J. Ind. Geophys. Union (September 2018)
v.22, no.5, pp: 459-467

2D Seismic reflection data filtering using Time Slice Singular Spectrum Analysis for noise suppression: A case study from Singareni coalfield, India

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ABSTRACT
Complex noises that arise due to the nonlinear interaction of unwanted seismic signals (coherent and random noises), alter the primary reflections and create severe problems than the simple random noise in recognizing geological structures from seismic stack sections. We present here Time Slice Singular Spectrum Analysis (TSSSA) for the suppression of such noises from seismic records in time domain. The TSSSA involves organizing the spatial data (corrected for NMO) which corresponds to constant time into trajectory matrix for the reduction of noises that do not show large spatial coherency. The singular value decomposition based rank reduction of the trajectory matrix formulated from constant time slice helps to identify the noise in TSSSA with low Eigen values. We test the method on synthetic data contaminated with complex noises to demonstrate its 'robustness' for the identification of faults and then apply to high-resolution seismic reflection observations from Singareni coalfield, India. We find a good correlation between de-noised and pure synthetic data, which indicates the suppression of complex noise without any loss of seismic features. The application of TSSSA to pre and post stack seismic field data suggests significant improvement in signal to noise ratio. The reflections resembling the coal beds in the pre and post stack TSSSA processed depth sections clearly match with the reflectors in the synthetic trace generated from well log data. Finally, improvement in SNR and clear matching of fault structures and coal beds identified in the TSSSA processed data with regional fault structures and available geological information suggest the TSSSA as a robust method for seismic data conditioning.

Keywords: Complex noise suppression, Rank reduction, Singular Spectrum Analysis (SSA), Seismic reflection data, Singareni coalfield.

INTRODUCTION

High-resolution seismic records are useful for locating the geological structures like faults, folds, caved pillars, mined-out areas, and coal seam etc (Greenhalgh et al., 1986; Tselentis and Paraskevopoulos, 2002). However, seismic reflection data from the coal field suffer from interference of seismic waves that produce composite reflection pattern (Lawrence, 1991, 1992). Regardless of constructive or destructive interference, the primary reflections from the coal bed of interest undergo significant alterations. Consequently, the interference of seismic waves reflected from different coal beds lead to the complex reflection patterns, which deter the identification of individual beds (Lawrence, 1991, 1992). For example, interference of seismic waves with the same phase may produce pseudo high amplitudes in the recorded data. In addition to the complex reflection pattern, diffraction of seismic waves at sharp discontinuities also produces pseudo reflection amplitudes. The presence of such pseudo amplitudes due to the combined effect of aforementioned processes significantly alters the primary reflection amplitudes. Furthermore, there are always certain amounts of other (random and coherent) noises present in the seismic records. Thus, the seismic data obtained from the field represent the amalgamated response of earth's layered structure and complex noise.

The complex noise, for brevity, we refer here as a combination of various noises e.g. random, coherent, and erratic etc., which might have arisen from the human activities, source footprints, structural discontinuities or sharp geological boundaries etc. Unlike the random noise, which produces the "flat spectrum" in frequency domain, it is often difficult to predict complex noise easily due to their deceptive nature. Hence, it is imperative to look for alternate robust schemes to recognize the reflector patterns and discontinuities more precisely in the seismic records. The accurate processing and interpretation of field seismic data require only primary reflections. Researchers have employed several techniques involving the domain conversions to suppress the random and coherent noises and to recover the missing amplitudes from the seismic data acquired at regular and irregular intervals.

Ulrych (1988) and Trickett (2003) have presented Eigen Image processing approaches in time and frequency domains respectively for noises suppression and missing data reconstruction. The singular spectrum of the data helps to identify the noise in Eigen Image processing as the additive noise and data gaps increase the rank of the matrix. De-noised signal reconstruction from Eigen triplets (row and column eigenvectors and Eigen value) with high variance is a kind of rank reduction procedure in the above methods. Another singular spectrum based efficient algorithm, which utilizes the data trajectory matrices for separating signal and noise is the Singular Spectrum Analysis (SSA) (Broomhead and King, 1986a, 1986b; Fraedrich, 1986; Golyandina and Zhigljavsky, 2013; Rekapalli and Tiwari., 2015). The SSA designed for the analysis of non-linear geophysical data, successfully removes the noise along with simultaneous reconstruction of missing or scattered signal amplitudes (Vautard et al., 1992; Ghil et al., 2002). The decomposition of the data using data-adaptive basis functions in SSA helps accurate reconstruction of signal compared to the methods which are using fixed basis functions. Recently, Sacchi (2009) and Oropeza and Sacchi (2011) have developed and employed SSA based FXSSA and Multichannel SSA for simultaneous de-noising and data gap filling of seismic signals in frequency domain. However, these methods have been applied to data in frequency domain. The domain (time domain to frequency domain) conversion of non-stationary seismic data with discontinuities and abrupt changes generates artifacts. The SSA and MSSA of the frequency domain data further enhance the artifacts in the processed output (Rekapalli et al., 2014; Rekapalli and Tiwari, 2016). It is difficult to provide physical interpretation of seismic data assorted with such artifacts, especially for recognizing thin coal beds and their discontinuities. Therefore, we present here Time Slice Singular Spectrum Analysis (TSSSA) in time domain, to suppress the complex noise from seismic reflection data. The signal decomposition and reconstruction in the TSSSA is based on SSA and involves the data adaptive basis functions of the spatial seismic data (i.e., the data of all channels correspond to a fixed time).

We illustrate the methodology of TSSSA for complex noise suppression and also for scattered amplitude reconstruction of seismic reflection data. First we provide testing of the method on synthetic data assorted with complex noise and then its application to pre and post stack seismic datasets from Singareni coalfield, Telangana, India to indentify the fault structures and coal beds. Finally, we verify the validity of identified faults and coal beds using available geology of the study region and well data.

METHODOLOGY

Although there are wide varieties of frequency domain techniques for data de-noising and missing amplitude recovery, the data adaptive decomposition in SSA based time domain techniques are robust for accurate signal recovery. We apply the SSA to spatial series (i.e., data of all channels) corresponding to fixed time. The crustal layers show high lateral quasi-homogeneity on regional scales compared to chaotic variations in depth direction. Since the correlation among the primary amplitudes from a constant time/depth slice is always stronger than the noise correlation, it is possible to extract the correlated lateral signal to distinguish the primary signals from complex noise background. In this way, the analyses of seismic data of all channels at a fixed time as spatial series, allow us to suppress the noise in the TSSSA method. The reconstruction in this method is also a singular or Eigen spectrum based rank reduction (Trickett, 2003; Tiwari and Rajesh, 2014). Hence, we can use the Eigen spectra to identify the signal with significant Eigen values and noise with relatively low Eigen values. Using basic mathematical description of SSA (Golyandina et al., 2013), the TSSSA methodology is explained as follows:

Embedding the trajectory matrix: The TSSSA processing begins with embedding the trajectory matrix from the spatial data series represented by $Y(x) = \{y(x_1), y(x_2) \ldots y(x_N)\}$ using a window length L ($2>L<=N/2$).Here N is number of traces in the data and K ($=N-L+1$) represents the number of lagged vectors of Y(x) that form the trajectory matrix (**T**) of size $L\times K$.

$$\mathbf{T}_{L\times K}= [X_1:\ldots\ldots: X_i : \ldots. : X_K] \tag{1}$$

Where X_i represents a vector of length L given by $X_i= \{y(x_i), y(x_{i+1}),\ldots, y(x_{i+L-1})\}$ and x_i (for i=1 to N) represent the spatial position of geophones/ receivers.

Singular Value Decomposition of trajectory matrix: In the second step, the trajectory matrix was decomposed into eigenvector(Left and Right) and a diagonal eigen value matrix using Singular Value Decomposition (SVD).The decomposition of T given by

$$T = \sum_{i=1}^{d} \sqrt{\lambda_i} U_i V_i^T \tag{2}$$

Where, λ_i is the i^{th} eigenvalue corresponding to the i^{th} eigenvector $\mathbf{U_i}$ of TT^T and d is the no of nonzero eigenvalues. The triple denoted by ($\sqrt{\lambda_i}$, **Ui**, $\mathbf{V_i}$) is called the i^{th} Eigen triple. As discussed above, the seismic data is a combination of amplitudes from different processes (reflection, interference, diffraction etc.). The SVD allows us to estimate the signal amplitudes of different Eigen processes using respective Eigen value. Thus it is possible to identify the Eigen processes of noise with low eigenvalues and randomly fluctuating eigenvectors.

Eigen triplet grouping and reconstruction of trajectory matrix: In the next step, the Eigen triplets with significant variance and periodicity are grouped to reconstruct the trajectory matrix using the following equation

$$Tr = \sum_{G} \sqrt{\lambda_i}\, U_i V_i^T = \begin{bmatrix} x_{(1,1)} & \cdots & x_{(1,K)} \\ \vdots & \ddots & \vdots \\ x_{(L,1)} & \cdots & x_{(L,K)} \end{bmatrix} \tag{3}$$

Here G represents the group of Eigen triples satisfying the criteria of variance and eigenvector periodicity. The Eigenvector periodicity is useful to eliminate the very low frequency carrier and high frequency noise components.

Diagonal averaging of reconstructed trajectory matrix: Finally, we average the reconstructed trajectory matrix (Tr) along its anti-diagonals to obtain de-noised data series. Let us denote the reconstructed series by $X_{rc}=\{g_1, g_2 \ldots g_k \ldots\ldots g_N\}$. The averaging procedure can be written as follows

$$\mathbf{g_k} = \frac{1}{k}\sum_{m=1}^{k} x_{m,k-m+1} \quad \text{for } 0 < k < L \tag{4a}$$

$$\mathbf{g_k} = \frac{1}{L}\sum_{m=1}^{L} x_{m,k-m+1} \quad \text{for } L-1 < k < K+1 \tag{4b}$$

$$\mathbf{g_k} = \frac{1}{N-k+1}\sum_{m=k-K+1}^{L} x_{m,k-m+1} \quad \text{for } K < k \leq N \tag{4c}$$

The TSSSA pseudo code used for the seismic data de-noising is shown below.

```
Pseudo Code
for i=1:Nt  (Nt→Number of sampling times/ time slices)
1) Take the i th  time slice of the data
2) Formulate the trajectory matrix
   Using an optimal window length (L)
3) Decompose the trajectory matrix into Eigentriplets
   i.e., (√λi , Ui , Vi) Eigenvalues and Eigenvectors
4) Group the eigentriplets
   Using Eiegnvector periodicity and Eigenvalue
5) Reconstruct the trajectory matrix (Tr) from selected triplets
6) Diagonally average Tr to obtain denoised data
end
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Window length and Triplet group selection

The window length selection is crucial in the singular spectrum analysis (Patterson et al, 2011; Hassani et al, 2011). Accordingly, the window length equal to the classical limit N/2 would resolve the principal components completely. But, for large data sets, the decomposition of signal at window length N/2 is computationally expansive and more over the number of signal component present in the data would be much smaller than N/2. In such cases, it is appropriate to choose an optimal window length much smaller than N/2 that serve to resolve the independent signals from different processes. Based on theoretical verification, Hassani et al, (2011) have suggested that median of (1…..N) would be an appropriate choice of L for most of the real world data. However, the selection of appropriate window length should be made on the apriori knowledge of the curvature of the reflectors in the TSSSA, such that the primary reflections must be linear within a window. Hence, one should be careful while dealing the seismic data with curved events/ reflectors, which would require smaller window lengths than usually adopted in other analyses. It would be appropriate to applying the TSSSA method to normal move out (NMO) corrected data to circumvent hyperbolic curvature of the reflections to avoid conflicts arising in the window length selection.

The second important parameter needed to be discussed here is the appropriate selection Eigen triple group for de-noised signal reconstruction. The improper grouping would generate artifacts in the reconstructed data. There are several recent approaches (Hassani et al, 2012) for estimating the separation between individual Eigen components. In general, de-noising scheme adopts the variance/ eigenvalue based grouping (Trickett, 2003; Golyandina et al., 2013; Rekapalli and Tiwari, 2015). The paired Eigen triplets with nearly same Eigen value share the same physical process. Hence in dealing such paired Eigen triplets, either both the triplets are to be considered for reconstruction or both should be dropped to avoid the artifact generation. Following the above procedure, we have grouped the Eigen triples on the basis of variance of eigenvalue and periodicity of the eigenvectors, which is appropriate for the objectives of de-noising and reconstruction.

ANALYSIS AND RESULTS

Testing the TSSSA on synthetic data of fault model with Complex noise

Initially, we test the efficacy of TSSSA on synthetic data. The synthetic reflection data (Figure 1a) of a normal fault model was generated using the finite difference method. The complex noise is generated using the following equation

$$a_{t+1} = \mu . a_t . (1 - a_t) \tag{5}$$

Here μ can take the values between 0 and 4. We have selected μ=3.9 and a_1=0.1 to generate the synthetic noise. Diffracted and scattered energies are assumed to give rise to chaotic/ complex noise in the composite seismic signal. The effect of such complex noise is more severe at far offset. We use mixture of the noise generated using the equation 5 and random noise to contaminate the data.

We applied the TSSSA algorithm at various complex noise levels ranging from 10% to 40%. In each of the cases, 10% random noise was added as the background to simulate more realistic field situation. The noisy synthetic data with 20% noise (10% random +10% complex noise) and its de-noised output reconstructed using TSSSA are respectively shown in Figure 1b and Figure 1c. The results suggest that the signal reconstruction is fairly good and the scattered energy has been recovered in TSSSA output even

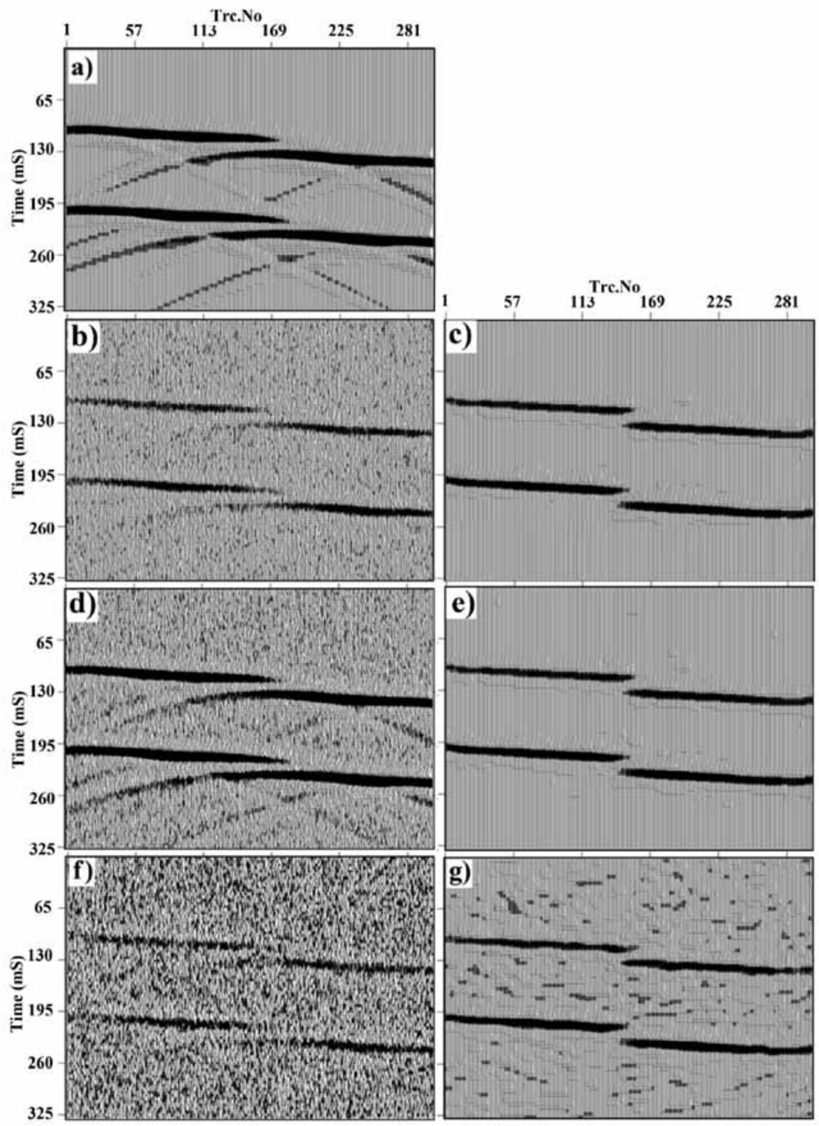

Figure 1. (a) Synthetic data of normal fault model with diffraction energy (b) Synthetic data contaminated with 20% complex noise (10% random +10% chaotic) (c)TSSSA output of Synthetic data shown in Figure 1b (d) Synthetic data contaminated with 30% complex noise (10% random +20% chaotic) (e) TSSSA output of Synthetic data shown in Figure 1d (f) Synthetic data contaminated with 50% complex noise (10% random noise +40% chaotic noise) (g)TSSSA output of Synthetic data shown in Figure 1f.

in the presence of diffraction energy. We have successfully removed the diffraction energy in addition to the added noise from the synthetic data. The synthetic data with 30% noise (10% random +20% complex noise) and 50% noise (10% random + 40% complex noises) and their TSSSA de-noised outputs are shown in Figure 1d to Figure 1g. The synthetic example demonstrates that the TSSSA is efficient up to 30% complex noise level (Figure 1e). Above this threshold, the method fails to suppress the noise. The noise in the TSSSA de-noise output shown in Figure 1g is an example that demonstrated the effect of above stated noise threshold.

Application to the field data

The study area Singareni coalfields (Telangana, India) as shown in Figure 2, is located near Ramagundam, in the Pranhita-Godavari (PG) Gondwana graben that formed in between the boundaries of Bastar and Dharwar cratons (Murthy and Rao, 1994). The Lower Gondwana rock formations in this region are affected by a complex system of faulting, which lead to the general eastern tilting, followed by erosion. The Overall strike is ~ NNW-SSE with ENE and WSW dipping. The NW-SE faults parallel to the PG basin boundary faults and NE-SW oriented faults

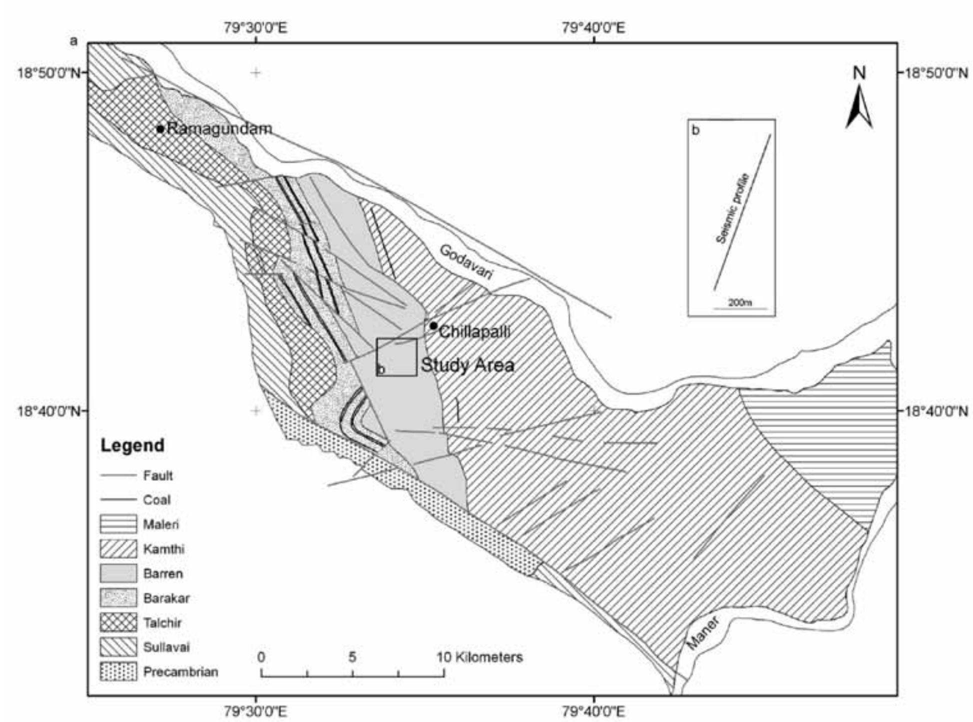

Figure 2. a) Geological map of the study area along with b) Location of the seismic profile.

are the two kinds of geologically probable faults which are could be observed in 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). According to the researchers, the fault systems observed are related to the Permian or Mesozoic fault systems (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, clay and sandstones in the depth range of ~200 to 500m. There are 7 coal seams, of which 4 are prominent with thickness varying in range 1 m 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^o to 9^o. Borehole litho-logs also suggest the 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 formation of complex graben and/or rifts in the study area. The vertical displacement of the faults in this region is nearly less than or equal to 5m. It is interesting to note that these small faults have kinematics history similar to the large-scale faults of the PG basin.

The high resolution seismic reflection data used in the present study was acquired from the study area shown in Figure 2 using 0.25mS sampling interval along the profile shown in Figure 2b. The 60 channels Geode system manufactured by geometrics was used in the data acquisition. Emulsion based explosive was used to generate high frequency energy to incorporate high resolution data. The common midpoint technique with end on shooting geometry, was used for data acquisition with 15m average shot depth and 5m geophone interval. The near and far offsets are chosen as 120 m and 415 m respectively and the recoding geometry ensures a nominal CMP fold of 15. After preliminary processing (e.g. reversal correction, muting, surgical mute etc.), the data was converted into CMP gather and velocity analysis was performed for NMO correction. The NMO corrected CMP gathers converted to shot gathers. We have applied the TSSSA to the NMO corrected field data for suppression of complex noise and scattered amplitude recovery.

Figure 3 depict the shot gathers before (top panel) and after (bottom panel) the application of TSSSA. Here, spatial data series corresponds to 60 channels in each shot gather which was processed using TSSSA with window length 21. The data of total 100 shots was processed. The reflection amplitudes in the raw data as shown in the top panel of Figure 3 are scattered due to the presence of complex noise. Thus it looks somewhat fuzzy to identify the primary reflections and their continuity from raw data. The TSSSA output reconstructed from the first 10 Eigen triplets is shown in the bottom panel of Figure 3. It can be

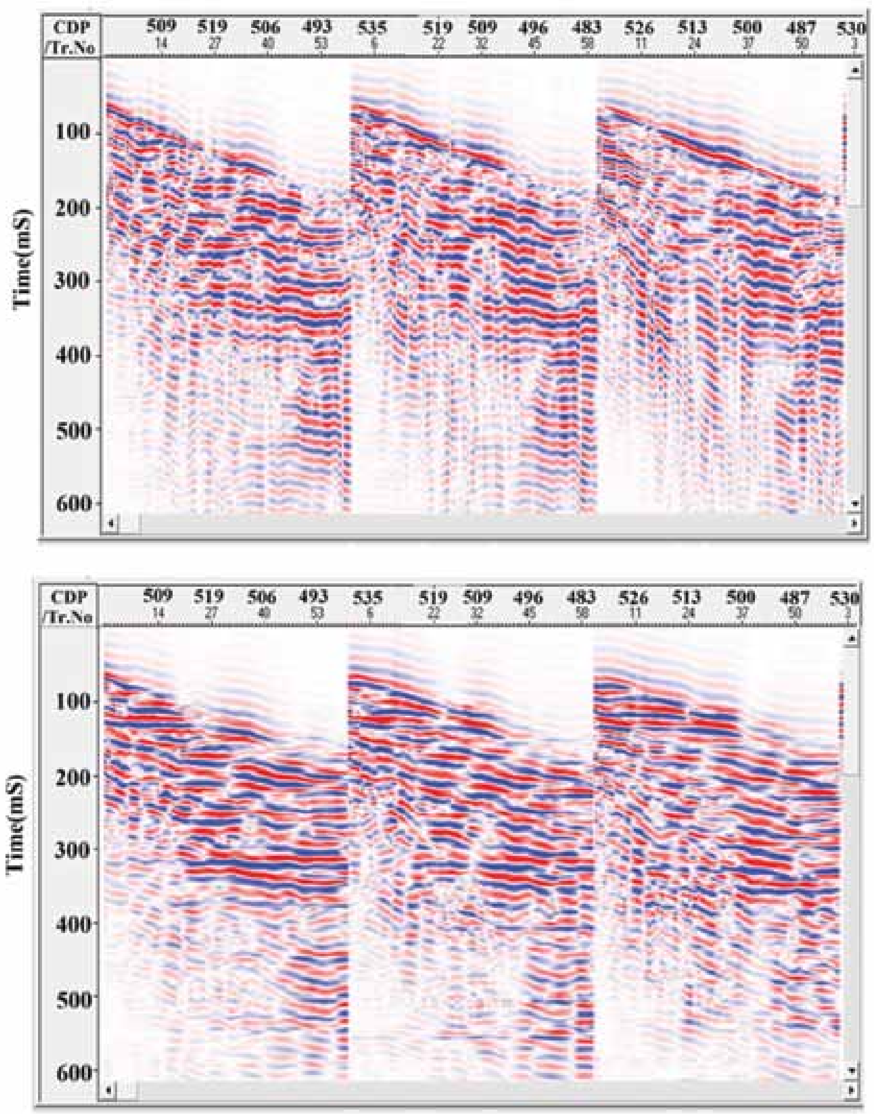

Figure 3. NMO corrected shot gather data before (top panel) and after (bottom panel) the application of TSSSA.

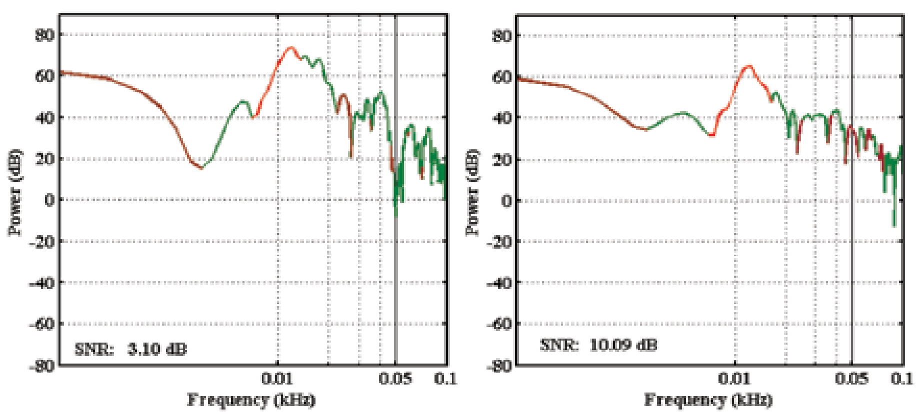

Figure 4. Spectral content of signal and noise portions compted for NMO correlcted gathers before (Left panel) and after (Right panel) the application TSSSA. Red color line indicate the component of fundamental mode, green color is the Noise and brown denotes the signal portion excluding DC and harmonic component.

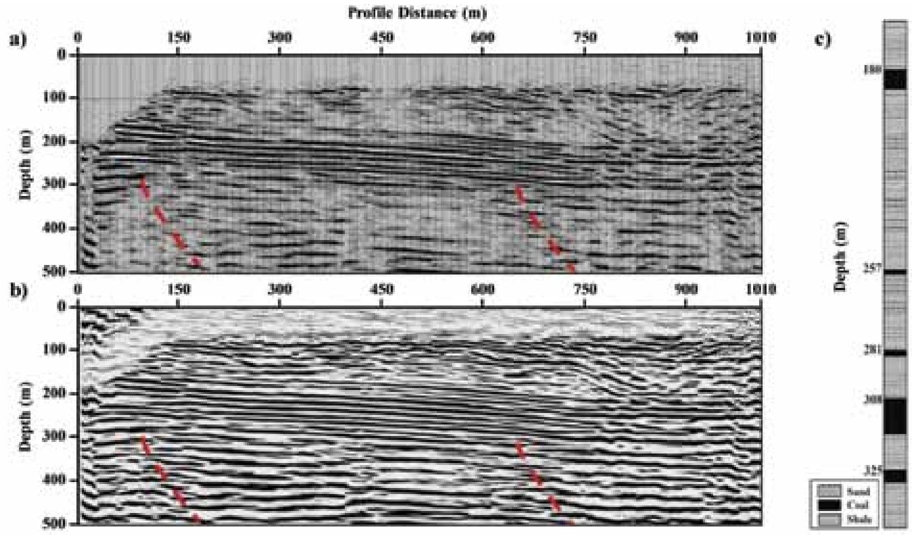

Figure 5. a) Stack section without TSSSA application (using convetional processing). (b) Stack section obtained from TSSSA processed shot gather data from singareni coal basin. (c) Bore hole litholog from the study region.

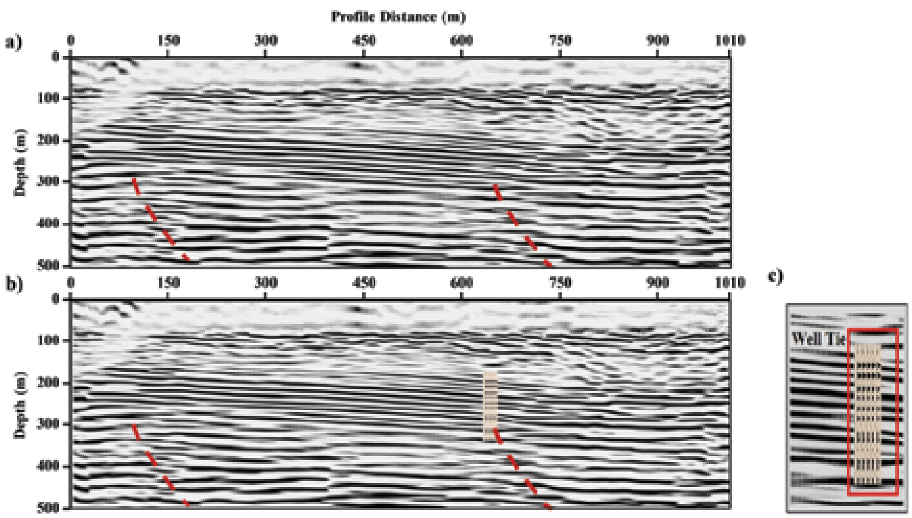

Figure 6. TSSSA output of stacked data shown in Figure 5b. (a) Reconstructed using window length 230. (b) Reconstructed using window length 30 along with Well tie (in rectangular box). (c) Zomed display of well tie.

observed that there is significant improvement in signal to noise ratio of the data after the TSSSA processing. Figure 4 shows the signal and noise spectral content present in the original NMO corrected data and its TSSSA processed output. One can notice that the SNR has increased from 3.10dB to 10.09dB in the TSSSA processing. The underlying method also facilitated the recovery of scattered reflection amplitudes for the clear identification of primary reflector patterns. Comparison of shot gathers before and after the TSSSA processing and respective signal to noise ratio demonstrate the robustness of the proposed method for noise suppression and signal reconstruction. We applied the deconvolution on TSSSA filtered data to sharpen the wavelet then band pass filtering to limit the frequency content of the data between 30 to 140 Hz. The shot gather data was converted into CMP gathers. Then preformed second pass velocity analysis on NMO removed CMP gathers to get best stacking velocity. The data was stacked to produce final stack section using best aligned NMO corrected CMP gathers.

Figure 5a and 5b respectively show the depth converted stack section of length 1010 m obtained from original (without TSSSA processing) and TSSSA processed shot gathers as explained above. The noise was significantly suppressed in the TSSSA processed data (Figure 5b) and the pseudo amplitudes in the stack section of original data

(Figure 5a) are also appropriately corrected in the TSSSA processed stack section (Figure 5b). The reflections below the depth 300m were smeared due to the non-linear interaction of scattered and diffracted signals from faults in the original stack data shown in Figure 5a. Whereas, such reflections are recovered for clear visualization in the TSSSA processing, as can be seen in Figure 5b. Although it is well known that the stacking procedure removes the effect of random noise, there are still certain amounts of deceptive complex colored noises in the data, possibly arising due to the various other sources as discussed earlier. Hence, we applied the TSSSA de-noising on post stack data shown in Figure 5b to alleviate the complex colored noises. The TSSSA output of the stack section data (Figure 5b) corresponding to the window lengths 230 and 30 are respectively shown in Figures 6a and Figure 6b. The TSSSA suppressed the low frequency (complex and colored) noise in the output at window length 30 (Figure 6b) comparative to the output at window length 230. There are strong reflections between the depth range of 200 m to 450 m in the TSSSA processed stack section corresponding to coal beds (Figure 6b), which agrees well with the available geological data in the study area (Murthy and Rao, 1994; Biswas, 2003).

To validate the field data, we use synthetic seismic traces generated from the borehole information within the study region that lies approximately around 200m distance perpendicular to the seismic line. The observed reflections from the stack section substantiated well with the synthetic data shown in Figure 6c. The geological information (Murthy and Rao, 1994; Biswas, 2003) of the study region also corroborate well with the minor as well as major faults as mapped on the post stack TSSSA processed section. Also the reflections observed in the stack section match well with the geologically inferred coal seam in the study area. A disturbance in the amplitude and continuity of seismic reflectors (inferences for faulting) is also observed at two places in the stack section. These disturbances are noticed as the signatures of a normal faulting detected at a distance of ~150 m from the WSW end and another fault at a distance of ~720 m from WSW direction. These faults locations are with geologically known faults. Our results show the presence of near normal faults with low vertical displacement in the stack section. In addition, few minor normal and near vertical faults present in the stack section are intrinsic to coal basin. The faults in the seismic sections show NE-SW direction across the half PG graben structure in the study area.

CONCLUSION

We have developed a robust Eigen analysis based Time Slice Singular Spectrum Analysis for time domain seismic reflection data de-noising. The method was tested on noisy synthetic seismic reflection data for its efficacy and then applied to the field data for complex noise suppression. Experiments on noisy synthetic data generated over the normal fault model with diffraction energy suggest that the underlying method is robust to suppress complex noise up to 30%. The application of the method to high resolution seismic reflection shot gather data from Singareni coal fields reveals that the method has significantly improved the signal to noise ratio paving the way to recognize geological structures more accurately. Finally, the applicability of the method for coherent noise suppression is demonstrated on post stack data. The results from post stack TSSSA application suggest that the underlying algorithm successfully suppressed the complex colored noise. The fault structures and coal beds mapped on the de-noised stack section correlated well with the geological information. High correlation (>75%) between the synthetic trace computed from the log data and the TSSSA processed stack section suggests the robustness of the method. Hence, we conclude that the TSSSA method is robust for complex noise suppression from seismic reflection data for the identification of geological structures.

ACKNOWLEDGEMENTS

We thank Director CSIR-NGRI for his permission to publish this paper. We are also grateful to DAE and CSIR for funding first and second author respectively. We thank team members of Engineering Geophysics Division for their support in the field data acquisition and Singareni Collieries Company limited for funding the project.

We also thank Editor for his encouragement and constructive suggestion.

Compliance with Ethical Standards

The authors declare that they have no conflict of interest and adhere to copyright norms.

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Received on: 9.5.18; Revised on: 6.7.18; Accepted on: 16.7.18