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Sample Size Automation in a Pseudo-random Model Uncertainty Workflow

T. Martin[1]*

[1]PGS

Summary

Velocity model building (VMB) using tomography produces one credible realization of an earth model, which, in turn, generates one conceivable subsurface image. The inversion, by its nature, is highly non-linear, and can lead to uncertainty with a single model and image approach. Uncertainty can be quantified by using a model population, rather than a single realization. In this scenario, all models must equally explain the data by producing flat gathers from the inversion. Defining what is an appropriate sample size for a nonlinear system using a pseudo-random approach to model uncertainty is critical for cost and turnaround. We automate a real-time constraint on the expanding model population using statistical relevance to the attributes produced through the uncertainty process. Analysis using cumulative distribution functions (CDFs) of the deviation in the model population define an automated threshold. The sample size threshold is met when there is no additional statistical relevance for the output attributes; the process stops and the model uncertainty metrics defining spatial reliability of the data are output. We demonstrate this method on data from the North Sea.

Introduction

Velocity model building (VMB) using tomography produces a single realization of an earth model. When used with an imaging algorithm this creates one plausible subsurface image. The inversion, by its nature, is highly nonlinear and is dependent on sampling; accuracy of constraint measurements; geological impedance and the tomographic inversion parameters. Despite the expertise of the model builder, using the single model and image approach can lead to uncertainty, especially when considering field development, as volumetric estimations are based on a single realization from a nonlinear system.

Uncertainty can be quantified by using a model population, rather than a single realization. In this situation, all models must equally explain the data by producing flat gathers from the inversion. This approach can involve a significant population, and therefore have a cost-turnaround effect, even if performed after the final model building process has completed. It is therefore critical to impose an automated, real-time constraint on the model population.

Methodology

A methodology for understanding uncertainty is to use a significant model population rather than a single one. These models must all generate an equivalent product, based on a gather flatness metric, from the tomographic inversion. For this we use a pseudo-random approach to model uncertainty. The workflow uses repeated and randomized sampling of the model space to determine estimates of the uncertainty in any model (Bell et al., 2016). The arbitrary perturbations to the model are constrained by an automated measure of the wavelength and magnitude modifications recoverable by the data used for the inversion.

Once the model population is created, tomographic inversions are performed on each model within the set. These are all constrained by the same data and recover a random perturbation that is individually applied to each model in the population. Quantitative metrics are used to evaluate the effectiveness of the inversion in recovering the perturbation, and are used to refine the useable model population.

The model population is automatically constrained by the statistical relevance to the attributes produced. Analysis using cumulative distribution functions (CDFs) of the deviation in the model population define an automated threshold. The sample size threshold is met when there is no additional statistical relevance for the processes output attributes.

The entire model sample set is used to migrate the data, and statistical analysis across the total population generates the mean, variance and standard deviation volumes of the inverted velocity. Subsequent migrations utilizing the model population allow for error envelope analysis studies at key target interpretations, and the production of a volumetric depth error metric.

Example

An example of the integrated use of the flows metrics is presented in Figure 1. The model population variance cube generated with the uncertainty workflow is co-rendered on the underlying 3D seismic image along with the error envelope analysis for a given target horizon. Model population variance correlates with depth deviation error, and is most pronounced in the lee of the salt (Figure 1 orange arrows), where the chalk interval is both thickest and most affected by the salt intrusion. The combination of these features provides important information as to the local reliability of the seismic image.

The automated sample set approach was tested to determine what the appropriate sample set size is for this case study. Figure 2 shows the graphical representation of the convergence criteria for the CDF differences of the model population deviation through progressive additions to the sample set. It can be seen that the running difference of the deviation stabilizes after 60 models are used; more models do not improve the sample set statistics. Figure 3 shows, for one inline, the deviation using 10, 60 and 109 models for the population. As indicated in Figure 2, the deviation of the model population shows no significant change after 60 models are used for the sample set. The optimum cost-turnaround sample size was 60 models for the uncertainty analysis.

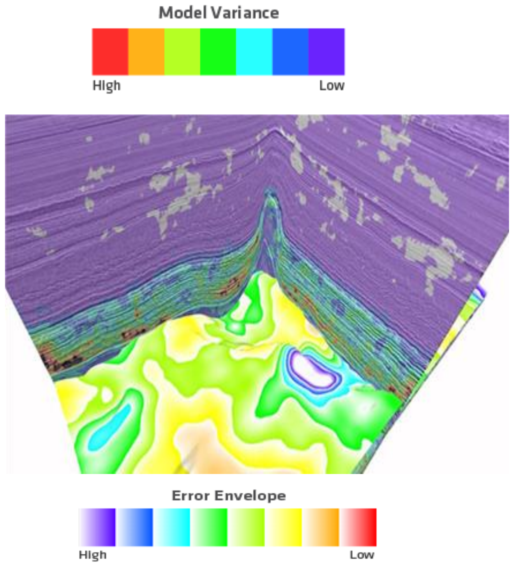

Figure 1 *Model variance is co-rendered on the seismic with an error envelope shown for a key horizon.*

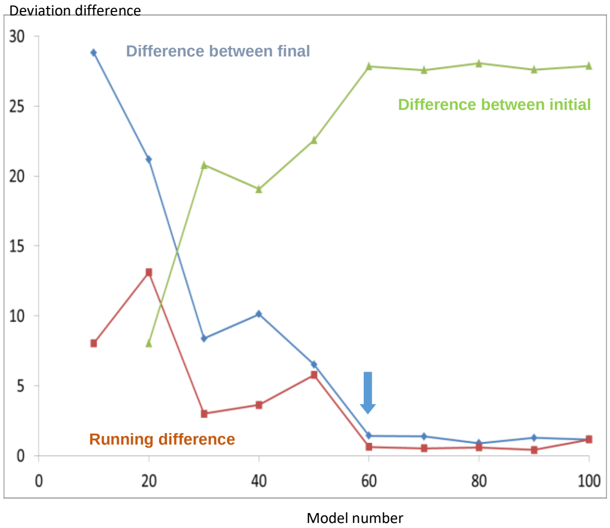

Figure 2 *Convergence criteria showing the cumulative deviation difference. The blue arrow indicates where additions to the sample set have no statistical relevance.*

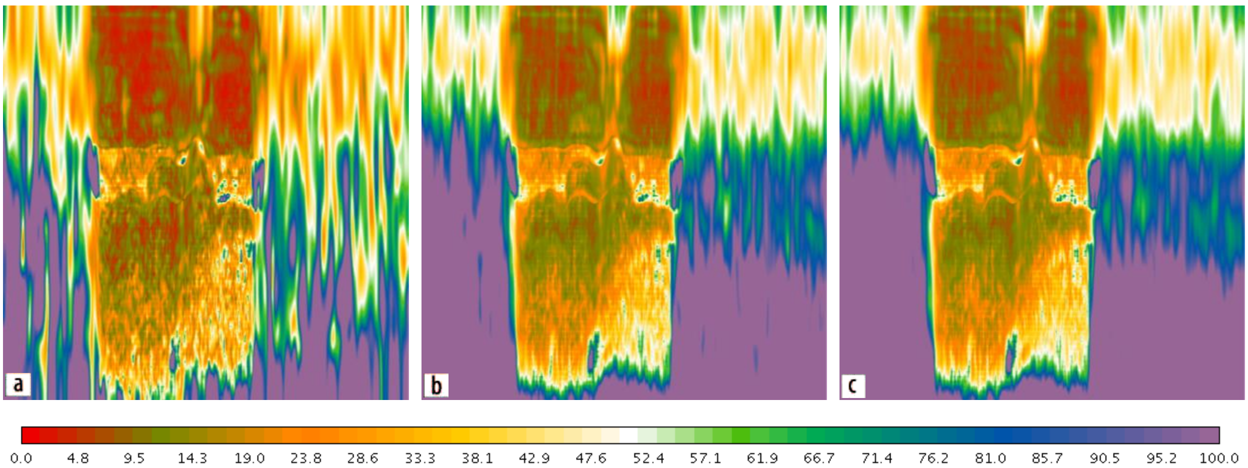

Figure 3 *Single line deviation running difference of 10 models (a), 60 models (b) and 109 models (c). There is little difference between b and c, suggesting 60 models is a suitable sample set for this data.*

Conclusions

To circumvent the nonlinear inversion system used for traditional model building, we have developed a pseudo-random modification to a standard tomographic workflow, with a statistically driven real-time loop for optimizing the model population sample size. We use this procedure to generate uncertainty attributes for a velocity final model. The products can be used in conjunction with seismic images to mitigate risk associated with ambiguity in target positioning and volumetrics.

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References

Bell, A.C, Russo, L., Martin, T., van der Burg, D., Caselitz. B. [2016] A Workflow to Quantify Velocity Model Uncertainty. *78th EAGE Conference and Exhibition.*