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Automating Velocity Model Building Using Monte Carlo Simulations - A West African Case Study

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Summary

Building velocity models for depth imaging can be time-consuming and regularly requires manual intervention. The workflows tend to be 'stop-go' chained processes. An approach using pseudo-randomness can be used to build a velocity model, mitigating some of the inefficiency challenges associated with traditional velocity model building. Monte Carlo simulations use random sampling to resolve problems where the solution may be insufficiently defined. Using a Monte Carlo approach for velocity model building firstly requires an understanding of how the data quality impacts the model, prior to creating a population of models to invert. A statistical analysis loop of the inverted population of models, followed by numerous repeated cycles, enables a level of automation in velocity model building. The protracted chained approach of classical model building can be replaced by parallelized compute intensive methods to achieve an accurate velocity model in a reduced timeframe. In this abstract we demonstrate the benefits for both quality and time, of weight of statistics and automation when using a Monte Carlo simulation for velocity model building.

Introduction

Building velocity models for depth imaging can be time-consuming and regularly requires manual intervention. The workflows tend to be 'stop-go' chained processes. An approach using pseudo-randomness can be used to build a velocity model, mitigating some of the inefficiency challenges associated with traditional velocity model building.

Monte Carlo simulations use random sampling to resolve problems where the solution may be insufficiently defined. Using a Monte Carlo approach for velocity model building firstly requires an understanding of how the data quality impacts the model, prior to creating a population of models to invert. A statistical analysis loop of the inverted population of models, followed by numerous repeated cycles, enables a level of automation in velocity model building. The protracted chained approach of classical model building can be replaced by parallelized compute intensive methods to achieve an accurate velocity model in a reduced timeframe.

Method

Martin and Bell (2019) outline a reverse engineering application to workflows that quantify uncertainty in depth imaging velocity model building (VMB), a prior work by Bell et al. (2016), and Martin (2019). The underlying work provides measures of uncertainty associated with a typical one model-one image seismic processing project, where the model building exercise creates a velocity model that produces flat common image point gathers (CIGs) when used in a data migration. To determine the uncertainty statistics the workflow uses a form of Monte Carlo simulation, the challenge being that a tomographic model building exercise is an under or mixed-determined system. The information used to constrain the inversion is incomplete and the model created is one of many that are equiprobable; many models may create equally flat CIGs.

The simulation is achieved by applying a random distribution function to the velocity model many times over to create a population of models that after inversion will all give equally flat CIGs. In the case of uncertainty analysis, the starting point is typically the final model. Prior to creating the random population, and a requirement for a probability simulation, the process must understand the underlying constraints of the data on the sensitivity of the model space (Martin and Bell, 2019). We apply a checkerboard perturbation (P) to a reference model (M_{mig}) yielding M_o. Following this, we tomographically invert and analyze the difference (δP) between the initial and the final (M_{inv}) model, identifying if the perturbation has been recovered. This is summarized below:

$$M_{mig} + P = M_0 \ \rightarrow invert \rightarrow \ M_{inv} \ - M_{mig} = \delta P$$

If δP nears zero then the inversion has recovered the perturbation (P) applied to the reference model (M_{mig}). δP is used to understand the ability of the data to constrain the model. By modifying both the magnitude and wavenumber of the perturbations we determine the number of tomographic iterations and the smoothing parameters to consider within a specific update. Figure 1 shows a schematic workflow of a checkerboard test. The example demonstrates where the inversion has resolved the perturbation.

Once the minimum wavenumber and maximum perturbation magnitude are determined, they are used to generate a population of random perturbations, before being applied to the velocity model. This is the model population, and is used in the simulation to create the measures of uncertainty in the reference model (M_{mig}).

Rather than determine measures of uncertainty in a final 'reference' velocity model, could we automate the building of a velocity model from a benign starting point using a Monte Carlo simulation? Using mechanization in model building transfers the inefficiencies of conventional model building from a manual and chained approach to a parallelized and compute intensive process. If achievable this kind of methodology could significantly reduce model building turnaround times for those projects needing an accelerated, but accurate velocity model and seismic volume.

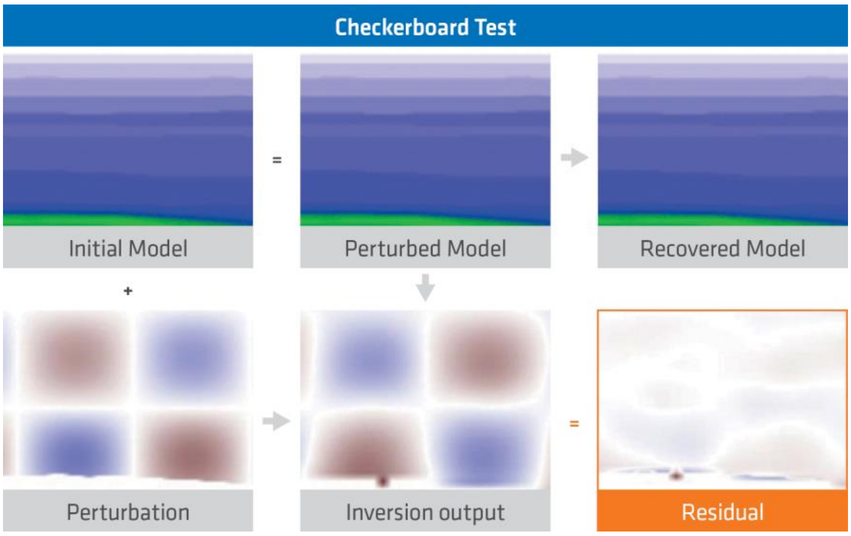

Figure 1. *Perturbation schematic to determine magnitude and wavenumber variation supported by the data.*

Using the same philosophy of a probability simulation, a population of models can be created to use in an automated velocity model building exercise. Prior to this, and similar to the approach used in the uncertainty measure extraction, analysis is performed to understand the data's limitations on the model space. Following this, a population of random perturbations are generated and applied to the starting model. All the models in the population are then passed through a tomographic inversion engine. A statistical pass is performed on the products, and the resulting global statistical analysis on the population difference of the resulting model set are added to the starting point; the starting point is therefore modified, and as the automation continues the model building evolves. The process is repeated in a number of cycles, and measures of convergence are generated after each cycle; the criterion being flat CIGs. Once a convergence criterion of gather flatness is met globally, the process stops and a usable velocity model is generated.

The initial Proof-of-Concept (POC) was tested by Martin and Bell (2019) on a small deep water data set where no noise contaminated the data used to constrain the inversion. In this paper we challenge the methodology by applying the automated scheme to a large (3500 km^2) volume that straddles shallow and deep water environments from offshore Guinea, West Africa.

Case Study – Guinea, West Africa

The seismic data were acquired in 2019 with 12 multisensor streamers, each 150 m apart and with 8000 m of offset, covering the A4 and A5 blocks in the underexplored Mauritania, Senegal, The Gambia, Guinea Bissau and Guinea Conakry (MSGBC) basin. The data were shot perpendicular to both the present-day shelf edge and the underlying regional subsurface structure, which in the Republic of Guinea are comparable to the successful North West Africa Transform Margin plays. This acquisition direction enabled optimal illumination of exploration targets.

Potential reservoirs are both Jurassic and Cretaceous in age, and can both clastic or carbonate in nature. Structural traps are influenced by the Guinea Fracture Zone (GFZ), with localized source rocks and low risk and short migration pathways.

The data set is approximately 9167 km^2 in size, and shot in water depths ranging from 60 m to 4500 m. The automated model building test was applied to 3680 km^2 of data covering both shallow and deep water data.

The initial model used for the Monte Carlo simulation had a water layer correction and a corrective global pass of tomography, the starting point having been a coarsely sampled manual velocity picking exercise performed in the data domain. The simulation was run with a model population of 30 per pass, converging globally after four passes. Figure 2 (left) shows a single inline section with the initial input model co-rendered on the data migrated with that model. The centre and right hand panels in Figure 2 show respectively the automated equivalent, run with a Monte Carlo simulation, and the conventional chained flow run as part of a production project.

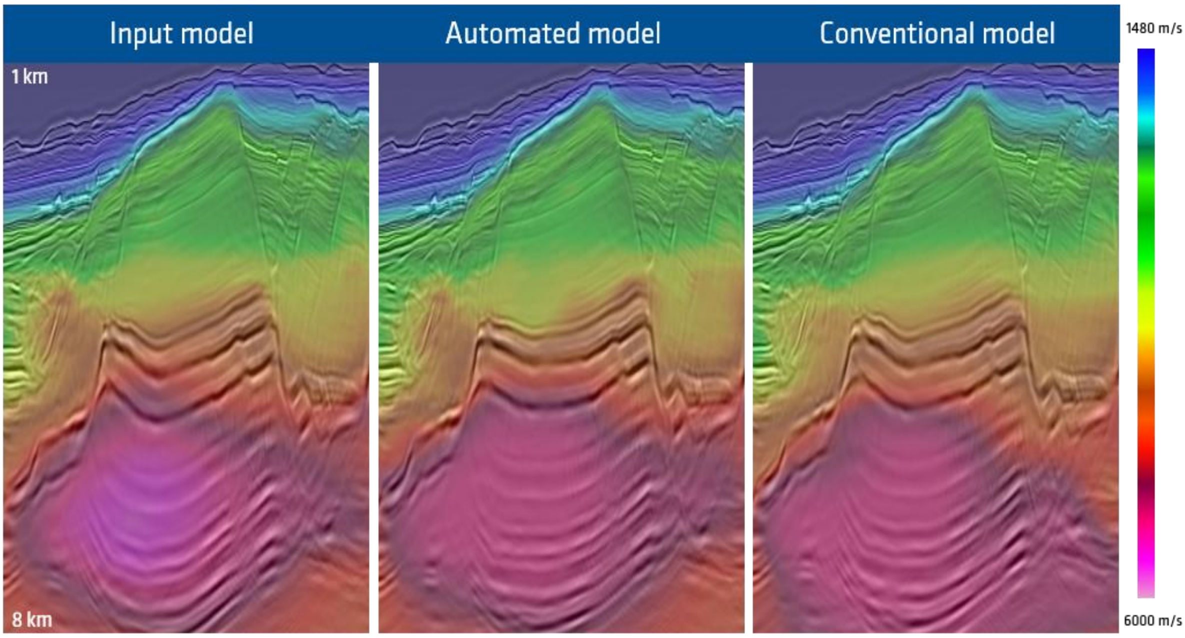

Figure 2. *Left – The input model for the exercise co-rendered on the data migrated with it; Centre – The Monte Carlo automated model; Right – the conventional chained production model.*

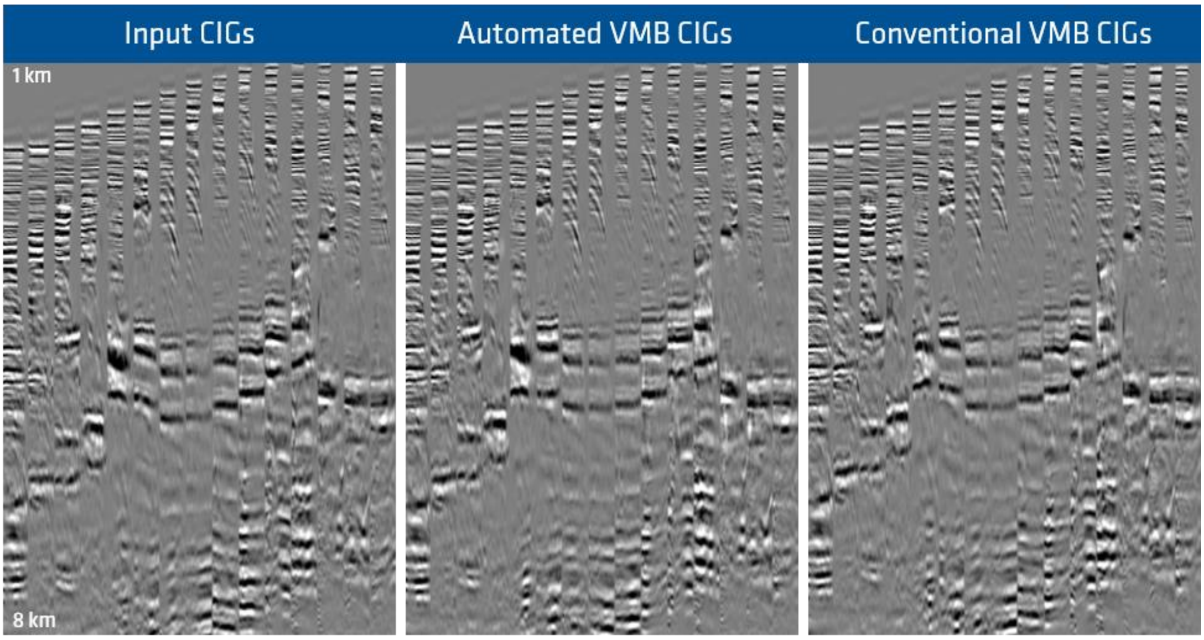

Figure 3. *Left – The Input CIGs for the exercise; Centre – The Monte Carlo automated VMB CIGs; Right – the conventional chained VMB CIGs.*

Figure 3 shows the migrated CIGs where the left, centre and right panels are the initial input model, the automated Monte Carlo model and the conventional chained production model respectively. Whilst the initial model already had a relatively accurate model for the overburden, deeper complex structures are better resolved with through the automation process, and in some locations gather flatness is better than the chained production version.

Figure 4 illustrates where the model differences occur through the probability simulation and conventional approach. Whilst there is some correlation between model updates, the simulation modified the initial model less, whilst achieving, in some locations, better gather flatness. No wells exist in the area to correlate and calibrate the differing models.

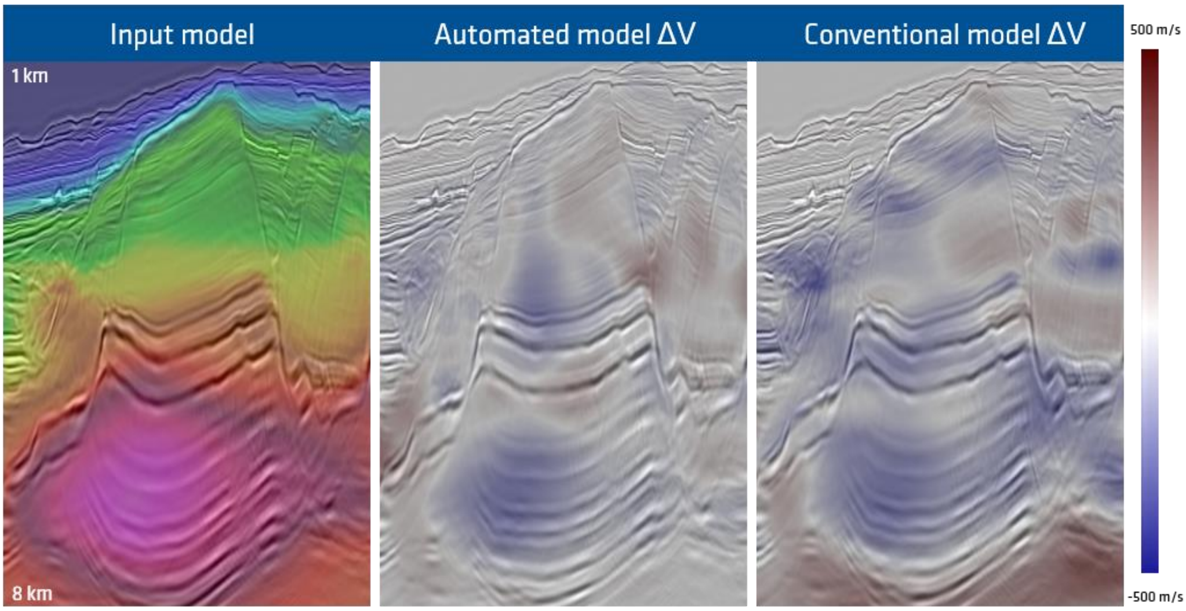

Figure 4. *Left – The input model for the exercise co-rendered on the data migrated with it; Centre – The Monte Carlo automated model difference; Right – the conventional chained model difference.*

Discussion - Conclusions

We have demonstrated that automating depth velocity model building can achieve comparable results to a stop-go chained conventional approach for a challenging West African data set. Using a Monte Carlo simulation we use randomized weight of statistics to transfer the burden of effort from an approach requiring manual intervention to a parallelized computer intensive one. This enables a significant reduction in turnaround by greater than an order of magnitude. Whilst the results are impressive, we are unable to calibrate them to a well and rely on gather flatness as a criterion of convergence. We also concede, at this point, we are only considering the case of velocity in the model building.

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