Adaptive spatial resampling as a Markov chain Monte Carlo method for stochastic seismic reservoir characterization

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Summary

Seismic reservoir characterization aims to transform obtained seismic signatures into reservoir properties such as lithofacies and pore fluids. We propose a Markov chain Monte Carlo (McMC) workflow consistent with geology, well-logs, seismic data and rock-physics information. The workflow uses a multiple-point geostatistical method for generating realizations from the prior distribution and Adaptive Spatial Resampling (ASR) for sampling from the posterior distribution conditioned to seismic data. Sampling is a general approach for assessing important uncertainties. However, rejection sampling requires a large number of evaluations of forward model, and is not efficient for reservoir modeling. Metropolis sampling is able to perform a reasonably equivalent sampling by forming a Markov chain. The ASR algorithm perturbs realizations of a spatially dependent variable while preserving its spatial structure. The method is used as a transition kernel to produce a Markov chain of geostatistical realizations. These realizations are converted to predicted seismic data by forward modeling, to compute the likelihood. Depending on the acceptation/rejection criterion in the Markov process, it is possible to obtain a chain of realizations aimed either at characterizing the posterior distribution with Metropolis sampling or at calibrating a single realization until an optimum is reached. Thus the algorithm can be tuned to work either as an optimizer or as a sampler. The validity and applicability of the proposed method and sensitivity of different parameters is explored using synthetic seismic data.

Introduction

Quantifying uncertainty in seismic reservoir modeling is always a critical issue because of inevitable difficulties and ambiguities in measurement, processing, and interpretation of geophysical data. Within obtained data, not only finding out the most likely model but quantitatively assessing a range of uncertainty is very important task for decision making. However, often seismic reservoir characterization methods apply deterministic optimization approach and focus on finding the best fit model with obtained data. In a Bayesian framework, rejection sampler can quantify uncertainty of models by theoretically perfect sampling of posterior distribution. However, since it requires enormously large number of evaluations, it is inefficient and not applicable for actual reservoir modeling. Metropolis sampling (Metropolis et al., 1953) is able to perform a reasonably equivalent sampling by forming a Markov chain of models such that the steady-state distribution of the chain is precisely the posterior distribution sampled by rejection sampler. Specifically in reservoir modeling, the issue is how to form and perturb a Markov chain while preserving spatial structure of geomodels in the chain. One way is to sample a subset of points from previous model in a chain, and use the points as conditioning data for the next simulated realization. Using Iterative Spatial Resampling (ISR) algorithm, we can perturb the Earth model while we preserve spatial distribution. The successive iterates display similar local features due to the conditioning data, but represents a different realization in a Markov chain (Mariethoz et al, 2010). Jeong et al. (2011) applied this algorithm in lithofacies characterization and showed its applicability using acoustic impedance data. In this work we propose Adaptive Spatial Resampling algorithm as an improved spatial resampling algorithm to form a Markov chain Monte Carlo (McMC) workflow consistent with geology, well-logs, seismic data and rock-physics information. We compare ASR to ISR and show how the new algorithm is more efficient and can better sample the posterior.

Methodology

The workflow is a seismic inverse modeling process in a Bayesian frame. It consists of rock-physics relations to link reservoir properties (m_{res}) and elastic properties (m_{elas}), geostatistical methods to provide geologically consistent prior models, and forward modeling to predict synthetic seismic data for comparing with obtained seismic data to calculate the likelihood. The final solutions are posterior models consistent with the expected geology, well data and seismic data. Thus, the posterior pdf can be expressed as (Bosch et al., 2010):

$$P_{post}(m_{res}, m_{elas}) = c\, P_{prior}(m_{elas}|m_{res}) P_{prior}(m_{res}) P_{data}(d_{obs} - g(m_{elas})), \quad (1)$$

where $P_{post}(m_{res}, m_{elas})$ is the posterior probability density, $P_{prior}(m_{res})$ is the prior pdf for the reservoir parameters (including their spatial distributions), c is a normalizing constant and $P_{prior}(m_{elas}|m_{res})$ is a conditional probability for the elastic parameters that summarizes the rock physics relationships between reservoir property and elastic property. The data-likelihood $P_{data}(d_{obs} - g(m))$ depends on the observations d_{obs} and their uncertainty, and the forward modeling operator g that maps the model space into the data space.

<u>Adaptive spatial resampling</u>

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Mariethoz et al. (2010) suggested Iterative Spatial Resampling (ISR) to perturb realizations of a spatially dependent variable while preserving its spatial structure. Jeong et al. (2011) presented its applicability in lithofacies prediction using acoustic impedance data. The search strategy of ISR performs successive steps in random directions for exploring various regions of the solution space. Since the search is stochastic, the global minimum will be reached after theoretically, an infinite number of iterations. However, in most practical applications, when the subset conditioning points are selected at random, it can get stuck in a non-optimal local minimum. In this work we improve the efficiency of ISR by adaptive sampling.

At the every iteration, we compare the predicted seismic data with the observed data and thus we have a spatial error map. We can use this information for generating the next step. Instead of just randomly sampling a subset of points to condition the next realization, we adaptively sample important points having lower residual error (see Figure 1). The algorithm probabilistically selects a subset of conditioning points with probability based on the residual error pdf; thus lower error points have a higher chance to be accepted as a conditioning point. Adaptive Spatial Resampling (ASR) accelerates to reach the posterior distribution and efficiently finds an optimal model consistent with the given data. The adaptive selection algorithm should be varied depending on a type of seismic data. Inverted acoustic impedance data in depth can be compared with predicted data directly to calculate a residual error map as shown in Figure 1 (left). However, since seismograms are recorded in time, direct comparison between data and prediction can be misleading because of timeshifts. Two seismograms in Figure 1 (right) show similar local features at CDP 20; however, since the seismic reflections are not exactly overlapped in time axis, directly subtracted residual error is still high regardless of similarity of underlying facies. Thus, we propose using trace-to-trace cross correlation coefficients as a probability of selection. Higher correlation coefficient assigns a higher chance to be accepted as a conditioning location for next step.

Performance of ASR can be sensitive to input parameters such as fraction of selected conditioning points and number of trace locations in a seismogram section. The fraction of subset points controls iteration steps for searching the next better model. A large fraction of conditioning points makes too small a progress at every iteration step while a small fraction can move in relatively large steps but it may lose a spatial structure of previous model. Optimal fraction can be varied depending on the problems. We tested the sensitivity to this parameter and found that adaptive resampling with 1% proportion performs slightly better than the other values (left, Figure 2). In this figure, we can find that retaining a large fraction rapidly reduces root mean square error (RMSE) at the beginning but it gets stuck in a local minimum after 100 iterations. In contrast, chains with 1% fraction move relatively slower but can reach lower RMSE. The number of selected traces is also an important parameter. More traces account more horizontal spatial structures while it may lose vertical information in the seismic trace since fewer points are selected per trace. Even though we assign the same 1% fraction, the number of traces can affect efficiency of the Markov chain. The right Figure 2 is a sensitivity test within our dataset, and it shows 8 trace locations with 1% fraction rate are relatively suitable in this case.

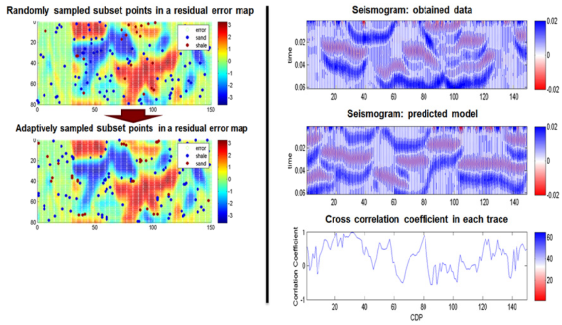

Figure 1: Sampling algorithm of the subset points in the ASR. Left: Background green zone is the low residual points while both red and blue have higher error. In the residual error map, randomly sampled points (top) are located in both low and higher error zone while adaptive sampling subsets (bottom) are located preferentially in low error zone. Right: Since the seismogram is traces consisted of wiggles in travel time, directly subtracted variability can miss similar local feature. We used cross correlation coefficients in each trace for adaptive sampling of subset points. A trace of high correlation coefficient has more chance to be selected as subset points.

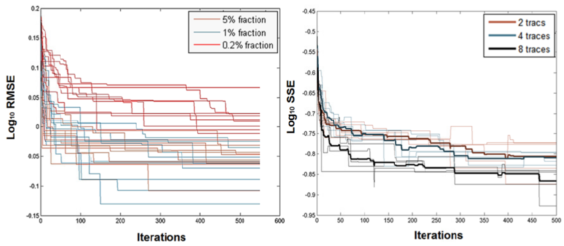

Figure 2: Performance assessment for testing different parameters. Left: adaptive resampling with 1% fraction performs slightly better than the other values, but this can be different depending on the problem; Right: The sensitivity of the number of traces is tested. 8 traces was an ideal setting in this case.

Case study

Synthetic facies and seismic dataset are presented to demonstrate the validity of the proposed technique. The two-dimensional models used were extracted from a modified version of the top layer of the Stanford VI

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synthetic reservoir created by the geostatistics group at Stanford University (Castro, et al., 2005) to test algorithms. All the information about the model relevant to this work is summarized in Figure 3. The reference facies model is a sand-shale channel system with 80 cells in the vertical (z) direction (dz=1m) and 150 cells in x (dx=25m). We show the use of ASR for two types of seismic data. One is where we have P-impedance inverted from the seismic section (say from a conventional impedance inversion), and we use the impedance as an attribute for the stochastic lithofacies inversion. The second is where the seismic data are the normal-incidence seismograms themselves, before inversion for impedance. Using appropriate rock physics models for the sand and shale, we compute acoustic impedance from the P-wave velocities and densities. We applied a frequency-domain Born filter for surface seismic reflection geometry with a 5~50 (Hz) bandwidth. This is the forward model for the impedance data type. For the second case to generate a reference normal-incidence seismic section, we assumed perfect seismic forward modeling without noise and applied a 50 (Hz) wavelet. For the inversion process, we assumed that we have only the acoustic impedance data or the seismogram section, two wells with log information, and a training image.

Case 1: acoustic impedance for lithofacies characterization

We generated multiple prior spatial models using multiple-point geostatistical algorithm. Rejection sampling is accomplished to represent posterior pdf as the reference. We tested ISR and ASR as equivalent sampling methods by comparing their results with rejection sampler. Figure 4 shows the results as the E-types (ensemble averages) of models. When we used acoustic impedance data as the seismic attribute, both rejection sampler and ASR found clear channel distribution and these results look the same while ISR found similar channel distribution with ambiguity (first row of the Figure 4). However, the result of rejection sampler is the average of 125 accepted models after evaluating 100,000 prior models while ASR with Metropolis algorithm uses 1 Markov chain with 500 iterations (94 posteriors sampled). ASR shows significantly better efficiency when compared to rejection sampling. The root mean square errors (RMSE) versus iterations for the 10 Markov chains are also shown in Figure 5. ASR chains reached lower error zone more rapidly than ISR chains.

Case 2: seismograms for lithofacies characterization

Since seismogram data has more uncertainty than acoustic impedance due to the wavelet effect and lower resolution, the predictability of sampling algorithm is critical in this case. The performance of ISR and ASR are compared in bottom of Figure 4, and it shows a big difference in the E-type result. ASR found similar channel distribution as rejection sampler while ISR lost channels away from wells. ASR sampled 51 posteriors in 1 Markov chain with 500 iterations while rejection sampler accepted 140 posteriors among 100,000 priors. Variance map (bottom figure in each section) shows that ASR keeps the range of uncertainty as compared with rejection sampler. Distance-based representation in Figure 6 also shows that the samples from ASR are distributed near the reference with the posteriors from rejection sampling. Thus we can conclude that ASR can be a fair approximation of rejection sampler. Since our reference is located away from the most of priors, rejection sampling is inefficient to find posterior models. Sampled posteriors by ISR could not reach the whole posterior distribution yet. Hence, ASR can be used as an efficient posterior sampler.

Case 3: Finding facies not seen in well data

In this case, we assume one oil sand distribution away from two well locations. We have seismogram data, well logs without oil sand information, and a training image (see Figure 8). For this task, we applied realistic rock physics relationship from actual well logs, and generated oil sand properties by Gassmann's equation. Figure 7 shows rejection sampler and ASR results as probability maps. Rejection sampler found nearly correct distribution compared to the reference after 50,000 evaluations while ASR found similar distribution using one chain of 1,000 evaluations. In more realistic task, ASR also shows its applicability as a fair and efficient sampler.

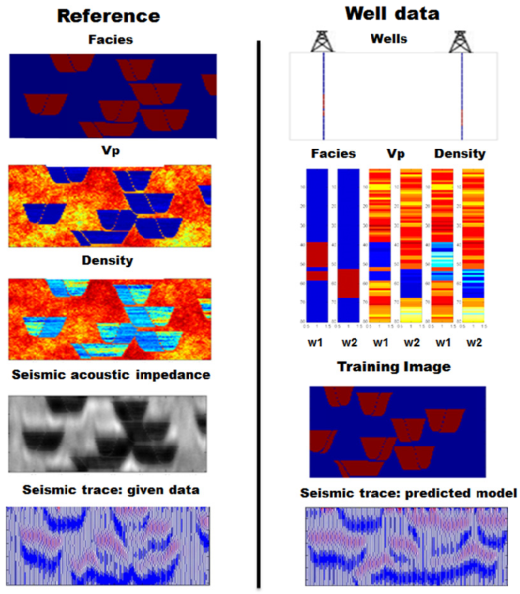

Figure 3: Left: The spatial distribution of the facies, P-wave velocities (Vp) and densities (ρ) are assumed as the reference. The filtered seismic band acoustic impedance is at bottom left. Right: The data of two wells are given as above and the wells are located at CDP25 and CDP125, respectively. Training image for MPS is shown at the bottom of the right column.

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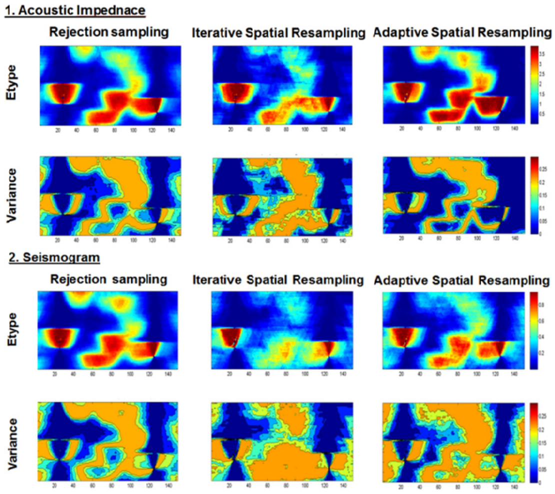

Figure 4: Representation of the averages of ensembles of models. Top: (first row) the etype of rejection sampling results, ISR and ASR using acoustic impedance as the obtained data; (second row) the variance of each algorithm, respectively. Bottom: (first row) the etype of rejection sampler, ISR and ASR using seismogram as the obtained data, and (second row) its variance. Within limited evaluations, ASR show the similar etype and variance map compared with the result of rejection sampling in both cases.

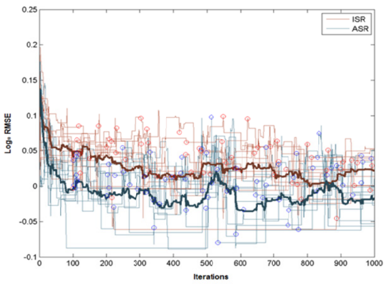

Figure 5: Adaptive spatial resampling (blue curves) and iterative spatial resampling (red curves) are compared as a posterior sampling method for 10 Markov chains. The average of 10 chains for each case is shown as a thick line, and sampled models are marked as circles.

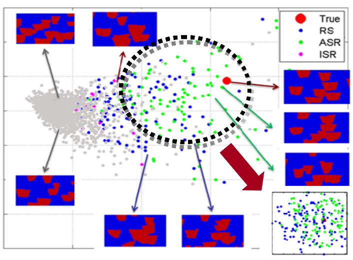

Figure 6: Multi-Dimensional Scaling (MDS) projection of all models. The gray points are prior models and the red point is the reference. The blue are the posteriors by rejection sampling and they clustered around the true model. ASR and ISR results are shown by green and magenta points, respectively.

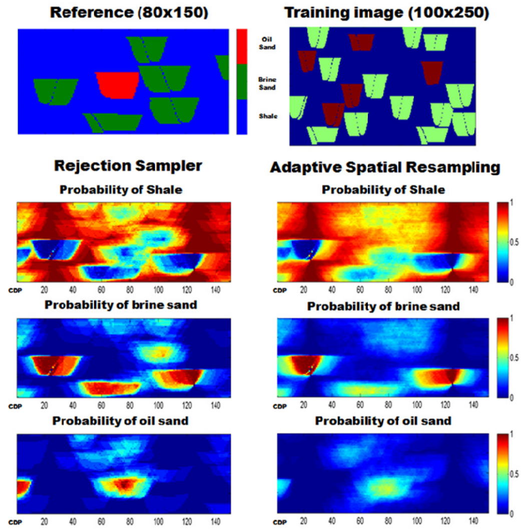

Figure 7: A case study for detecting oil sand distribution away from wells, when wells do not have any oil sand. : Representation of the averages of ensembles of models. Top: (left) the reference three facies and (right) a training image; Bottom: (left) the probability map of rejection sampler in each facies and (right the probability map of the posteriors sampled by ASR. Within relatively limited evaluations, ASR show similar probability map compared with the result of rejection sampler.

Conclusions

We presented the Adaptive Spatial Resampling method (ASR) as a Markov chain Monte Carlo method for stochastic seismic reservoir characterization. ASR perturbs realizations of a spatially dependent variable while preserving its spatial structure. ASR also accelerates the sampling efficiency without decreasing range of uncertainty. In the studied cases, it yields posterior distributions reasonably close to the ones obtained by rejection samplers, with important reduction in time and computing cost. Thus ASR is suitable for conditioning facies models or characterizing reservoir properties to spatially distributed seismic data. Depending on the acceptation/rejection criterion in the Markov process, it is possible to obtain a chain of realizations aimed either at characterizing a certain posterior distribution with Metropolis sampling or at calibrating one realization at a time. This study will be applied in actual field data as future task.

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EDITED REFERENCES

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REFERENCES

Bosch, M., T. Mukerji, and E. F. Gonzalez, 2010, Seismic inversion for reservoir properties combining statistical rock physics and geostatistics: A review: Geophysics, **75**, no 5, A165–A176.

Castro, S, J. Caers, and T. Mukerji, 2005, The Stanford VI reservoir: 18th Annual Report, Stanford Center for Reservoir Forecasting, Stanford University.

Jeong, C., Mukerji, T., and Mariethoz, G., 2011, Iterative spatial resampling applied to seismic inverse modeling for lithofacies prediction, 81st Annual International Meeting, SEG, Expanded Abstracts, 2011–1764.

Mariethoz, G., P. Renard, and J. Caers, 2010, Bayesian inverse problem and optimization with iterative spatial resampling, Water Resources research, **46**, W11530, doi:10.1029/2010WR009274

Metropolis, N., A. Rosenbluth, M. Rosenbluth, and A. Teller, 1953, Equation of state calculations by fast computing machines: Journal of Chemical Physics, **21**, 1087–1092.