA (Oropeza and Sacchi, 2011) and Fourier filtering. Comparative results show that the ringing effect is present in the FFT filtered data, which has altered the real features of the original reflectors. Similarly in the MSSA output also the reconstruction of frequency slice fills up the gaps and thereby enhanced the ringing effect, which can be seen between 200 and 350 mS time range (Fig. 2). Clearly these techniques enhance artifacts and hide the real reflectors, which are present in the original data. However, as can be seen from Fig. 2 the seismic signals filtered using the SSA filtering approach clearly reproduced the reflectors of original record, which are of geological significance.

According to Golyandina and Zhigljavsky (2013) (3, Section 3.9) periodograms of eigenvectors are almost the same as frequency response of s of filters that produce reconstructed series from l-th to k-th points. Fig. 3 shows the comparison of power spectral density of