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# Complex noise suppression and reconstruction of seismic reflection data from fault structures using Space Lagged Singular Spectral Analysis

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## Abstract

The seismic reflection data processing to identify thin coal beds and intrinsic fault structure associated with coalmines suffers from the coherent noise that arises due to interference and diffraction of seismic signals from adjacent horizontal boundaries on either sides of the fault structure. The amplitudes of the interfering reflections mislead the interpretation of geological features like faults, curved reflectors, etc. In particular, correlated and erratic noise create more severe problem than the random noise in the interpretation of such complex geological structures. Here, we employed Space Lagged Singular Spectral Analysis (SLSSA) algorithm, which decomposes the amplitudes from a constant time/depth to determine the original signal amplitude based on eigen properties of the signal. Thus, we can de-noise seismic signal to delineate the concealed discontinuities and to map the fault structures. Initially, we tested the algorithm on the synthetic data of fault structure embedded with complex mixed noise (random and colored) of known percentage. Finally, the method was employed on high-resolution seismic reflection observations recorded from Singareni coalfield, India. The SLSSA method reveals some significant kinematic fault structures in the coal-bearing zone, which agreed with regional fault structures in the PG basin and correlates well with available geological information in the area.

## 1 Introduction

Coalmine assessment using high-resolution seismic exploration is popular and credible in determining the detailed information of geological faults, folds, caved pillars, mined-out areas and coal seam changes (Greenhalgh et al., 1986; Tselentis and Paraskevopoulos, 2002). The seismic reflection data from coal bearing zones suffers with pseudo reflections because of interference and diffraction from thin beds and discontinuities (fault edges). As a result, the nonlinear effect of such interference and diffraction alters the real picture of the reflection amplitudes. Thus the actual

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seismic data obtained from the field is an amalgamated response of pure seismic signal resembling the subsurface features and the unnecessary nonlinear noises. Coexistence of such complex noise with real seismic signal gives rise to various problems at the time of data analyses and interpretation. The presence of random noise in the record could be easily identified in spectral components as a “flat spectrum” but the complex (chaotic) and colored noise creates severe problem in identifying reflector patterns and discontinuities. Such erratic noises interfere with real reflections and mislead the true picture of geological features like curved reflectors; faults etc, and thereby complicate the physical structural interpretation. Especially the seismic reflections from the coal basin suffer further from some peculiar problems associated with the interference of reflections, which produces the composite reflection pattern (Lawrence, 1991, 1992). Regardless of constructive or destructive interferences, the initial reflection from the coal bed of interest undergoes significant alterations. Consequently, the interfering reflections from thin beds lead to the complex reflection patterns, which hinder the identification of individual beds (Lawrence, 1991, 1992). Thus the complex noise in the form of multiple reflections, complex reflections along with the chaotically evolved high degree crustal noise modify the original reflection pattern.

The pseudo zero amplitude generated due to the destructive interference need to be appropriately recovered in the data processing in order to provide accurate/precise interpretation. In such a situation, it is therefore imperative to reconstruct the amplitude from the available nearby channel data. Several interpolation methods have been employed to recover the missing amplitudes with regular and irregular intervals using the domain conversions. The recovery processes provides better results only if the data are noise free. Unfortunately, however, the geophysical field data always contain certain amount of inescapable noise. The Singular Spectrum Analysis (SSA) is a well-known technique since past three decades (Broomhead and King, 1986a, b; Fraedrich, 1986) to analyze the dynamical components of the non-linear noisy data sets (Vautard et al., 1992; Ghil et al., 2002) and for data gap filling. Trickett (2003) presented

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Eigen Image Processing approach to suppress random noise from seismic data, which also involves the scheme for recovery of missing amplitudes. More recently, several researches (Sacchi, 2009; Oropeza and Sacchi, 2011) developed and applied alternative efficient techniques (FXSSA and MSSA) for simultaneous de-noising and reconstruction of seismic signals in frequency domain. However, researchers have not tested these methods on complex crustal noisy seismic signal.

Here in the present work, we employed Space Lagged Singular Spectral Analysis (SLSSA) (Rajesh et al., 2012) in time domain to suppress the complex and colored noises, which is based on data adaptive basis function and makes use of the data correlation in the spatial domain. We present here an example of suppression of such complex colored noise using the real seismic reflection data to resolve the fault structures and coal beds from Singereni coalfield, Andhra Pradesh, India. We also demonstrated the efficacy of the method for the reconstruction of scattered reflector amplitudes arising due to the nonlinear interaction of intrinsic coherent complex noises in the seismic reflection data from the coalfields.

## 2 Methodology

The SLSSA algorithm involves the following four steps (Golyandina et al., 2001).

- I. Embed the phase portrait/trajectory matrix of the seismic data series of all channels at a particular time using an appropriate window length ( $L$ ).
- II. Obtain eigenvectors and eigenvalues of trajectory matrix using singular value decomposition (SVD).
- III. Analyze the eigenvector periodicities to drop the eigen components with fluctuating eigen vectors and low eigen values, as they resemble incoherent or slightly coherent noise (Trickett, 2003). The selected triplets grouped to reconstruct the trajectory matrix.

IV. Obtain the reconstructed denoised data by diagonal averaging of reconstructed trajectory matrix.

The justification of Space Lagged (SL) consideration comes from the lateral quasi homogeneity of the crustal layers on regional scales. Hence the correlation among seismic data from a constant depth slice is much stronger compared to noise correlation. Thus, it is possible to extract the correlated lateral data trend to distinguish the signals from complex noise background. In this way, analysis of seismic data of all channels at a fixed time as spatial series permits us to suppress the noise component in SLSSA. Trickett (2003) has explained that the incoherent random processes tend map on the tail of eigen spectrum. Thus, it is possible from the eigen spectra to identify the significant dynamical components and trends through their variance. As the SLSSA combines the geological features of the subsurface strata and eigen properties of signal and noise, it is possible to visualize the fault structure even from the complex reflection pattern.

The SLSSA processing begins with embedding spatial data series  $Y(x) = \{y(x_1), y(x_2), \dots, y(x_N)\}$  in a vector space of dimension  $L$  ( $2 > L \leq N/2$ ) where  $N$  is number of traces in the data. The  $K$  ( $= N - L + 1$ ) lagged vectors of  $Y(x)$  engender a  $L \times K$  trajectory matrix ( $\mathbf{T}$ ) in the phase space.

$$\mathbf{T}_{L \times K} = [\mathbf{X}_1, \dots, \mathbf{X}_i, \dots, \mathbf{X}_K] \quad (1)$$

Where  $\mathbf{X}_i$  represents a vector of length  $L$  given by  $\mathbf{X}_i = \{y(x_i), y(x_{i+1}), \dots, y(x_{i+L-1})\}$ .

This trajectory matrix decomposed into eigenvectors and values using Singular Value Decomposition (SVD). The SVD process decomposes the trajectory matrix to left/row and right/column eigenvector matrices and diagonal matrix consisting of eigen values. From the eigen values, one can estimate the contribution of different eigenvectors to the original signal. In other words, the principle processes in the data identified from the SVD of trajectory matrix to proceed towards the reconstruction of denoised signal.

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The decomposition of  $\mathbf{T}$  given by

$$\mathbf{T} = \sum_{i=1}^d \sqrt{\lambda_i} \mathbf{U}_i \mathbf{V}_i^T \quad (2)$$

where,  $\lambda_i$  is the  $i$ th eigen value corresponding to the  $i$ th eigenvector  $\mathbf{U}_i$  of  $\mathbf{TT}^T$  and  $d$  is the number of nonzero eigen values. The triple  $(\sqrt{\lambda_i}, \mathbf{U}_i, \mathbf{V}_i)$  is called the  $i$ th eigen triplet.

In the next, the eigen triplets with significant variance and periodicity are grouped to reconstruct the trajectory matrix.

$$\mathbf{Tr} = \sum_G \sqrt{\lambda_i} \mathbf{U}_i \mathbf{V}_i^T = \begin{bmatrix} X_{(1,1)} & \cdots & X_{(1,K)} \\ \vdots & \ddots & \vdots \\ X_{(L,1)} & \cdots & X_{(L,K)} \end{bmatrix} \quad (3)$$

Here  $G$  represents the group of eigen triples satisfying the criteria of variance and with systematic eigen vectors.

Finally, diagonal averaging of reconstructed trajectory matrix ( $\mathbf{Tr}$ ) yield the denoised series of  $\mathbf{Y}(x)$ . Let us denote the reconstructed series by  $\mathbf{X}_{rc} = \{g_1, g_2, \dots, g_k, \dots, g_N\}$ . The elements of  $\mathbf{X}_{rc}$  can be computed as follows.

$$g_k = \frac{1}{k+1} \sum_{m=1}^{k+1} x_{m, k-m+2} \quad \text{for } 1 \leq k < L$$

$$\frac{1}{L} \sum_{m=1}^L x_{m, k-m+2} \quad \text{for } L \leq k < K$$

$$\frac{1}{N-k} \sum_{m=k-K+2}^{N-K+1} x_{m, k-m+2} \quad \text{for } K \leq k < N \quad (4)$$

and  $g_1 = x_{(1,1)}$

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The flow chart of the SLSSA program used to perform the seismic data processing provided in Fig. A1.

## 2.1 Testing the SLSSA on synthetic data of fault model with complex noise

The efficacy of SLSSA for the identification of the fault structures from complex (colored and correlated/chaotic) noise background tested initially on synthetic data and then the algorithm was applied on the field data. The pure synthetic data shown in Fig. 1a was generated by convolving Ricker wavelet (Sheriff, 1994) of frequency 30 Hz with presumed reflectivity coefficient series over the normal fault structure model and then contaminated with complex and correlated noise generated using the equation:  $a_{n+1} = \mu \cdot a_n \cdot (1 - a_n)$  (where  $\mu$  can be chosen between 0 and 4). We have added 40% mixed noise (30% erratic and 10% random) to the pure synthetic data. The noisy synthetic data and its SLSSA processed output using the window length 12 are shown in Fig. 1b and c. It is clear that the application of SLSSA allows us to identify the fault structures with very low vertical displacements even in the presence of complex noise backgrounds. The results suggest that the signal reconstruction is good and the scattered energy has been recovered clearly in SLSSA output.

## 2.2 Application to the field data

The high-resolution seismic reflection data from the Singareni coal block was processed using the SLSSA method for suppression of correlated and erratic noise and thereby to identify the complex reflection patterns as well as the intrinsic geological features associated with coal reserves. The study area is located near Ramagundam, in the Pranhita–Godavari (PG) graben, which is formed in between the boundaries of Bastar and Dharwar cratons (Murthy and Rao, 1994). The Lower Gondwana rock formations are affected by a complex system of faulting, which lead to a general eastern tilting, followed by erosion in the study area. The Overall strike is ~NNW–SSE and with ENE and WSW dipping. The NW–SE faults parallel to the PG basin

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boundary faults and NE–SW oriented faults are the two kinds of geologically probable faulting could be observed from the study region. These faults are largely dip-slip faults (normal-sense) and appear to cut across all the Lower Gondwana formations, although there is a minor left-lateral strike-slip component (Murthy and Rao, 1994).

5 According to the researchers, in general, the fault systems observed, may be related to either the Permian or Mesozoic fault systems of Biswas (2003). The borehole litho-logs (< 500 m deep) in the study area reveal that the coal seams are found in the lower segments of the boreholes, and are associated with carbonaceous shale's, clay and sandstones. There are 7 coal seams, of which 4 are prominent with thickness varying  
10 in range of < 1 to ~ 10 m. The above rock formations have been deformed, giving rise to dipping sedimentary bedding surfaces. The overall strike is ~ NNW–SSE and dips gently towards ENE. The amount of dipping varies from 6 to 9°. Borehole litho-logs also suggest existence of two sets of wrench NW–SE to NNW–SSE and NNE–SSW oriented faulting in the study area. It appears that the fault interactions lead to the  
15 formation of complex graben and/or rifts in the study area. It is interesting to note that these small faults have kinematics history similar to the large-scale faults of the PG basin.

The SLSSA method was applied on seismic shot gathers data as well as on stacked data. Figure 2a and b respectively depicts the shot gathers before and after the application of SLSSA. Here, the spatial series of data (all 60 channels corresponding to a constant time) corresponding to individual time slice was processed using SLSSA with window length 21. One can notice that the true reflection patterns in the raw data (Fig. 2a) is scattered due to the presence of noise and thus it looks somewhat fuzzy for the interpreter to infer the geological information. The SLSSA output reconstructed from the first 10 triplets is shown in Fig. 2b. One can clearly see that after the SLSSA processing, there is significant improvement in signal to noise ratio that facilitates the recovery of scattered reflector amplitudes and thereby help in identifying reflector patterns more clearly. Comparison of Fig. 2a and b (encircled) demonstrate the robustness of SLSSA in noise suppression and signal reconstruction.



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Finally, the SLSSA shot gather data was stacked to produce seismic section. The seismic stack section of original data of length 1010 m of SLSSA, processed shot gather data and its SLSSA outputs corresponding to window length 30 and 230 are shown respectively in Fig. 3a–c. After stacking the seismic data, the affect of random noise is negligible but the coherent and coloured noise arising due to the various nonlinear effects, as discussed earlier, will still be there. Hence, the application of SLSSA on stack section allows us to suppress such remnant coherent noise. Figure 3 shows one such example of the SLSSA output in which, low frequency content (coloured noise) is significantly reduced. The output with window length 30 provides the maximum suppressed low frequency (complex and correlated) noise. Figure shows that there are strong reflections in-between the depth range of 200–450 m in the stack section which agrees with the available geological features in the area suggesting that the depth of the coal seams is approximately at around 200 m. Thus, the reflections observed in the stack section matched well with the geological inferences about coal seam in the study area. A disturbance in the amplitude and discontinuity of seismic reflectors is also observed at two places in the stack section. Signatures of a normal faulting are detected at a distance of  $\sim 150$  m from the WSW end and another fault at a distance of  $\sim 720$  m from WSW direction. Our result also shows that there are low vertical displacement and normal faults in the stacked section. As it is an intrinsic property of coal basins, there are minor normal and near vertical faults present in the stack section. The seismic sections show good correlation with nearest borehole data. The faults in the seismic sections show NE–SW direction across the half PG graben structure in the study area. The geological information of the study region evidently agrees with the minor as well as major faults patterns as mapped on the SLSSA processed stack section.

### 3 Conclusion

We conclude that the applicability of SLSSA algorithm to seismic data is a combined approach for de-noising as well as reconstructing of missing data. The testing of the method on synthetic data of fault model demonstrates its ability to identify the fault structures even from the complex noise background. We achieved good correlation among the reconstructed and original synthetic data up to the presence of 30% complex noise along with 10% random noise. The application of this methodology on the shot gather data has significantly enhanced the signal strength of the reconstructed scattered reflectors. The SLSSA method is robust in reducing the effect of random as well as remnant coherent noise from the stacked data. The fault structure identified on the processed seismic section employing the above method correlates well with the PG graben structure in the study area.

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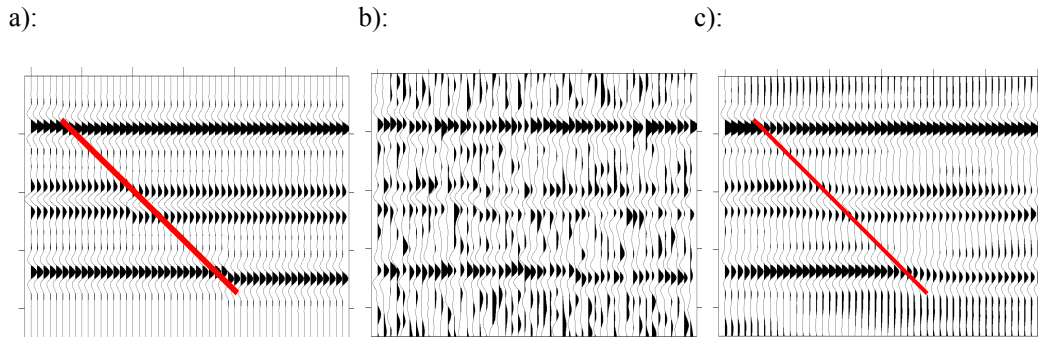
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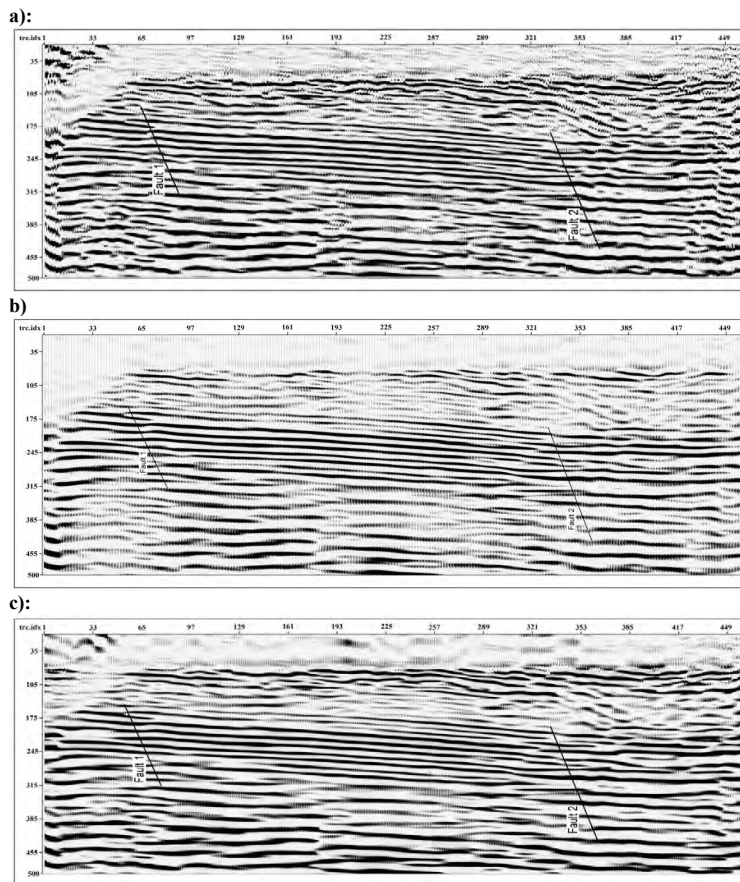
**Fig. 1.** (a) Synthetic data of normal fault model over parallel reflectors with low vertical displacement. (b) Synthetic data with added mixed noise (20% random + 20% chaotic). (c) SLSSA output with window length 12.

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**Fig. 3.** (a) Stacked data (corrected for NMO) from singereni coal basin. (b) SLSSA output of above stacked data with window length 230 and (c) with window length 30.

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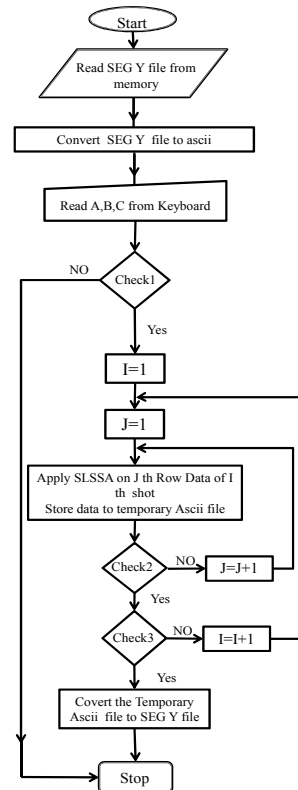
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**Fig. A1.** SLSSA flow chart. Here the user inputs A, B and C represents the number of shots, channels and samples per channel respectively. The program performs the following checks: *Check 1*: in the initial check the program compares the user inputs (A, B, C) with headers. *Check 2* ( $J > C$ ): after the completion of all the spatial Series in one shot this check will be passed. *Check 3* ( $I > A$ ): after the completion of the all shots in the data this check will be passed.