# Assisted Seismic Matching: Joint Inversion of Seismic, Rock Physics and Basin Modeling

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**Summary**

Inverse methods are useful tools for deriving estimates of unknown parameters of the subsurface. In this study, we apply numerical optimization techniques to jointly invert parameters for basin modeling, rock physics, and seismic attributes, including seismic amplitude to match seismic data.

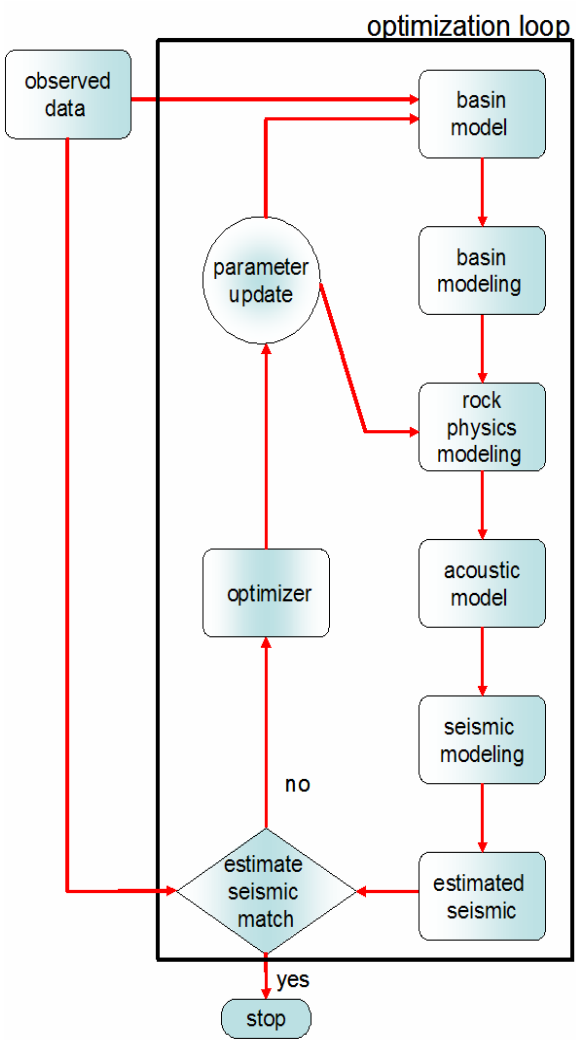


Figure 1: Fluxogram of the joint inversion loop

**Introduction**

In this study, we apply advanced numerical optimization techniques to extend the work of Imhof and Sharma (2005, 2006) to integrate geological and geophysical data and infer the sedimentary parameters that produce a match to seismic data. In particular, we seek to match not just event timing (phase) but also reflection strength (amplitude). This inverse problem of quantitatively matching present-day measurements of structure, stratigraphy, petrology and/or fluids is inherently ill-posed and computationally difficult. In our approach we automatically adjust parameters, which control numerical forward models such as numerical basin models, petrophysical models, and seismic acoustic models, to match observed seismic data and observed stratigraphy. Note that the problem we tackle is more complex than traditional seismic inversion, which just estimates the velocity and reflectivity model that fits the seismic data. Here we also estimate the geological layer composition, as well as rock physics parameters controlling the relationships defining the bulk rock density and velocity.

Although our work has been inspired by Imhof and Sharma (2005, 2006) our approach differs significantly from theirs. The main goal of Imhof's and Sharma's work was to estimate the key parameters controlling the transport of sediments and consequently their geometry. Thus their quantitative stratigraphic inversion aims at understanding sedimentary deposition processes using a convection-diffusion synthetic stratigraphy to model the deposition. In our approach, our main goal is to produce a seismic match and thus we are mainly interested in the parameters controlling seismic attributes. In our case, the geometry of the geological layers is mainly controlled by lithology, porosity, and pressure regime estimated from the basin modeling tool.

This proof of concept study is divided in two parts. In the first, we describe the theory and methods and apply it to a simple but realistic synthetic model. In the second part, we apply this methodology to a dataset from offshore West Africa.

**The Joint Inversion Approach and Tools**

In Figure 1 we describe the main elements of the optimization loop used to perform the joint inversion of the seismic acoustic model, petrophysical model and basin model. To implement this loop, we selected Basin2 Release 5.0 (Bethke, Lee and Park, 2002) as our forward basin

modeling package. This is a mature 2D numerical hydrogeological flow and transport program which provides the ability to specify physical and hydrologic sediment properties, e.g. sand and shale content, porosity, permeability, and outputs the evolution of fluid pressures and temperature history. Basin2 is freely available, making it eminently suitable for comparisons and an inter-company collaboration such ours. Moreover the needed models calculations are fast enough to enable the necessary hundreds or thousands of iterations for our inversion/optimization algorithms. Having selected a suitable sedimentary simulator, we next constructed a model using the available data. This model is input into the basin simulator, which produces the output necessary to feed the empirical rock physics relationships (petrophysical model) used to generate the initial seismic reflectivity model. Estimated seismic sections are created using either a 1D convolutional model or a 2D finite difference wave propagation software. We then compare the estimate seismic with the observed seismic data and if there is misfit, we apply the optimizer to minimize the misfit by searching for the best controlling parameters. These parameters are continuously updated in the optimization loop until the match is acceptable.

To tackle parameter inversion/optimization for this model, we experimented with a number of algorithms, some in the derivative-free (DF) class and the remainder requiring an analytical or a numerical derivative (gradient-based). In the derivative-free category are: (1) DFO (Derivative Free Optimization) from http://projects.coin-or.org/Dfo/ due to Conn, et al. (1997, 1998); (2) NEWUOA algorithm (Michael J.D. Powell, 2004), and (3) ASA (Adaptive Simulated Annealing) from http://www.ingber.com/#ASA developed by Ingber (1989). The gradient-based methods are: (1) IPOPT (Interior Point OPTimizer) from http://projects.coin-or.org/Ipopt/ which implements and extends the work of Wächter & Bigler (2006); (2) CBB (Cyclic Barzilai-Borwein) from Dai, et al. (2006) and a Conjugate Gradient CGCBB variant (Hager & Zhang, 2006), and (3) LMDIF (Levenberg-Marquardt w/forward DIFerence Jacobian estimation) from the MINPACK library at http://www.netlib.org/minpack/ due to Moré (1978).

Unlike traditional economic applications of optimization, where one optimizes, say, net present value dollars of return, seismic matching has the additional challenge of constructing a "good" measure of fit. In the initial stages of our present investigation, we encountered poor convergence, or even non-convergence, in directly applying least-squares optimization to seismic amplitude. This traditional sum of squared differences between the actual and modeled seismic amplitude data exhibited many (spurious) local minima. This indicated that we needed a smoother measure of seismic match. After numerous experiments we found that the amplitude envelope or the envelope of the amplitude envelope were the best attributes to measure the match.

**Synthetic Model**

In order to validate our approach, we created a synthetic model (Figure 2) which was sufficiently realistic and yet would expose many of the challenges in successfully applying state-of-the-art optimization, while simultaneously not be so large that progress in understanding and overcoming inherent issues would slow to a crawl. We opted for a progradational environment, with sand and shale sediment supplied from the more proximal right-hand-side of the model, since it would possess many similarities with the West Africa model to be used later. This synthetic model defined our "ground truth" geologic and geophysical model, which we want to recover during the inversion process if our approach is to prove to be effective.

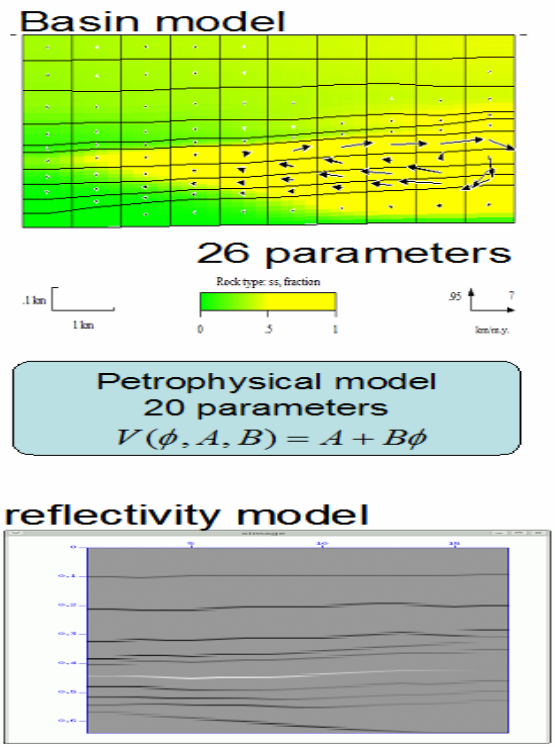


Figure 2: Syntethic model used to validate the approach described in Figure 1

This model has 10 geological layers composed of sand-shale content determined by two Gaussian parameters (μ

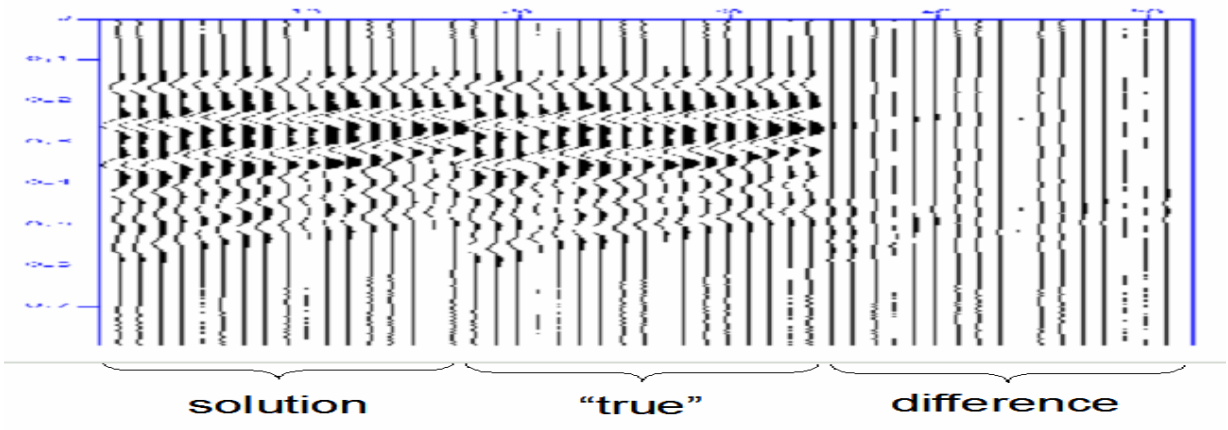


Figure 3: Match between the true and estimated solution for the synthetic model shown in Figure 2.

and σ) per layer. In addition, both sand and shale require 3 parameters each to define its porosity curve. The acoustic velocity is assumed to be linear in each layer requiring 2 additional parameters per layer, yielding a total of 46 parameters to be inverted. We used Basin2 to forward evolve the basin over time and Fig. 2 shows the basin at present-day time. In Fig. 3, we show the final match between the "true" and the estimated solution. More details on the experiments performed with this model can be found in Levin et al. (2007) and Lopez et al. (2007). Among the optimization algorithms used, NEWUOA provided the best result in the class of the DF algorithms while the LMDIF was the best in the gradient-based methods. ASA also provided good global results but was in general much more expensive than the others algorithms tested.

As can be seen in Fig. 3, the good match obtained encouraged us to apply this methodology to a larger, real dataset, which is described in the next section.

**The West Africa Model**

This model is from a shallow, deltaic environment offshore West Africa, where an erosional feature was filled in with a prograding delta (Imhof, 2005). In Fig. 4 we show a picked time-migrated seismic section with 30 geological layers defined. Assuming two lithologies (sand and shale) in the layers, and a constant velocity within each layer, 96 parameters are required to be optimized to minimize a possible mismatch.

Figures 5 and 6 show our very first results at fitting these data. As may be readily observed, the amplitude fit is poor in the shallower section and marginal in the deeper portion, with too much contrast in material properties at a number of layer boundaries. It is important to take into consideration that the synthetic model had a known functional that would be zero when the "true" solution were found and this is why the Levenberg-Marquardt (LMDIF) algorithm performed so well. For field data we can have no such expectation of a perfect fit. To address these real world issues, we will take a page from the wavelet decomposition

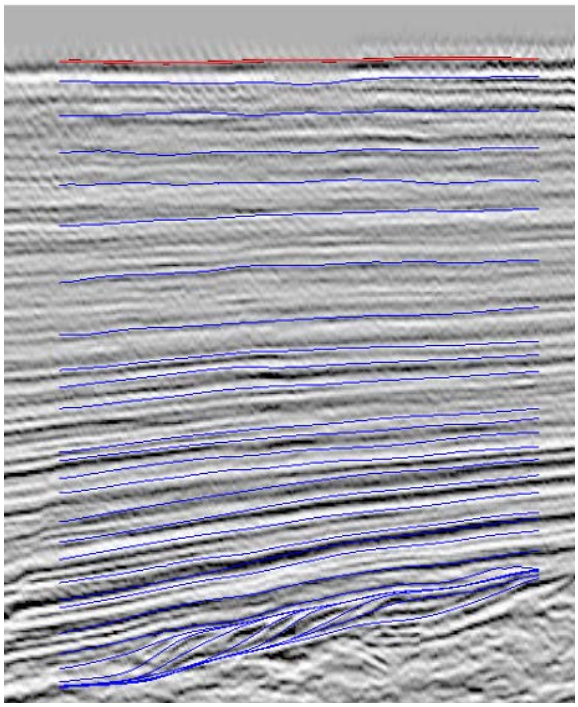

Figure 4: Picked seismic from a shallow deltaic environment offshore West Africa

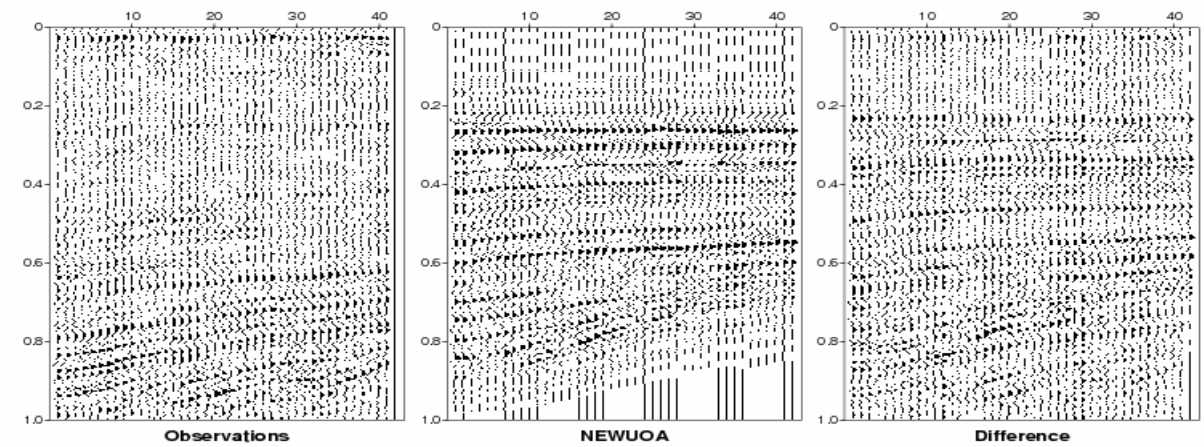


Figure 5: Match between the true and estimated solution for the synthetic model shown in Figure 2.

playbook, attaching an estimated waveform to each of the layer boundaries we have picked and using a local shaping filter to adjust this interpretation to the seismic data. This preconditioned seismic section can then serve as a proxy for the original seismic data, making the input we wish to match more consistent with the layered model assumed in the sedimentary modeling. At the time of submission of this abstract, we do not yet have these results.

## Conclusions

There are various aspects to this model study meriting further attention. First, we still want to explore techniques to smooth the functional being optimized and improve the match of selected seismic attributes. We continue to explore scaling and other preconditioning to improve convergence speed and conserve computational resources. And, ultimately, we must stochastically explore the space of parameters that provide acceptable data matches, not only to the seismic, but also to other measurements such as well logs. Based upon our progress to date, however, we are reasonably confident that our basic approach and framework are feasible with modern industrial computing resources for tackling these larger problems of incorporating field data. However, as the problem grows in size, and the number of control parameters exceeds 500, most likely it becomes infeasible to use derivative free methods such as DFO, or NEWUOA. Given the size of the parameter space, ASA can be also very expensive and would require a parallel environment to solve larger problems. The use of gradient-based methods with adjoint methods could also be developed for the most expensive parts of the optimization loop.

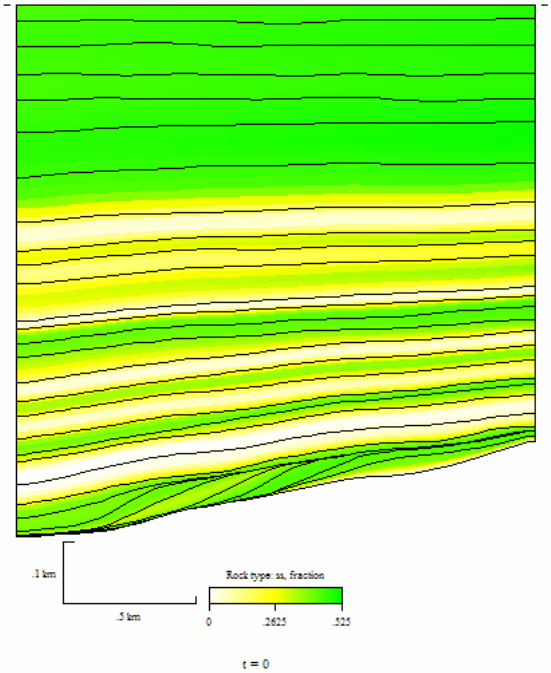


Figure 6: Basin model inverted for the seismic data shown in Figure 4. Color represent shale (green) and sand (yellow) content.

## Acknowledgments

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