Assessment of Singular Spectrum and Wavelet based de-noising schemes in generalized inversion based seismic wavelet estimation

Rekapalli Rajesh, Engineering Geophysics, CSIR-NGRI, AcSIR-NGRI, Hyderabad, India; Shubham K. Priyadarshi, Indian School of Mines, Dhanbad, India; R.K.Tiwari, Engineering Geophysics, CSIR-NGRI, AcSIR-NGRI, Hyderabad, India.
shubham@agp.ism.ac.in

Keywords

Seismic Wavelet, Inversion, Deconvolution, Reflectivity, Spatial Singular Spectrum Analysis, Multivariate Wavelet, De-noising, Gaussian noise.

Summary

Seismic wavelet estimation is very important in the processing and interpretation of seismic data. The noise present in seismic data deviate the wavelet estimates and thereby mislead the processing and interpretation. We present Spatial Singular Spectrum Analysis (SSSA) and Multivariate Wavelet (MW) based de-noising accompanied with generalized inversion based wavelet estimation to surmount the above problems. We apply the algorithm on a three layer model synthetic data contaminated with Gaussian white noise. Our results suggest that the usage of SSSA or combined usage of SSSA and MW is robust scheme for de-noising. The seismic wavelet and reflectivity series estimated from noisy synthetic data using the proposed methods are matching well with the original seismic wavelet and reflectivity series data. Thus, we conclude that the SSSA or combined SSSA and MW de-noising of seismic data is essential as a pre filtering for precise wavelet estimation via generalized inversion method.

Introduction

In seismic reflection prospecting, the precision of estimated seismic wavelet plays a vital role for successful identification of profitable oil and gas reserves. Several researchers have discussed the deterministic Wavelet estimation from seismic surface and well data (Danielson and Karlsson, 1984; Nyman et al., 1987; Poggiagliolmi and Allred, 1994). Deterministic seismic wavelet estimation (source signature) is the robust one of the methods and a reasonably well developed subject (Poggiagliolmi and Allred, 1994; Broadhead, 2008), where the well log data are available. It allows the integration of down-hole and surface seismic data for seismic interpretation purposes. The deconvolution of surface amplitude data with estimated wavelet allows us to compute the subsurface reflectivity series for structural and stratigraphic interpretation. Reliable wavelet estimation is crucial to reservoir geophysics for using in seismic data processing such as deterministic deconvolution, seismic-to-well tie, forward modeling, spiking deconvolution and seismic inversion. Hence the accuracy of seismic data processing and interpretation depend on accuracy of the estimated seismic wavelet. Researchers have also reported the probabilistic Wavelet estimation approaches (Buland and Omre, 2003a, 2003b; van der Baan and Pham, 2008), where well log data are not available to go for deterministic approach. Edgar and van der Baan (2011) have discussed the accuracy of statistical seismic wavelet estimation methods.

The noise (mixture of unwanted random, coherent and colored seismic signals) is a unavoidable component in the seismic reflection data. It corrupts the data quality and thereby impacts the wavelet certainty. Broadhead (2008) has discussed a generalized inversion scheme based on deterministic approach to reduce the effect of random noise using the concepts of Monte Carlo and coherency filtering methods. Although seismic data processing involves several filtering stages to remove the noise present in the data, Singular Spectrum Analysis (SSA) based data adaptive filtering scheme appeared during last decade (Trickett, 2003; Oropeza and Sacchi, 2011; Rekapalli et al., 2014, Tiwari and Rajesh, 2014; Rajesh and Tiwari, 2015). Researchers have also reported the Wavelet method as one of the robust methods for de-noising the non-stationary signals (Chakraborty and Okaya, 1995; Cao and Chen, 2005; Wang et al., 2015). In this paper, we assess the effect of (SSA, Wavelet and their combined) de-noising strategies on wavelet estimation using generalized inversion on the presumption of the exact ness of well log data. The objective of the paper is therefore to estimate and compare the seismic wavelet from the (i) synthetic data contaminated with Gaussian white noise (ii) de-noised output of Spatial SSA (SSSA) (Tiwari and Rajesh, 2014) (iii) de-noised output of Multivariate Wavelet (MW) method (Aminghafari et al., 2006) and (iv) de-noised output of combination of SSSA and MW methods.

Methodology

Generalized Inversion based Wavelet estimation: The methodology in the discrete setting considers the seismic data in its general convolutional model as represented in equation (1).

$$\boldsymbol{d(t)}=\int \boldsymbol{r(\tau)w(t-\tau)d\tau+\varepsilon} \textbf{(1)}$$

Here $\boldsymbol{d(t)}$ denotes the measured seismic data, $\boldsymbol{r(t)}$ is the reflectivity series of subsurface. The source wavelet $\boldsymbol{w(t)}$ is unknown and $\boldsymbol{\varepsilon}$ is the additive random noise.

For simplicity, we presume that there is uncertainty only in the measured seismic data (due to noise), but not in the reflectivity series.

Employing the generalized least square inversion method, for given $\boldsymbol{d}$ and $\boldsymbol{r}$ we can solve for $\boldsymbol{w}$. Using linear inverse theory, the method of least squares (which assumes Gaussian noise) yields the wavelet estimator,

$$\boldsymbol{w_{est}=R^{+}d} \textbf{ (2)}$$

Where $\boldsymbol{R}$ is the convolutional matrix form of the normal incidence reflection coefficients($\boldsymbol{r}$), $\boldsymbol{R^{+}}$ is the generalized inverse. The generalized inverse can be written as

$$\boldsymbol{R^{+} = (R^{T}R + \epsilon)^{-1}R^{T}} \textbf{ (3)}$$

Where $\boldsymbol{\epsilon}$ is a small constant for stability of the solution (regularization parameter). As we believe that the de-noising strategies will reduces the noise considerably, we can write

$$\boldsymbol{d \approx Rw} \qquad \textbf{(4)}$$

Thus the expected value of our wavelet estimator is given by

$$\boldsymbol{West = R^{+}Rw} \qquad \textbf{(5)}$$

Although it looks like that the estimator is biased, the bias is small for sufficiently small values of $\boldsymbol{\epsilon}$ (i.e., $\boldsymbol{R^{+}R \approx I}$).

The accuracy of the estimated wavelet purely depends on the efficacy of the de-noising method. The methodologies of SSSA (Rekapalli et al., 2012; Tiwari et al., 2014; Tiwari and Rajesh, 2014) and MW method (Aminghafari et al.,2006) discussed elsewhere.

Analysis and Results

Synthetic seismic data of simple three layer 2D model (two reflectors) was generated by the convolution of model reflectivity series with Ricker wavelet of 30 Hz. The pure data was contaminated with White Gaussian Noise (WGN) (Jeruchim et al.,2006) to achieve 0.3 signal to noise ratio (SNR). Figures 1a, 1b and 1c respectively depict the pure synthetic data, Gaussian white noise and noisy synthetic data. Figure 2a and Figure 2b respectively show single trace of the pure and noisy synthetic data and the wavelets estimated using generalized inverse algorithm from the pure and noisy synthetic data.

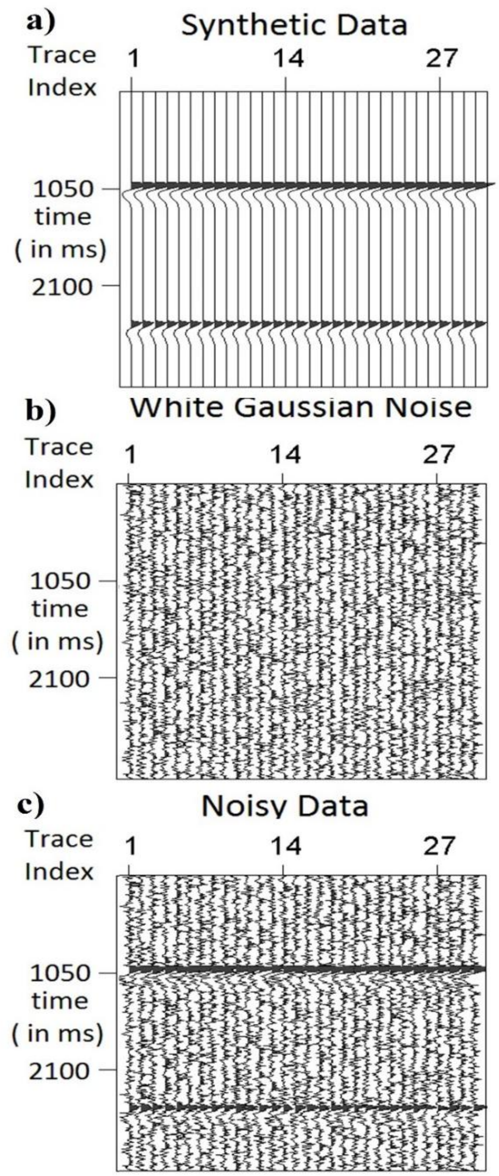

Figure 1: a) Pure Synthetic data b) White Gaussian Noise c) Noisy data.

The original reflectivity series and reflectivity series computed from the deconvolution of noisy synthetic data and corresponding new wavelet estimated are respectively shown in Figure 2c and Figure 2d. It can be seen from the Figure 2b that the wavelet estimated from the noisy data (without any de-noising approach) is not matching with the wavelet estimated from pure synthetic data. Similarly, reflectivity series obtained from the noisy synthetic data

(Figure 2d) is not matching with the original reflectivity series (Figure 2c) used in the forward computation of the synthetic data.

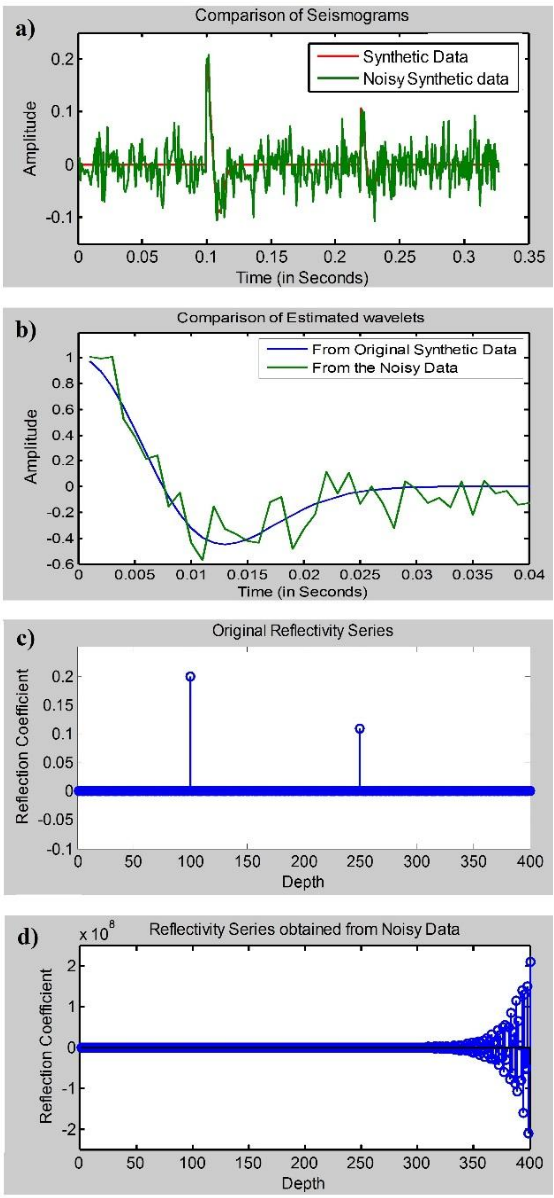

Figure 2: (a) Comparison of the pure and noisy synthetic data, (b) Comparison of estimated wavelets from data and (c) Original reflectivity series, and (d) Obtained reflectivity series from noisy data.

Although we use generalized inversion based approach for wavelet estimation, the presence of noise deviate the wavelet estimation and hence reflectivity series.

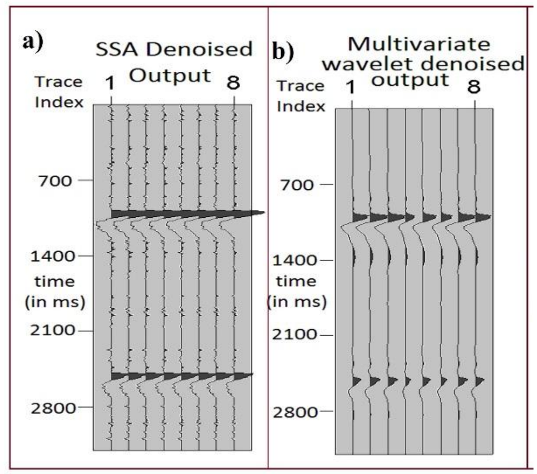

Figure 3: De-noised output of noisy synthetic data using a) SSSA b) Multivariate Wavelet methods.

In the next step, we have de-noised the noisy synthetic data using SSSA (Rekapalli et al., 2012; Tiwari et al., 2014) and MW (Aminghafari et al.,2006) methods. The de-noised outputs of SSSA and MW methods are shown respectively in Figure 3a and Figure 3b.One can notice from Figure 3a that there is small amount of noise present in the output of SSSA method and the reflections are very clear. Whereas MW de-noised output does not contain any noise, but certainly there is a severe amplitude distortion in the output.

We applied the generalized inversion based wavelet estimation algorithm on the de-noised outputs of SSSA and MW methods. Figure 4 depicts comparison of single trace of pure synthetic data, SSSA output, MW output, original wavelet and wavelets estimated from SSSA and MW outputs. One can see that the SSSA de-noised trace and pure synthetic trace are correlated well with correlation coefficient of 0.92. The amplitude of MW de-noised signal is nearly 0.25 times to the original signal amplitude in addition to the amplitude distortions compared to pure synthetic trace.

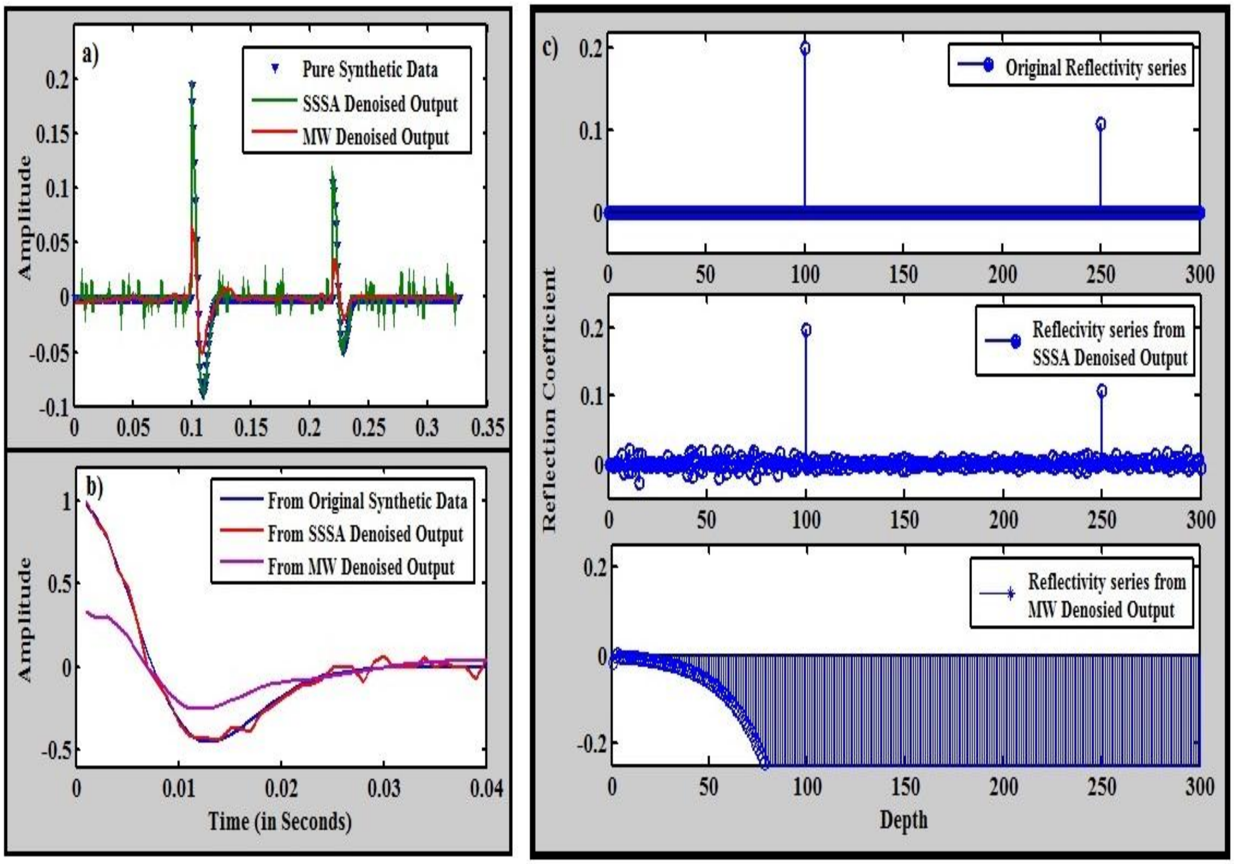

Figure 4: a) Pure synthetic trace and SSSA and MW de-noised output of noisy synthetic trace b) Original wavelet and wavelet estimated from SSSA and MW de-noised signals using generalized inversion c) Original reflectivity series and reflectivity series estimated from SSSA and MW de-noised signals using deconvolution.

The reflectivity series computed from the deconvolution of de-noised outputs with their respective wavelets. The reflectivity series obtained from SSSA and MW outputs are shown in Figure 4c. The reflectivity series obtained from SSSA de-noised data is clearly matching with the original reflectivity series with correlation coefficient 0.72. The reflectivity series obtained from the MW de-noised output is not matching with the original reflectivity series.

Finally, we have applied the WM method on the SSSA output to suppress the remnant noise. The output from this process is analyzed for seismic wavelet and reflection coefficient series as discussed above. The MW de-noised output of SSSA de-noised data, the estimated wavelet and reflectivity series correlate well with the pure synthetic trace, original wavelet and reflectivity series data with correlation coefficient >0.9.

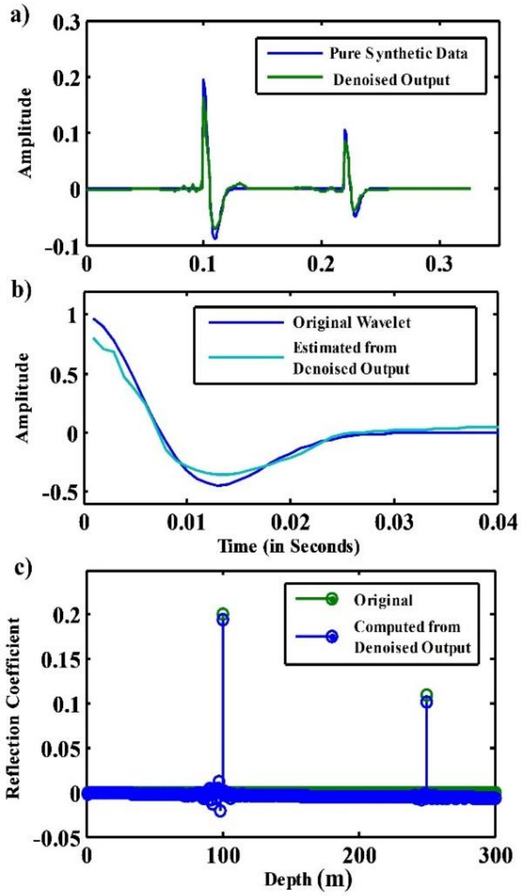

Figure 5: Comparison of pure seismic trace, wavelet and reflectivity series with the MW de-noised output of SSSA de-noised data a) Pure synthetic data and De-noised output b) Original wavelet and wavelet estimated from above de-noised data using generalized inversion procedure c) Original reflectivity series and reflectivity series estimated from above de-noised data respective wavelet using deconvolution.

Conclusions

We have presented here SSSA and MW based de-noising strategies in deterministic wavelet estimation via generalized inversion. The application of the method on synthetic data contaminated with Gaussian white noise shows that the proposed method surmounts the problems associated with noise in wavelet estimation. The seismic wavelets and reflectivity series extracted from de-noised outputs of SSSA and combination of SSSA and MW correlate well with original wavelet and reflectivity series. Hence, we may conclude that the generalized inversion based seismic wavelet estimation from the SSSA and combination of SSSA and MW de-noised seismic surface data is robust and accurate.

References

Aminghafari, M., Cheze, N., & Poggi, J. M. (2006).Multivariate denoising using wavelets and principal component analysis.Computational Statistics & Data Analysis, 50(9), 2381-2398.

Broadhead, M. K. (2008). The impact of random noise on seismic wavelet estimation. *The Leading Edge*, *27*(2), 226-230.

Buland, A., & Omre, H. (2003*a*). Bayesian wavelet estimation from seismic and well data. Geophysics, 68(6), 2000-2009.

Buland, A., & Omre, H. (2003*b*). Joint AVO inversion, wavelet estimation and noise-level estimation using a spatially coupled hierarchical Bayesian model. Geophysical Prospecting, 51(6), 531-550.

Cao, S., & Chen, X. (2005). The second-generation wavelet transform and its application in denoising of seismic data. *Applied geophysics*, *2*(2), 70-74.

Chakraborty, A., &Okaya, D. (1995).Frequency-time decomposition of seismic data using wavelet-based methods. Geophysics, 60(6), 1906-1916.

Danielsen, V., & Karlsson, T. V. (1984).Extraction of signatures from seismic and well data. *First Break*, *2*(4), 15-21.

Edgar, J. A., & van der Baan, M. (2011). How reliable is statistical wavelet estimation?. *Geophysics*, *76*(4), V59-V68.

Jeruchim, M. C., Balaban, P., &Shanmugan, K. S. (2006). *Simulation of communication systems: modeling, methodology and techniques*. Springer Science & Business Media.

Nyman, D. C., Parry, M. J., and Knight, R. D.(1987).Seismic wavelet estimation using well control.*57th Ann. Internat.Mtg., Soc. Expl.Geophys., Expanded Abstracts*, 535–537.

Oropeza, V., &Sacchi, M. (2011).Simultaneous seismic data denoising and reconstruction via multichannel singular spectrum analysis.Geophysics, 76(3), V25-V32.

Poggiagliolmi, E., & Allred, R. D. (1994). Detailed reservoir definition by integration of well and 3-D seismic data using space adaptive wavelet processing. *The Leading Edge*, *13*(7), 749-754.

Percival, D. B., & Walden, A. T. (1993). *Spectral analysis for physical applications*.Cambridge University Press.

Rekapalli, R., Tiwari, R. K.,&Tangirala, S. (2012). De-noising and clean reconstruction of seismic signals using Space Lagged Singular Spectral Analysis (SLSSA). In AGU Fall Meeting Abstracts (Vol. 1, p. 1578).

Rekapalli, R., & Tiwari, R. K. (2014).Windowed SSA (Singular Spectral Analysis) for GeophysicalTime Series Analysis. *Journal of Geological Resource and Engineering*, *3*, 167-173.

Rajesh, R., & Tiwari, R. K., (2015).A short note on the application of Singular Spectrum Analysis for Geophysical Data processing. J. Ind. Geophys. Union, 19(1), 77-85.

Tiwari, R. K., & Rajesh, R. (2014).Factorized Hankel optimal singular spectral approach for erratic and noisy seismic signal denoising. Journal of Applied Geophysics, 111, 95-101.

Tiwari, R. K., Rajesh, R., Seshunarayana T., &Dhanam K. (2014).Complex noise suppression and reconstruction of seismic reflection data from fault structures using Space Lagged Singular Spectral Analysis. Nonlinear Processes in Geophysics Discuss., 1, 649–663.

Trickett, S. R. (2003). F-xyeigenimage noise suppression. Geophysics, 68(2), 751-759.

Van Der Baan, M., & Pham, D. T. (2008).Robust wavelet estimation and blind deconvolution of noisy surface seismics. *Geophysics*, *73*(5), V37-V46.

Wang, G., Chen, L., Guo, S., Peng, Y., &Guo, K. (2015). Application of a New Wavelet Threshold Method in Unconventional Oil and Gas Reservoir Seismic Data Denoising. *Mathematical Problems in Engineering*, *501*, 969702.

Acknowledgements

The authors thank Director, CSIR-NGRI for his permission to publish this work. The first author is grateful to CSIR-NGRI for funding Senior Project Fellowship and AcSIR for academic guidance. The second Author express his sincere thanks to Department of Applied Geophysics, Indian School of Mines, Dhanbad and Student Affairs Committee, CSIR-NGRI.