Constraining Stochastic Inversion with Frequency Domain Seismic Signature for Seismically Thin-bed Interpretation

EkoWidi Purnomo and Deva Prasad Ghosh
Center for Seismic Imaging, Faculty of Petroleum Geosciences UniversitiTeknologi PETRONAS Malaysia
ekowidip@gmail.com

Abstract. An alternative technique in interpreting thin-bed structure has been developed. The technique involved stochastic inversions which use frequency domain energy spectral attribute as a constraint instead of time domain seismic amplitude. Maximum Amplitude Weighed Integrated Energy Spectra is a proposed energy spectral attribute which was used to constrain the stochastic process. Amplitude Weighed Integrated Energy Spectra is a deployed seismic attribute obtained by multiplying integrated energy spectra with maximum amplitude of a seismic trace. It is shown that Amplitude Weighed Integrated Energy Spectra provides a more separable signature in responding to bed thickness changes than seismic signature. A lower degree of ambiguity of Amplitude Weighed Integrated Energy Spectra in sensing thin-bed seismic is a potential method of reducing thin bed interpretation uncertainty. Qualitatively, Amplitude Weighed Integrated Energy Spectra is capable of showing one of the reported very thin meandered channel complexes of gas reservoir of Stratton field which is difficult to be seen in seismic amplitude. In this research, Amplitude Weighed Integrated Energy Spectra is incorporated in a stochastic seismic inversion to improve both accuracy and precision (certainty) of thin-bed interpretation. Synthetic data testing shows that the proposed method significantly improves both accuracy and precision of a single wedge model seismic inversion. The thickness and reflection coefficient are estimated more accurately, although limited information is used. The proposed method was tested to invert a structurally subtle gas production zone of Stratton field. Confirmed by well log data, a cross section of inverted impedance showed that some channel complex structure of gas reservoirs are able to be imaged.

1. Introduction

Reservoir characterization is subject to uncertainty. One of the biggest uncertainty contributors is structural interpretation. Seismic inversion is a widely used tool to define reservoir structure. However, the band limited frequency character of seismic data precludes seismic to recover all frequency band of reservoir. Interpretation of reservoir structure beyond the seismic band is uncertain and difficult. Such structure can not be resolved by seismic. Thin bed is defined as reservoir with thickness below the seismic resolution. When the reservoir thickness goes to below seismic resolution (tuning), the seismic response are remain unchanged. For any reservoir thinner than the tuning thickness, there are infinite numbers of reservoir thickness and impedance combinations that give the same seismic amplitude.
Stochastic inversion [1] is a model-based seismic inversion which commonly used to handle the reservoir characterization uncertainty. Stochastic inversion uses a forward model to generate synthetic seismic data as part of the inversion algorithm. Several or may be a lot of different synthetic seismic are generated and then comparing to the real seismic to be inverted. The ‘good fit’ synthetic seismic, then are kept as output of the inversion and the ‘bad fit’ one are discarded. There are different families of stochastic inversion algorithms, from simple acceptance/rejection schemes to more complex Bayesian formulation [2].

To model a higher-than-seismic frequencies, where thin-bed structure associate with, a blocky model earth’s impedance is described. This is not valid assumption actually; however uniqueness issue is come from here. Theoretically, stochastic inversion outputs all of the acceptable property models (or a representative distribution of those models) [1]. But, reported by Gunning et.al [2], that stochastic inversion still has problem when inverting thin-bed structure. Thin-bed structures are precluded in stochastic seismic inversion result.

This paper aims to improve the uniqueness (certainty) of thin-bed interpretation and its accuracy as well. The aim will be accomplished through three step of work i.e. deploying energy spectral-based thin-bed seismic attribute, developing thickness-reflectivity coefficient modeland constructing a stochastic inversion with spectral attribute used as constraint.

2. Theory and Methodology

2.1. Maximum Amplitude Weighted Integrated Energy Spectra Deployment

The bed thickness is related to energy spectra of seismic. As the peak frequency is shifted when the bed going below seismic tuning, the integrated energy spectra (INTENS) can consistently detect the bed thickness [3]. Mathematically, an Integrated Energy Spectra of a time series data at frequency f is defined as:

$$E(f) = 100 \frac{\int_{f_l}^{f_u} A(f)A^*(f)df}{\int_{f_l}^{f_u} A(f)A^*(f)df}$$  \hspace{1cm} (1)$$

where $A(f)$ and $A^*(f)$ are the amplitude spectra of the time series at frequency f and the conjugate consecutively. $f_l$ and $f_u$ is the lowest and highest frequency value consecutively.

Maximum weighed integrated energy spectra (MAWIES) is a new seismic attribute which is developed based on previous technique of estimating thin-bed thickness [4][5] and seismic attribute combination [6][7]. The attribute is product of integrated energy spectra (Eq. 1) and its corresponding maximum amplitude. Mathematically, the attribute can be expressed as:

![Figure 1. Bed-thickness response of Maximum Amplitude response (rect angled curve), Integrated Energy Spectra (diamoned curve) and Maximum Amplitude Weighed Integrated Energy Spectra (triangled curve).](image-url)
\[ E_{m}(f) = A_{m} \times E(f) \]  
\[ \text{where } E_{m} \text{ is the new attribute, } A_{m} \text{ is maximum amplitude, } E \text{ is Integrated Energy Spectra and } f \text{ is frequency.} \]

Comparing with the integrated energy spectra, the new attribute has more linear response to layer thickness changes (Fig 1). It indicates that Maximum Amplitude Weighed Integrated Energy Spectra is a good probe of bed thickness.

2.2. Constraining Stochastic Inversion with Maximum Amplitude Weighed Integrated Energy Spectra

The stochastic inversion proposed is build base on Bayesian theorem as following

\[ P(RC, d|E_{m}) = \frac{P(E_{m}|RC,d) \cdot P(RC,d)}{P(E_{m})} \]  
\[ \text{Where } P() \text{ expresses the probability density function pdf. RC refers to Reflectivity Coefficient between layer interfaces, } d \text{ refer to thickness of layer. } P(E_{m}|RC,d) \text{ is posterior model of } RC \text{ and } d, \text{ as the result of the inversion. } P(E_{m}|RC,d) \text{ is likelihood model which defines degree of fit between Maximum Amplitude Weighed Integrated Energy Spectra of true seismic with Maximum Amplitude Weighed Integrated Energy Spectra of synthetic seismic. The synthetic seismic is generated by convolution between reflectivity model (combination of RC and thickness) with an assigned wavelet. } P(RC,d) \text{ is prior model of modeled reflectivity. And, } P(E_{m}) \text{ is distribution function of true Maximum Amplitude Weighed Integrated Energy Spectra. The inversion aim to solve the Eq. 3 including analysis of posterior distribution resulted. Markov Chain Monte Carlo is used to populate the posterior model.} \]

3. Result and Discussion

3.1. Single Trace Synthetic Model Inversion

The proposed method has tested to invert a seismic trace from a thin porous sand with velocity of 3048 m/s and density of 2.3 g/cc encased in a non porous sand with velocity of 4267 m/s and of 2.502 g/cc. The time thickness of encased is 4 ms, while the seismic tuning thickness [4] is about 16 ms. Figure 7.(i) shows ‘spaghetti’ plot of the inversion.
Comparing to the prior model (before inversion) Figure 2.(i). (a) and (b), the narrower blue curves in spaghetti of posterior model (after inversion) Figure 2.(i). (c) and (d), indicate that the accuracy and precision of thickness and impedance are increased during the inversion.

Figure 2.(ii) is a quantitative analysis of posterior model resulted in Figure 2.(i). The analysis is commonly called marginalization. Twenty thickness estimations are extracted from both of twenty posterior and twenty prior models. The distributions of estimated thickness are then plotted and analyzed. Distribution’s mean of 3.0952 and standard deviation of 1.8683 is resulted from prior model. In different, mean of 2.8571 and standard deviation of 0.6547 are resulted from posterior distribution. The mean of distribution expresses the thickness estimation and the standard deviation quantifies the uncertainty or the estimation error. Comparing to the true thickness of 2, the mean of posterior distribution is closer to the true thickness than the prior’s. It indicates that the inversion increases the accuracy of thickness estimation. The smaller standard deviation of posterior distribution than prior’s informs that the inversion improve the precision in other word reduce the uncertainty. Figure 2.(iii) shows analyzes of impedance estimation at time depth level of encased porous sand. From a real impedance of -0.2073, prior model estimates -0.04381 with standard deviation 0.22558 and posterior model estimates -0.19714 with standard deviation of 0.10996. Again, the distribution shows that the accuracy and precision of relative impedance estimation are increased by the inversion.

3.2. Real Seismic Data Inversion

The proposed stochastic inversion method has been tested to invert the gas production zone 3D seismic of Stratton field [8][9]. The inverted seismic covers a time window from 1633 to 1700 millisecond time depth, where which two very close F37 and F39 reservoir are located. Hardage et.al [8] reported that the F37 reservoir was approximately 20 ft (6 m) above the F39, which is only 4 ms (2 seismic sampling rates) two-way travel time different. The shallowest and deepest marker of F37 reservoir is identified 1633 and 1667 millisecond, respectively. While the F39 reservoir is at depth 1639 and 1673 millisecond. Through a static pressure study, Hardage et.al [8] found that both two reservoirs are segregated into at least 4 compartments. All compartments are very thin and difficult to be seen in seismic data. Twenty realizations have been inference from every twenty prior impedance sample. Figure 3 shows a cross section of one of realizations cube. The cross section is drawn along cross line number 154 where the well number 7 (Well#7) and 8 (Well#8) located. Well#7 marks the F37 reservoir at 1631 ms and 1639 ms for F39 reservoir, while Well#8 marks the F37 reservoir at 1644 ms and 1653 ms for F39 reservoir. It is shown very interesting in Figure 3 (shown by white ellipses), that both the well markers are coinciding with relatively similar inverted impedance value.

Another interesting figure is shown by Well#10. Well#10 is located at cross cline number 158, 4 trace intervals different with Well#7 and Well#8 locations. It is interesting because the F37 and F39 marker at Well#10 (1650 and 1662 ms) coincide with similar impedance value at Well#7 and Well#8. This leads a lateral extension interpretation of F37 and F39 reservoir from cross line number 154 to 158 along in line number of Well#10. It can be concluded that the F37 and F39 reservoir are identified by this inversion and possible to further characterization.

Figure 4 shows the probability analysis of ’net reservoir volume’ estimation of F37 and F39 reservoirs when 0 to 0.05 relative AI range is taken as reservoir character. That is very rough volume estimation. The estimation calculates the run sum impedance ratio between reservoir and non reservoir from whole volume of inverted impedance. The ratios are calculated from all of twenty realization volume and the distribution then analyzed. The estimated P90 ‘net-volume’ is the "pessimistic" ‘net-volume’ that is exceeded by 90% of the realizations (there is a 90% chance the ‘net-volume’ will be achieved). The estimated P10 reservoir ‘net-volume’ is the "optimistic" ‘net-volume’ that is exceeded by only 10% of the realizations. There might be many very different realizations that give that P90 or that P10 ‘net-volume’.
Figure 3. Cross section of cross-line 154 of inverted F37-F39 reservoir seismic. Seismic section (above) and Inverted Relatif AI (below). Well log data are Spontaneous Potential (SP), full-line, and Gamma Ray (GR), dash-line. Black Ellipses indicate reservoir’s well marker.

Figure 4. Cumulative Density Function of reservoir’s ‘Net-Volume’ if range of 0 to 0.05 runsum AI is taken for reservoir character.
4. Conclusion

A new energy spectral attribute has been deployed. The deployment is done by combining the rapid changes of maximum absolute amplitude and wide range linearity of integrated energy spectra in responding thin-bed thickness changes. The new attribute is a product of integrated energy spectral and its maximum absolute amplitude. The attribute is called Maximum Amplitude Weighted Integrated Energy Spectra (Maximum Amplitude Weighed Integrated Energy Spectra). The multiplication makes integrated energy spectra weighted and, in turn, makes its signature more separable to detect thin-bed thickness changes. The derivative of the attribute, i.e. Maximum Amplitude Weighed Integrated Energy Spectra at dominant frequency, is capable of qualitatively image a complex thin channels structure better than seismic amplitude.

A new approach of stochastic seismic inversion has been developed in order to improve both accuracy and precision of thin-bed structure interpretation. The technique includes building a prior model utilizing apparent indicator from seismic data and constraining stochastic inversion with Maximum Amplitude Weighed Integrated Energy Spectra. Seismic amplitude and extracted wavelet is two main indicators which used to constrain the development of prior model. Constraining inversion with Maximum Amplitude Weighed Integrated Energy Spectra means utilizing the Maximum Amplitude Weighed Integrated Energy Spectra to control the ‘degree of match’ of model with the data. Bayesian theorem and Markov Chain Monte Carlo is side by side used to generate realization and sampling the generated realization, respectively. Twenty realizations have been generated from twenty simulations of twenty samples both for synthetic model and real seismic data. The result shows that the technique improves both accuracy and precision of thin bed interpretation. Improving accuracy affects to increasing resolution, while precision affects the reducing uncertainty of interpretation. Many reservoir characterization scenarios then can be built from the result of inversion.

Acknowledgment

Authors thank to UniversitiTeknologi PETRONAS for supporting the research.

References

[1] Cooke D. and Cant J., 2010, Model-based Seismic Inversion: Comparing deterministic and probabilistic approaches, CSEG Recorder p 28-39
[2] Gunning, J. and Glinsky M. E., 2004, Delivery: an open-source model-based Bayesian seismic inversion program, Computers & Geosciences 30.
[3] Marangakis, A. J. K., Costain, and C. Coruh, Use of integrated energy spectra for thin-layer recognition: Geophysics, Vol. 50, No. 3, p. 495-500, 1985.
[4] Kallweitth, R. S., and L. C. Wood. 1982, The limits of resolution of zero-phase wavelets: Geophysics, Vol. 47, No. 7, p. 1035-1046, 1982.
[5] Partyka, G.A., 2001, Seismic thickness estimation: three approaches, pros and cons: 70th Annual International Meeting Society of Exploration Geophysicists, Expanded Abstracts, 503-506.
[6] Taner, M.T., F. Koehler, and R. E. Sheriff, 1979, Complex seismic trace analysis: Geophysics, 44, 1041-1063.
[7] Ghosh D. P. et. al., 2007 Seismic Attributes add new dimension to prospect evaluation. SEG 2007 Denver
[8] Hardage, B. A., Levey R. A., Pendleton V., Simmons, J., and Edson R., 1994, A 3-D Seismic Case History Evaluating Fluvially Deposited Thin-Bed Reservoir in Gas-Producing Property: Geophysics, Vol. 59, No. 11, p. 1650-1665.
[9] Kerr, Dennis R., and Jirik, Lee A., 1990, Fluvial architecture and reservoir compartmentalization inthe Oligocene middle Frio formation, south Texas: Transactions of the Gulf Coast Association ofGeological Societies, Volume XL, p. 373–380.