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Model based seismic inversion using non-Gaussian autoregressive moving average initial model

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Summary

Often exploration seismic data lacks low and high frequency band signals. The low frequency information provides crucial information about the mean model. Thus, estimation of absolute models using inversion schemes is difficult in case of band limited seismic data. We present a new method to synthesize initial model for inversion of seismic data using autoregressive and moving average modeling. The technique uses available well logs to estimate ARMA model. The estimated ARMA models are used to synthesize initial model as an input to the inversion algorithm. The use of ARMA based modeling ensures realistic frequency band in the initial model which are close to the frequency band available in the well log. The inversion is carried out using very fast simulated annealing (VFSA) technique. This technique offers directed Monte Carlo search of the model space. ARMA based initial model facilitates better search of the models residing in the null space. The method has been tested on synthetic and real data.

Introduction

Seismic inversion is becoming a common tool for the modeling of seismic data. Inversion results provide more meaningful results in terms of physical properties of the subsurface and add great value in reservoir characterization. Though, well logs present accurate information about the petrophysical properties of a subsurface reservoir, spatial description of a reservoir at the well log scale is not available due to limited wells. Therefore, seismic data being most continuous information available (although at a lower vertical resolution), inversion of seismic data provides map of the lateral and vertical variation of physical properties. Such physical property maps are very important for the understanding and development of the reservoir. Seismic inversion is a process which converts seismic information into petrophysical property such as acoustic impedance and shear impedance (Sen, 2006) which are then mapped to reservoir characteristics.

The common inversion methods fall under the category of deterministic inversion and their results are average estimates of the subsurface properties (Dimri, 1992; Torres-Verdin et. al, 1999; Francis, 2006a,b). Further, inversion results are devoid of low and high frequencies due to the band limitation of the seismic data and thus falls way below the resolution desired by reservoir engineers. Increasing demand of high resolution results for reservoir characterization needs more accurate and high resolution methods of parameter estimation. Another category of inversion methods known as stochastic inversion methods provide the solution to some extent. The accuracy and reliability of stochastic estimate depends on the density of the well logs. However, using a realistic high resolution initial model in stochastic inversion one can achieve high resolution results. Stochastic methods exploit the high vertical resolution from well logs and horizontal resolution from seismic data to provide the high resolution subsurface model estimates.

Theory

ARMA system identification with only output measurements is a well-defined problem in several science and engineering areas such as speech signal processing, adaptive filtering, and spectral estimation. Various algorithms have been developed for estimating the parameters of a general ARMA model (Cadzow, 1982; Giannakis and Mendel, 1989; Lii, 1990; Pillai et al. 1993). Most of these algorithms are based on second-order statistics. The use of second-order statistical information is

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motivated by the implicit assumption that the processes are Gaussian. However, most real world signals are non-Gaussian. Hence, second-order based techniques often have serious difficulties in practice (Aboutajdine et al. 1996). That is, second-order spectral estimators are inherently phase blind and sensitive to additive noise. Signal processing with higher order statistics, known as cumulants, have attracted considerable attention in the literature (Feng and Chi, 1999; Giannakis and Mendal, 1990; Tugnait, 1994). There are several motivations behind this interest. First, higher order cumulants are blind (Mendal, 1991) to all kinds of Gaussian noise; that is, higher order statistics for a Gaussian process are identically zero. Hence, when the processed signal is non-Gaussian and the additive noise is Gaussian, the noise will vanish in the cumulant domain. In this paper we present application of non-Gaussian ARMA model to generate initial model for acoustic impedance inversion. Further this initial model is used in Very Fast Simulated Annealing (VFSA) optimization technique to obtain the model parameters. Here, we present application of the method on a demo data set given in STRATA module of Hampson and Russell software of CGG Veritas. The data consists of post stack seismic section with three well logs. Theoretical details of non-Gaussian ARMA is given in Al-Smadi and Alshamali (2002) and VFSA is detailed in the research work of many geophysicists few of them are Sen and Stoffa (1995); Srivastava and Sen (2009).

Examples

We test our algorithm on a known data set - poststack seismic data and well logs given as a demo data set in the Strata module of Hampson Russell software. We selected a cross line (number 42) that has 3 wells which can be used to constrain the analysis. The seismic data along cross line 42 is shown in figure (1). The well log used in the inversion analysis is shown in figure (2). We picked two horizons shown as top and bottom horizons in the seismic data for our analysis (figure 1). After a horizon pick, we performed well tie at all the three well locations available across the seismic line. Subsequent to well tie, we extracted a wavelet using seismic and well log data. As a part of data preparation for a model based inversion, available acoustic impedance logs were interpolated and extrapolated along the picked horizons to generate acoustic impedance corresponding to each seismic trace. Interpolated well logs serve as input to our inversion algorithm for estimating initial model using non-Gaussian ARMA model for use in our stochastic inversion. Smooth logs are used to choose model bounds in the stochastic inversion.

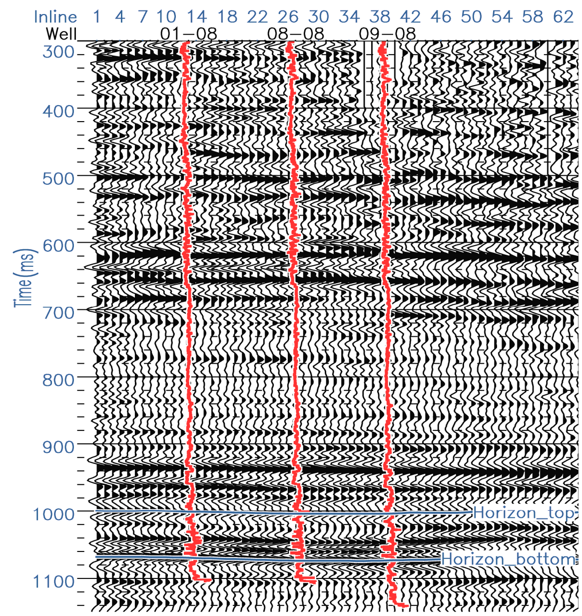

Figure 1: Poststack seismic data used in inversion, Red curves show available three well logs. Horizon top and bottom are marked by blue line shows zone of interest. Seismic data between 980ms to 1110 ms has been used for inversion. (Courtesy, D. Hampson and B. Russell).

Stochastic inversion result at a well location is shown in figure (3a,b), this shows model estimate (acoustic impedance), data fit and comparison of stochastic model estimate.

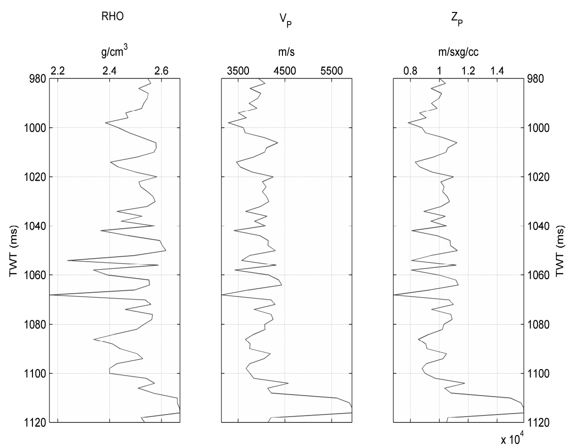

Figure 2: Computed acoustic impedance (right panel) using density log (left panel) and P-wave (middle panel) at well -2 located at Xline-42, Iline-27. Zone of interest is between 980-1120 ms. Analysis for inversion parameters are done using this well log.

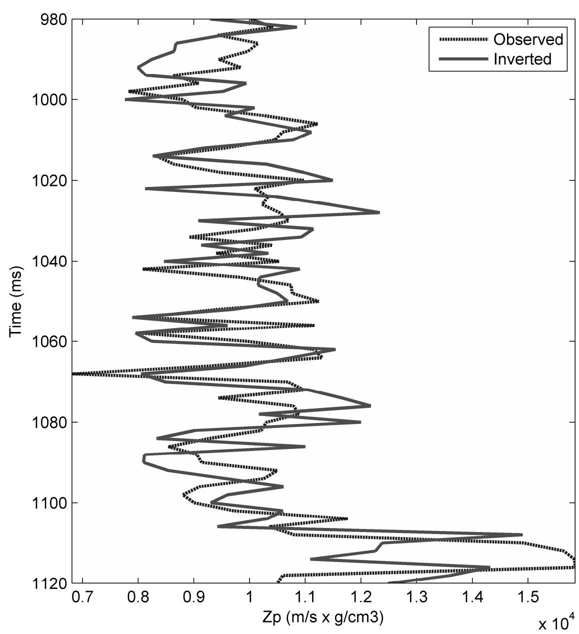

Figure 3: Estimate of acoustic impedance using our stochastic inversion algorithm at a well location. Note the high resolution characteristic of the results which picks major peaks at 1040, 1055 and 1068 ms. At the well location, inversion analysis was performed between 980 to 1120 ms interval.

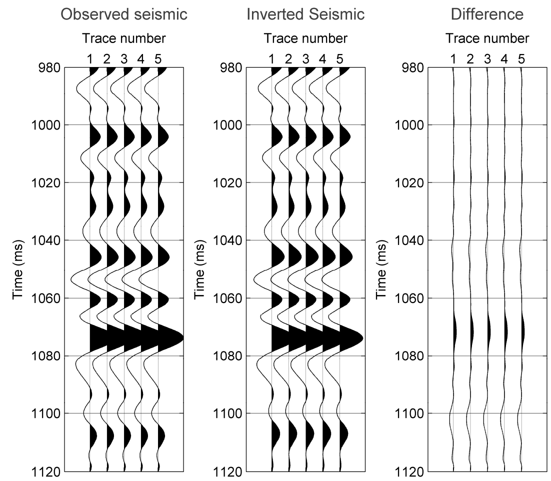

Figure 4: Data match and residual at a well location using our stochastic inversion algorithm. The left panel shows observed seismic trace at well location, middle panel is the seismic obtained from the best fit model using stochastic inversion and the right panel shows data residual. A single trace is displayed five times.

The inversion analysis was carried out for the entire line using the method proposed in this paper. An inversion result for the entire line is shown in figure (5) and figure (6). Figure (5) shows estimated acoustic impedance and figure (6) shows data match. Further, the continuity of the events starting at 1020, 1040, and 1060 ms is better defined in the stochastic inversion results (figure 5). The vertical resolution in our stochastic inversion results is consistent with the well log measurements and helps to delineate thin beds.

Conclusions

A stochastic inversion using non-Gaussian ARMA prior facilitates to achieve models with realistic frequency band similar to those observed at a well location. It is shown in case of poststack seismic inversion that it is possible to accurately detect and delineate spatial reservoir units (thin beds beyond seismic resolution limit) by our method, which would otherwise go undetected. Also ARMA based prior provides an intelligent initial guess to the VFSA modeling module which facilitates faster convergence.

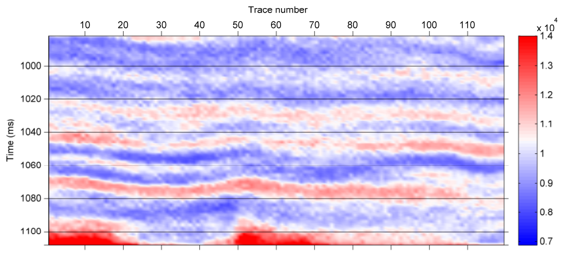

Figure 5: Acoustic impedance along a line using stochastic inversion algorithm. Also poor continuity of the event at 1030 ms after trace number 70 is obvious. Colour bar shows acoustic impedance values in (m/s x g/cc).

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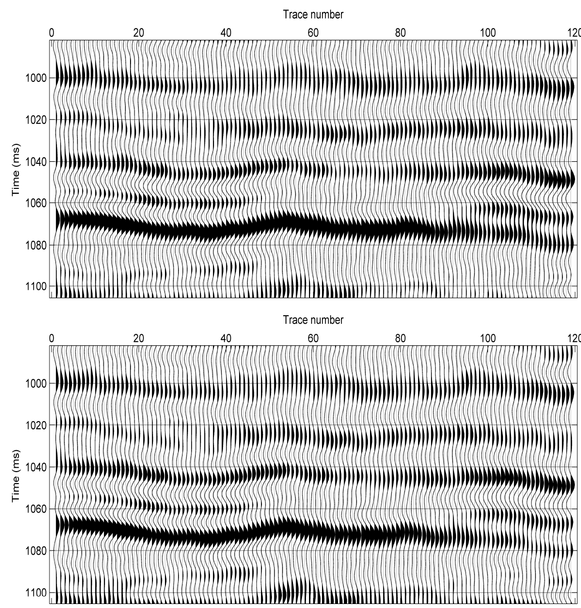

Figure 6: The input seismic data (observed seismic) is shown in the upper panel; lower panel shows synthetic seismic data corresponding to the best fit model derived by our stochastic inversion algorithm.

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