

Stochastic inversion of Post-stack seismic data using fractal-based initial model

Abhishek Dubey, Arka Das*, Kalachand Sain

CSIR-National Geophysical Research Institute, Uppal Road, Hyderabad, India

arkadas.ism@gmail.com

Keywords

Stochastic Inversion, fractal-based initial model, Hurst coefficient, Genetic Algorithm

Summary

Stochastic inversion has been employed to the post-stack seismic data using fractal-based initial model to enhance the resolution by integrating with high resolution well log data. A synthetic initial model of reflectivity series has been developed using statistical parameters like mean, standard deviation and the Hurst coefficient of well log data. Further, the initial model is globally optimized using Genetic algorithm with reflectivity series obtained from both seismic and well log data simultaneously. The final synthetic reflectivity series of three CDPs (1661, 1662 and 1663) adjacent to well log (at CDP 1662) show high correlation and less error, exhibiting the higher frequency components or enhanced resolution.

Introduction

Inversion of seismic data plays a vital role in reservoir characterization. The reflectivity series derived from low frequency seismic section has very poor resolution as the high frequency content gets attenuated. On the other hand, well log data have high vertical resolution, but lacks horizontal resolution. And due to the high cost of drilling, well log data are limited. Thus, a stochastic inversion to integrate seismic and well data to produce higher resolution seismic data helps in reservoir characterization (Srivastava et al., 2010).

Theory and Method

The whole exercise has been carried out on the 2D seismic reflection data and well log data of NGHP-01-9A well in the Mahanadi offshore basin (Sain et al., 2012) (Figure 1). Workflow given in Figure 2 has been followed. The Post-stack seismic data has been used in our study. Statistical deconvolution on the seismic data has been used to find the reflectivity series. The reflectivity series has been calculated

using the sonic and density log data. The log data provides high frequency content.

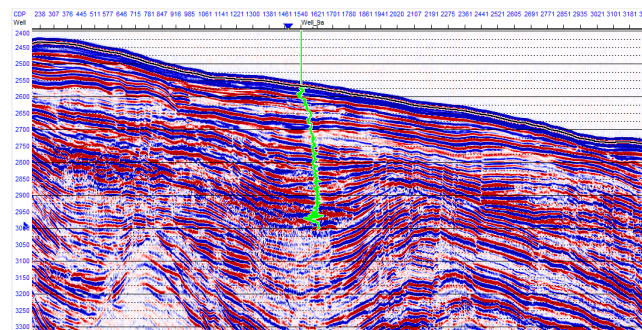


Figure 1. Seismic section of Mahanadi Basin

Computation of the mean, variance, and the Hurst coefficient of the reflectivity series has been done from the log data. The Hurst coefficient is the scaling exponent for the power law (scaling) behavior which is followed by power spectrum, variogram and covariance of well logs (Hewett, 1986; Emanuel et al., 1987; Hardy, 1992; Dimri, 2000; Dimri, 2005). Several methods are available for computing the Hurst coefficients (Caccia et al., 1997; Turcotte, 1997; Chamoli et al., 2007). To compute the Hurst coefficient, R/S analysis (Hurst et al. 1965) was used.

Initial synthetic reflectivity series is created by generating random numbers, keeping the mean and variance same as the reflectivity series obtained from the well log data. This synthetic reflectivity series is then globally optimized using the genetic algorithm (Sen, Stoffa, 1995) with both the reflectivity series obtained from seismic data at each CDP and well log data simultaneously.

The objective function for the optimization is:

$$E = a * \sum |d_{obs} - d_{cal}| + b * \sum |\mu_{obs} - \mu_{cal}| + c * \sum |\sigma_{obs} - \sigma_{cal}| + d * \sum |H_{obs} - H_{cal}|$$

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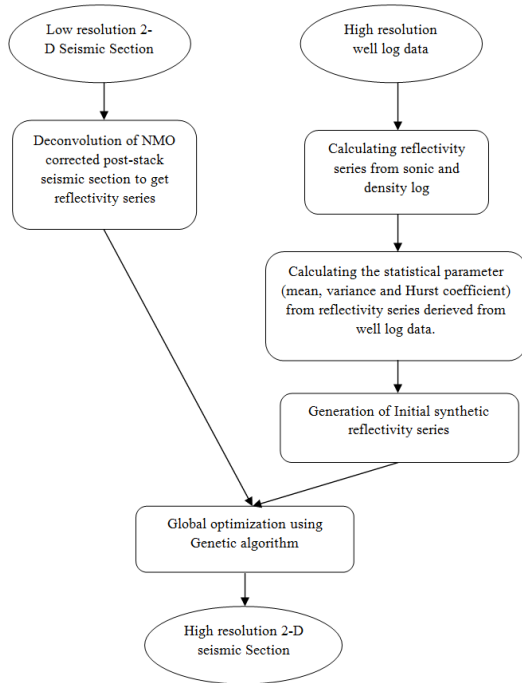


Figure 2. Computational Workflow

where d_{obs} , μ_{obs} , σ_{obs} , H_{obs} are the reflection coefficient obtained from seismic section, mean, standard deviation and Hurst coefficient from well log data. d_{cal} , μ_{cal} , σ_{cal} , H_{cal} are reflection coefficient, mean, standard deviation and Hurst coefficient from synthetic reflectivity series. The values a, b, c and d are weighting factors, $|l|$ represents absolute data value and the sum is over the number of data points. For optimization problem, a, b, c and d are obtained by trial and error.

Results

After having applied the stochastic inversion to the 2-D seismic data (Figure 3(a)), we generate a high frequency reflectivity section (Figure 3(b)).

High correlation coefficient is found between well log data at CDP 1662 (Figure 4) and synthetic reflectivity series for three adjacent traces of CDP 1661 (Figure 5a), 1662 (Figure 5b), 1663 (Figure 5c) respectively using above given methodology.

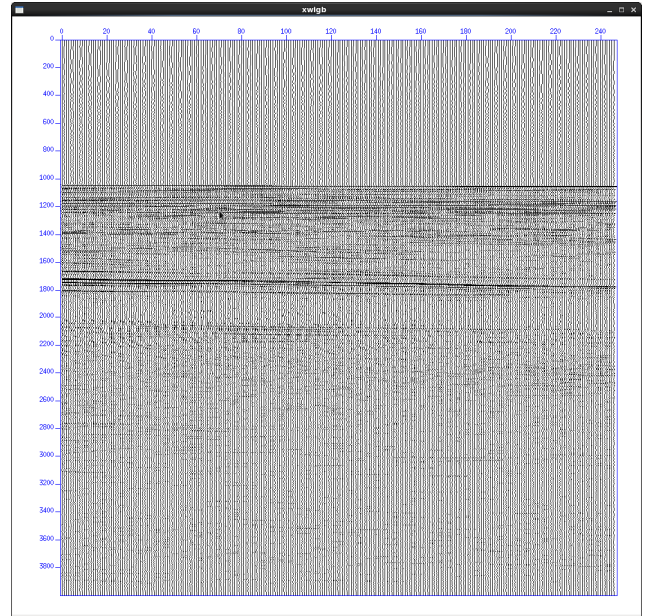


Figure 3 (a). Wiggle plot of original reflectivity section

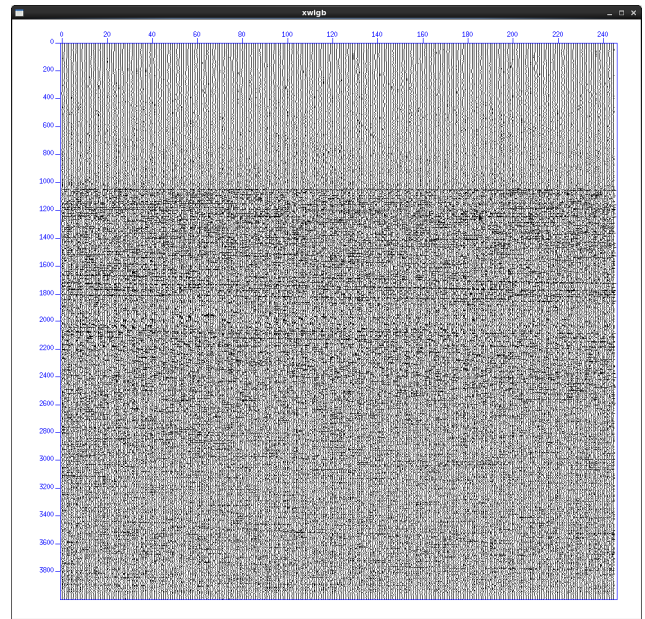


Figure 3(b). Wiggle plot of reflectivity section after stochastic inversion of poststack seismic data using fractal-based initial model

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Table 1: Absolute Error of mean, variance and Hurst coefficient and Correlation Coefficient between Synthetic reflectivity series trace and reflectivity series trace from well log.

	Absolute Error	Correlation Coefficient
Trace 1 (CDP 1661)	0.0571	0.9968
Trace 2 (CDP 1662)	0.0730	0.9953
Trace 3 (CDP 1663)	0.0801	0.9984

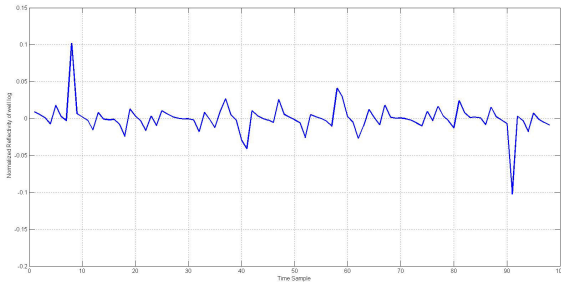


Figure 4. Original Reflectivity Series of well log at CDP 1662

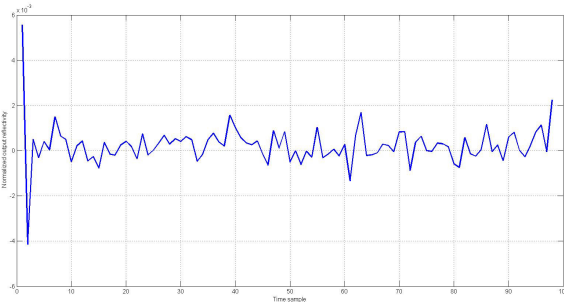


Figure 5 (a) Reflectivity series of output trace 1 at CDP 1661

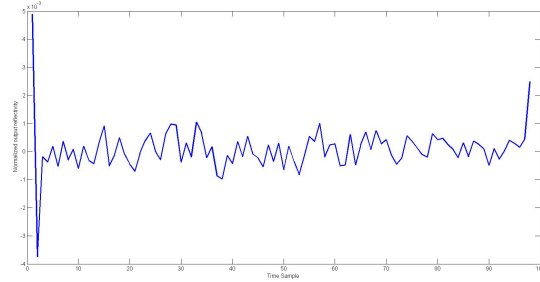


Figure 5 (b) Reflectivity series of output trace 2 at CDP 1662

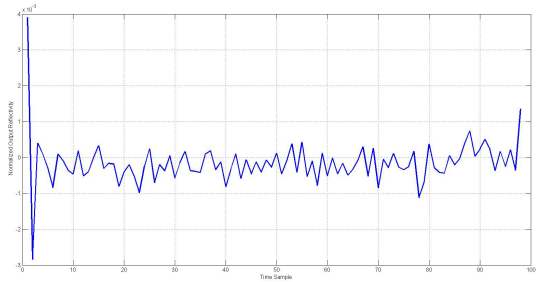


Figure 5 (c) Reflectivity series of output trace 3 at CDP 1663

Conclusions

We have got high correlation and low error between the synthetic reflectivity series and well log data. Stochastic inversion of post-stack seismic data using fractal-based initial model helps in increasing the resolution of seismic section by incorporating higher frequency content from well log data. Thus, this approach helps for detecting and delineating thinner spatial reservoir units.

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