

Automatic Parameter Selection for Robust Deterministic Seismic Inversion using Particle Swarm Optimization

Introduction

Robust deterministic seismic inversion, e.g., constrained sparse spike inversion requires tuning a large number of parameters to obtain optimum results satisfying both seismic and well data as well as well conforming to the geological and rock physical trends. Estimation of the correct values of these parameters depend on several factors, such as the availability and quality of data. Manual (user-driven) parameterization is often tedious and time-consuming because it requires inspecting numerous inversion runs through QC processes across multiple parameters combinations. Moreover, sequential optimization algorithms used in widespread practice can take from tens of minutes to several hours to run, even on modern computers. This creates a significant bottleneck, as users must evaluate and analyze results across various combinations of multiple inversion parameters and scenarios.

We present the Particle Swarm Optimization (PSO) algorithm as an efficient method for automatically tuning the parameters of our deterministic inversion product. PSO was originally introduced in 1995 by Kennedy and Eberhart and later applied to geophysical data by Shaw and Srivastava (2007). Since then, the method has received significant attention, with multiple variants developed, particularly in the context of machine learning applications. But at the core of this algorithm and its variants, lie the idea of mimicking the collective behavior of a social group in multi-agent search analysis to solve optimization problems.

For this work, the goal of the method is to find the global minimum of an objective function called Combined Misfit comprising mismatches in observed and modeled seismic and well data as well as constraints to geology. To minimize the combined misfit, the PSO algorithm searches for the best set of parameters that simultaneously matches seismic data with synthetics and well logs with inverted properties. In the Combined Misfit, the well-log match compares the statistical properties of the inverted result with the corresponding well logs, including correlation, cross-correlation between different property types, and standard deviations. Since this is not a direct constraint on the log data, all wells remain blind in our analysis.

In this paper, we present a simple variant of the Particle Swarm Optimization (PSO) algorithm to optimize the combined misfit. The method fulfils the two major requirements of being both accurate and fast. For typical configurations, the automatic optimization time is in the order of minutes or even less. The calculation speed is significantly increased through parallelization, since the expensive test inversions can be run independently.

Method and Theory

Particle Swarm Optimization method consists of selecting multiple points, referred to as particles, in a multidimensional space. Each particle samples the values of a given objective function, in our case, the Combined Misfit function, where the minimum value represents the optimal solution. Through each iteration, the particles move in space, searching for the global minimum of the objective function. Three contributions define the particle movements. The one is the so-called inertia, as the movements can dampen faster for a small mass parameter. The second is the individual bias. Based on this contribution alone, the particles would move independently in space, without influencing each other. The last contribution is the social bias, that is, each particle's move is biased towards the current best position from the entire swarm.

Let us consider a set of N particles in a D -dimensional space. Each particle's position is defined by a vector, $\mathbf{r} = (r_1, \dots, r_D)$. At each iteration, each particle updates its position given its velocity, $\mathbf{v}_i$:

$$\mathbf{r}_i^{\text{new}} = \mathbf{r}_i + \mathbf{v}_i, \quad i = 1, \dots, N$$

The velocities themselves are updated as:

$$\mathbf{v}_i^{\text{new}} = \mu \mathbf{v}_i + w_p (\mathbf{r}_i^{\text{best}} - \mathbf{r}_i) + w_s (\mathbf{R}^{\text{best}} - \mathbf{r}_i)$$

The first term is the inertia contribution, with μ as the mass parameter. The second term is the individual contribution, where $\mathbf{r}_i^{\text{best}}$ is the best historical position of particle, I and w_p is a positive random number from $[0,1]$ interval. The last term is the social contribution, where $\mathbf{R}^{\text{best}}$ is the historical best from all particles, w_s is a random number independent of w_p and limited also to $[0,1]$ interval.

In our method, each dimension corresponds to an inversion parameter that we optimize to minimize the Combined Misfit. These parameters represent different quantities with distinct units and value ranges. Hence, we need to scale the velocities for each dimension to numerically balance them to reasonable values. To do this, we introduce a scaling vector λ , such that

$$\lambda_\alpha = p_{\alpha, \text{max}} - p_{\alpha, \text{min}}, \quad \alpha = 1, \dots, D,$$

with $p_{\text{max}}, p_{\text{min}}$ being the maximum and minimum values of the parameter, p_α . The scaling works by replacing the mass scalar, μ with a diagonal matrix, that is, for each dimension, we set:

$$\mu_\alpha = \lambda_\alpha \mu, \quad \alpha = 1, \dots, D.$$

We therefore count to 3 hyperparameters: inertia, personal bias, and social bias. These parameters are hard-coded, as their values turn out to be universal in our deterministic inversion problem. The personal and social biases are kept constant during iterations, while the scalar mass, μ decreases linearly by a factor of ≈ 10 towards the last iteration. This decrease in magnitude is desirable as the velocities dampen when the particle cluster is getting closer to the convergence point. If particles move too quick, they tend to overshoot the global minimum, which in turn slows overall convergence.

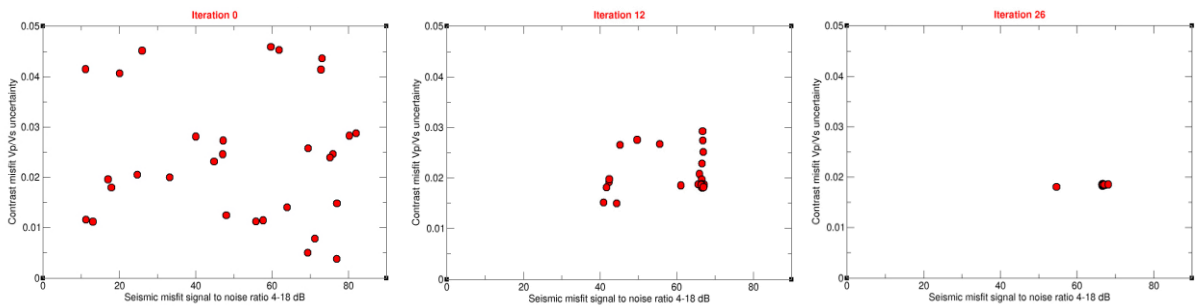


Figure 1 Example of a 2-dimensional cross-section from a multidimensional parameter space, using 30 PSO particles. Left: particles are initialized at random positions, distributed evenly across search space. Middle: after 12 iterations, the particles are getting closer toward promising region, and a coalescent cluster becomes visible. Right: at iteration 26, all particles have converged to the same location, except one. This configuration qualifies as a convergent cluster.

Figure 1 shows an example of a two-dimensional cross-section through a multidimensional parameter space. The particles are assigned random positions in the parameter space. After 12 iterations, the particles are getting close together, forming a converging cluster. This clustering is driven by the social component of the iteration formulas, as particles “communicate” their social historical best.

After 26 iterations, all particles except one occupy the same region, and the solution corresponds to the best position within this tight cluster, where the optimum is very likely located due to the particles' near-identical positions.

For the same example in Figure 1, one dimension corresponds to the signal-to-noise ratio parameter of a stack of 4-18 degrees angle, from a test project. This is the weighting parameter for the seismic – synthetic misfit contribution to the inversion objective function. The other dimension, which is called the contrast misfit uncertainty, is the inverse of the weighting for V_p/V_s contrast of the same objective function. Small uncertainty means large weighting for suppressing the V_p/V_s contrast.

Examples

We present an application of the PSO method for a study field located offshore of West Africa. There are 6 wells available with extensive petrophysical data and compressional and shear velocity logs. The well logs indicate large V_p/V_s values above the oil-water contact. There are four partial angle stacks available, with 5-15, 15-25, 25-35, 35-45 degrees ranges, all calibrated to well data. Three interpreted horizons divide the reservoir into two intervals.

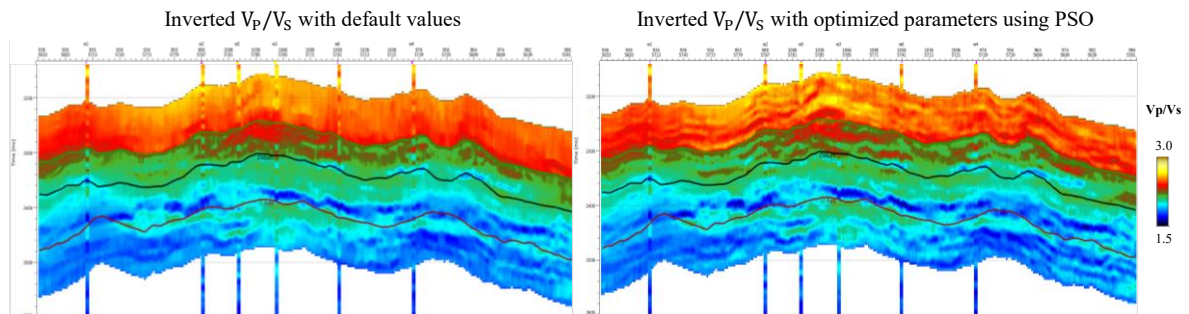


Figure 2 Inverted V_p/V_s with default values (left), and with optimized parameters using PSO method (right). The contrast suppression weighting from PSO is less than the default values, allowing higher resolution for inversion output and a very good match with blind wells.

The inversion objective function had 24 parameters, which had to be optimized. Their optimal values depend on many factors, such as the seismic data to be inverted, the availability of wells, available information for trend modelling, or even on the geological features. Thus, any preset (default) values of all parameters may not be suitable for inversion. For this presentation, the most relevant parameters are signal-to-noise ratio (SNR) coefficients and contrast misfit uncertainties. SNR coefficients are assigned for each of the stacks, which are 4 in our case, since we run inversion on all available 4 partial stacks. These define the contribution to the objective function as L_2 -norm misfit between seismic and inverted synthetics. The contrast misfit uncertainties define a L_1 -norm contrast misfit for the inverted elastic properties. There are 3 of them, as we have inverted for compressional impedance Z_p , V_p/V_s , and density ρ .

We use LASSO (L_1 -norm) as a regularization method for inversion (Debeye and van Riel, 1990, and Pendrel van Riel, 1997), which, unlike ridge regression (L_2 -norm), suppresses most of the samples to exactly zero contrast. That is the indelible mark of the constrained sparse spike inversion method. A small weighing, or equivalently, a large uncertainty, means that large contrasts are allowed for the inverted properties, leading, therefore, to large output resolution.

In our case, the default values for the contrast parameters are mostly conservative estimates that are tailored for sparse spike inversion. This delivers inverted properties with minimal details and limited vertical resolution, as the best result in the absence of sufficient a priori information (e.g., having no wells, or little geological knowledge to build a viable trend model).

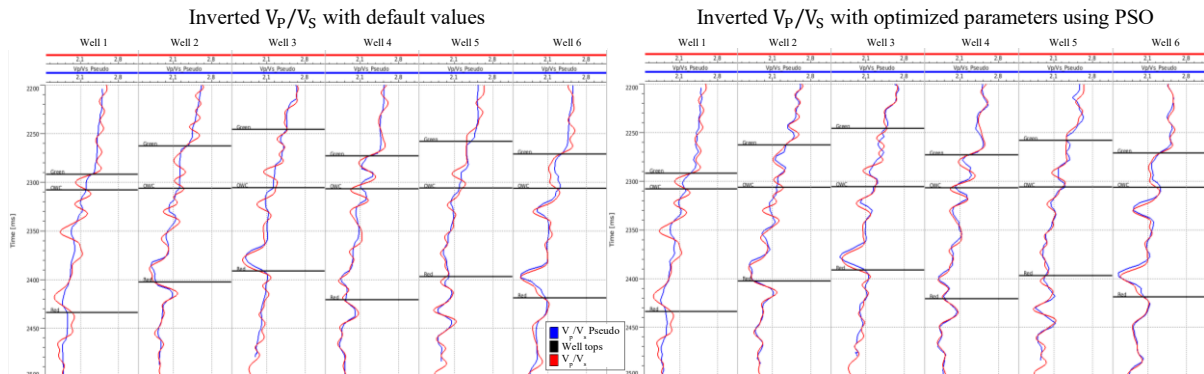


Figure 3 Same result as in Figure 2, visualising the match between the well logs and inverted V_p/V_s . Left: default parameter values. Right: optimized parameterization.

We used PSO to optimize all the 24 inversion parameters, using all 6 wells with 10 seismic traces selected around each one of them. The process completed the calculation in about 1 minute on a machine with nowadays average specifications. Then we used the optimized parameters to invert for Z_P , V_p/V_s , and density ρ . In Figure 2, we compare the V_p/V_s inversion results for default and optimized parameterization. The optimized contrast misfit uncertainties had values slightly higher than the default ones, hence allowing a higher resolution content in the results. Indeed, compared to the default, the optimized inversion provided a significantly better match with the available wells. Figure 3 displays the same comparison with more details.

Conclusions

We have presented an application of Particle Swarm Optimization algorithm for tuning many parameters that are used in constrained sparse spike seismic deterministic inversion. For comparison, while for a typical configuration, older sequential algorithms usually take more than 5 hours to complete, the new algorithm completed the job in minutes. This is mostly due to independent inversions for trial parameters, which can be run in parallel. As a bonus, this significant time gain allows running many particles during each iteration cycle, which has the great advantage of covering large regions within the parameter space. Hence, a good sampling of trial values during optimization.

As a validity test, we demonstrated very good inversion results for a case study, having both good well match and high-resolution details for elastic inversion. Finally, tuning many parameters is still challenging, as it requires in-depth analysis and QCs. Having now a fast optimization tool, the user has the possibility to output in a short time many competing combinations and scenarios for the inversion parameter settings.

References

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