Multivariate Formation Pressure Prediction with Seismic-derived Petrophysical Properties from Prestack AVO inversion and Poststack Seismic Motion Inversion

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Introduction

A new multivariate seismic formation pressure prediction methodology is presented, which incorporates high-resolution seismic velocity data from prestack AVO inversion, and petrophysical data (porosity and shale volume) derived from poststack seismic motion inversion. In contrast to traditional seismic formation prediction methods, the proposed methodology is based on a multivariate pressure prediction model and utilizes a trace-by-trace multivariate regression analysis on seismic-derived petrophysical properties to locally calibrate model parameters in order to make accurate predictions with higher resolution in both vertical and lateral directions.

Multivariate Model

The multivariate formation pressure prediction model proposed by Sayers (2003) is well balanced between conciseness and representativeness. Three petrophysical properties (velocity, porosity, and shale volume) are used to describe the variation of effective stress in this model:

$$V = a_0 - a_1\varphi - a_2C + a_3\sigma^B$$

The porosity term φ describes the degree of compaction while the shale volume term C describes the relative influence of different rock type.

Though proposed as a model that can only deal with abnormal pressure generated by compaction disequilibrium, it can be used in predicting abnormal pressure caused by fluid expansion when combined with the unloading model proposed by Bowers. The corresponding equation for unloading can be formulated as:

$$V = a_0 - a_1\varphi - a_2C + a_3\left[\sigma_{max}\left(\frac{\sigma}{\sigma_{max}}\right)^{\frac{1}{U}}\right]^B$$

Seismic Motion Inversion

Developed from traditional geostatistical inversion methodologies, Seismic Motion Inversion (SMI) is a inversion method that utilize thin bed tuning effect for determining and optimizing the structure of reflection coefficient and simulate the distribution of sand bodies. Lateral variation of seismic motion instead of traditional variogram is used to describe the spatial variation of reservoir.

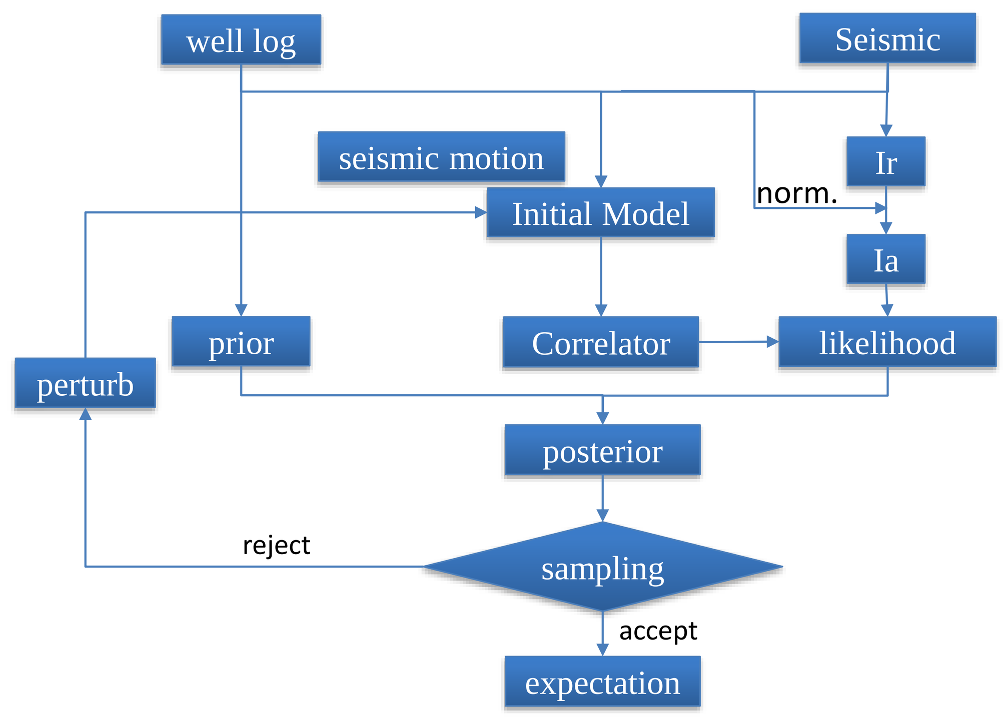


Fig 1. SMI workflow

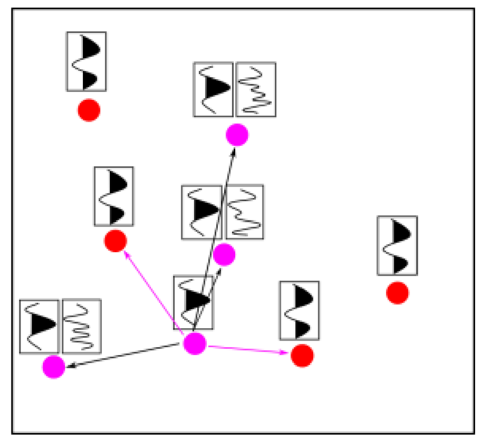


Fig 2. SMI samples according to wave motion similarity and distance to well location.

Methods

With prestack time migration velocity as initial velocity model, an AVO inversion was first applied to prestack dataset to obtain high-resolution seismic velocity with higher frequency that is to be used as the velocity input for seismic pressure prediction, and the density dataset to calculate accurate Overburden Pressure (OBP).

Porosity and shale volume are first interpreted on well logs, and then combined with poststack seismic data using SMI to build porosity and shale volume datasets for seismic prediction. A multivariate effective stress model is used to convert velocity, porosity and shale volume datasets to effective stress.

After a thorough study of the regional stratigraphic and sedimentary characteristics, a regional normally compacted interval model is built, and then the coefficients in the multivariate prediction model are determined in a trace-by-trace multivariate regression analysis on the petrophysical data. The coefficients are used to convert velocity, porosity and shale volume datasets to effective stress and then to calculate formation pressure with OBP.

Results

Strat from prestack time migration velocity, a MVCI is applied to the velocity dataset to minimize the error between low-frequency seismic velocity and up-scaled well log acoustic velocity.

Then this modified velocity dataset is used as the initial velocity model for AVO inversion of prestack seismic dataset which will generate high-frequency AVO velocity.

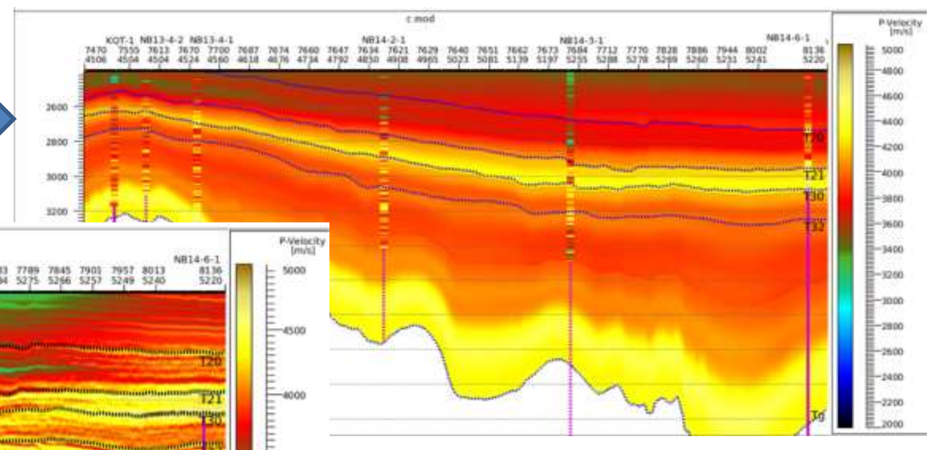


Fig 3. low-frequency interval velocity generated by MVCI.

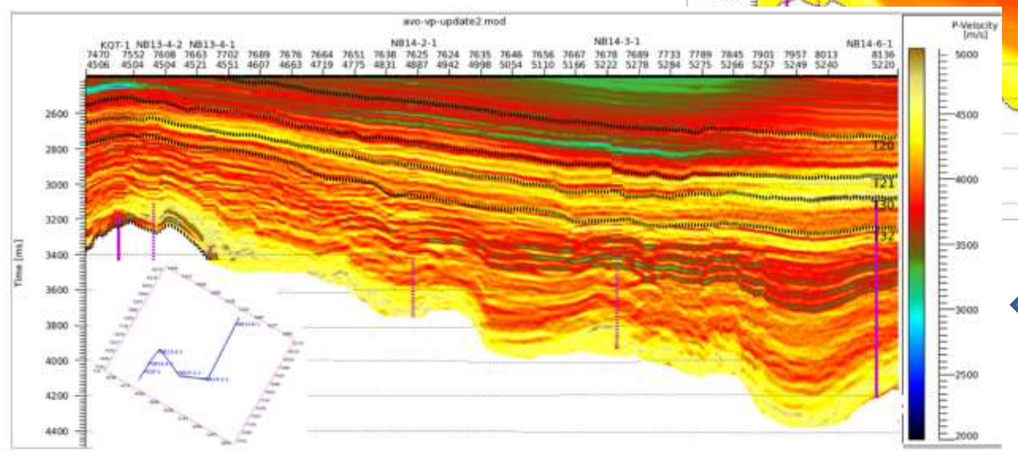
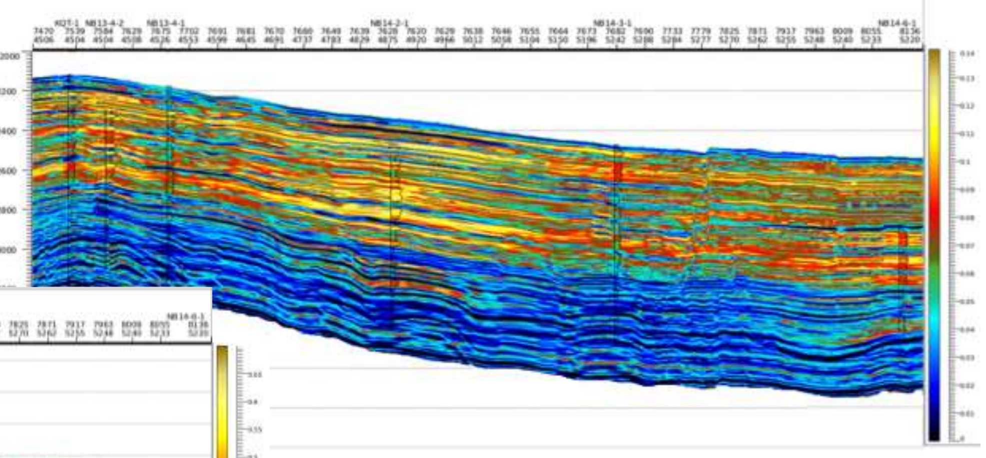


Fig 4. high-frequency velocity data obtained from prestack AVO analysis..

With porosity and shale volume from well logging as input, SMI was performed on poststack seismic dataset to construct 3-D porosity and shale volume dataset.



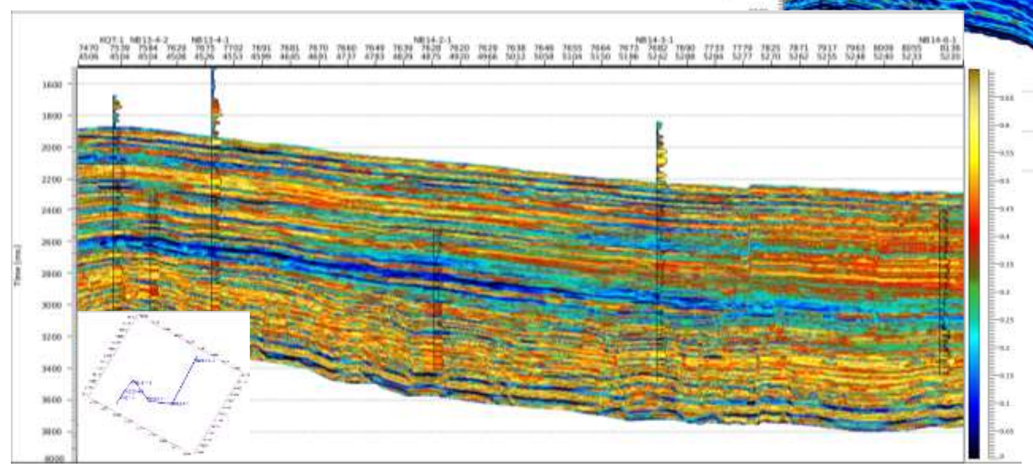


Fig 5. Porosity (upper) and Shale Volume (left) dataset obtained from SMI

Results

One of the difficulties in applying multivariate prediction model to seismic pressure prediction is that very few pressure measurements can be used to calibrate the model which has quite numerous coefficients.

Our solution here is to apply a multivariate regression on data within normal compaction zone to obtain coefficients for loading model on each CDP. With a trace-by-trace fashion, a coefficient surface with 5 coefficient value on each point is constructed.

For unloading model, the U parameter is first determined on each well within the area. Assuming pressure varies smoothly (on the scale of research), a U distribution can be constructed with geostatistical algorithms.

With coefficients determined, the effective stress cube can be calculated, with OBP cube, the predicted pressure is obtained using Terzaghi relation.

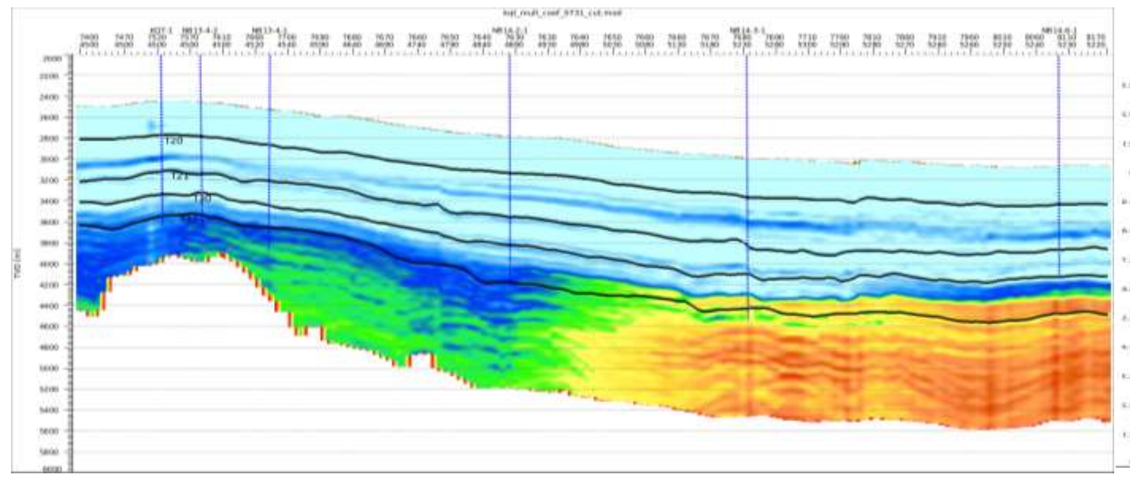


Fig 6. Pressure prediction using the proposed methodology

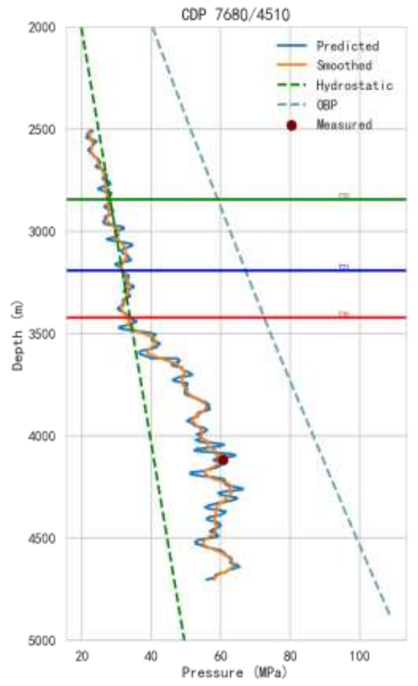


Fig 7. Predicted pressure on CDP adjacent to well location with measured pressure on well

Well name	MD (m)	TVDSS (m)	Measured (MPa)	Predicted (MPa)	abs Error (MPa)	rel Error (%)
OC13-4-1	4159.5	4118.5	60.605	60.608	0.003	0.005
OC13-4-2	4120.8	4079.8	48.132	48.124	-0.008	-0.017
OC14-2-1	4237.9	4196.9	50.378	50.599	0.221	0.439
	4194.6	4153.6	42.160	45.504	3.344	7.932
	4116.3	4075.3	42.912	47.071	4.159	9.692
OC14-3-1	4557.5	4519.5	66.926	66.924	-0.002	-0.003
LRU-1	3545	3522	38.305	38.007	-0.298	-0.778
	3567	3544	41.325	38.546	-2.779	-6.725
	3816	3793	46.088	44.424	-1.664	-3.610
	4300	4277	51.969	55.914	3.945	7.591
average	3.679%					

Table 1. Error between Predicted pressure at well locations and the corresponding prediction in regard to measured pressure data obtained from well testing(DST and RFT).

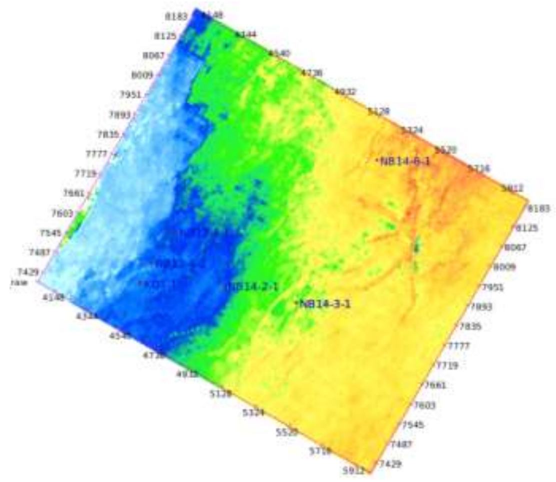


Fig 8. Horizon slice of predicted pressure cube

Conclusions

Application of the proposed methodology to an research area in East China Sea has shown that the method:

- bridge the gap between seismic and well log pressure prediction;
- give prediction values close to pressure measurements from well testing;
- provide more detailed pressure variation both vertically and horizontally.

Future works:

An Uncertainty Analysis will be included in this pressure prediction workflow, not only as a quality control process but also as a measure of how reliable the predicted pressure data is when used in well planning and casing design.

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References

1. Sayers, C. M., et al. "Use of reflection tomography to predict pore pressure in overpressured reservoir sands" SEG Technical Program Expanded Abstracts 22.1(2003):1362.
2. Gu, W., et al. "Application of seismic motion inversion technology in thin reservoir prediction: A case study of the thin sandstone gas reservoir in the B area of Junggar Basin" Natural Gas Geoscience 27.11(2016).

py GeoPressure

Code for basic part of this project has been published as an open source python package -- pyGeoPressure.
https://github.com/whimian/pyGeoPressure