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Particle Swarm and Differential Evolution – Optimization for stochastic inversion of post-stack seismic data

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Summary

Inversion of pre- and post-stack seismic data for acoustic and shear impedance is highly non-linear and ill-posed. A deterministic inversion of band-limited seismic data produces smooth models which are devoid of high frequency variations observed in well logs. Stochastic inversion methods often based on Gaussian priors can produce high frequencies in the desired model. In this paper we report on the application of two new global optimization schemes, namely, Particle Swarm Optimization (PSO) and Differential Evolution (DE) to the problem of stochastic inversion of post-stack seismic data. A starting model is drawn from a fractional Gaussian distribution (based on a fractal model) and a suitably defined objective function is optimized in search of acceptable models using PSO and DE. Our investigations reveal that both the methods have nice convergence properties. However, the DE converges at least 10 times faster than PSO. We demonstrate the performance of these methods with application to synthetic and field seismic data.

Introduction

Inversion of seismic data plays a vital role in reservoir characterization. High resolution inversion methods add significant value to the inversion results and increase the confidence level in interpretation of seismic data. Well logs present most accurate information about the petrophysical properties of a subsurface reservoir. However, spatially continuous description of a reservoir at the well log scale is not available due to limited well data. Results from seismic inversion are usually integrated with well log data to derive reservoir models in 3D. A typical deterministic seismic inversion derives blocky or coarse subsurface model well below the resolution of the well logs. A stochastic inversion that combines well logs with seismic inversion has the potential to estimate subsurface models at the well log resolution in 3D. It is well recognized that the low and high frequency part of the subsurface model reside in the null space of the seismic data and can only be incorporated through a priori information. Common stochastic inversion methods employ Gaussian probability density function to describe prior impedance models. Most recently Srivastava and Sen (2009 a, b) made use of fractal based a priori model for acoustic impedance in post- and pre-stack seismic inversion. They showed that geologically realistic acoustic impedance models can indeed be estimated by this approach. Srivastava and Sen (2009a, b) employed very fast simulated annealing, VFSA (Sen and Stoffa 1995) in the search for optimal models. Our approach is very similar to that used in Srivastava and Sen (2009 a, b). However, we employ two new global optimization methods, namely, particle swarm optimization (PSO) and differential evolution (DE) in stochastic inversion of post-stack seismic data. To the best of our knowledge, this is the first application of DE to geophysical inversion. We demonstrate performance of our approach with application to field data.

Theory/Method Involved

Before, inversion, spectral analysis of seismic traces at different well locations in 3D data volume has been carried out to ascertain the reliable spectral bandwidth, signal to noise ratio and phase variations. Statistical analysis of well log data has been carried out for understanding the relation among log derived seismic parameters, i.e., acoustic impedance, velocity and density which provide a solid base for prediction of lithology. Synthetic seismograms generated using sonic, density logs and VSP surveys are used to calibrate geologic picks of different wells to seismic reflections. A composite full wavelet has been estimated using both seismic and several well logs available in the 3-D study areas. Initial 3D impedance models were generated using seismic,well log and picked horizons. Different techniques of inversion are being used by the industry to perform stratigraphic inversion from post stack seismic data.

In a typical 3D seismic volume, well logs are interpolated and extrapolated in the entire volume guided by the interpreted horizons. These are then used to estimate a mean, covariance and Hurst coefficient at each CMP location which are then used to generate a realization of well log(Using Fractional Gaussian Process) (Srivastava and Sen ,2009) for evaluation by PSOand DE. The models are modified by PSO/DE update (constrained to honor the statistics) such that they match the seismic data

The basic approach to estimating high resolution acoustic impedance map from stochastic inversion of post-stack seismic data is shown in figure 1 (taken from Srivastava and Sen 2009a). The algorithm requires (1) definition of an objective function, (2) choice of a starting model and (3) choice of optimization methods. Below we describe each one of these including our choice of two optimization methods, namely, DE and PSO.

Objective function: We consider an error function based on the median properties of the Observed and Computed seismogram

Let

F1=(Observed-Computed)

F2=(Observed+Computed)

Thus we use the following function for minimization

F=F1/(F1+F2) (2)

Differential Evolution Optimization: Differential Evolution (DE) (Storn and Price 1996)is a novel parallel direct search method which utilizes NP parameter vectors

$x_{i,G}$, i = 0, 1, 2, ... , NP-1. (11)

as a population for each generation G. NP doesn't change during the minimization process. The initial population is chosen randomly if nothing is known about the system. As a rule, we will assume a uniform probability distribution for all random decisions unless otherwise stated. In case a preliminary solution is available, the initial population is often generated by adding normally distributed random deviations to the nominal solution $x_{nom,0}$, The crucial idea behind DE is a new scheme for generating trial parameter vectors. DE generates new parameter vectors by adding the weighted difference vector between two population members to a third member. If the resulting vector yields a lower objective function value than a predetermined population member, the newly generated vector replaces the vector with which it was compared. The comparison vector can, but need not be part of the generation process mentioned above. In addition the best parameter vector $x_{best\,G}$, is evaluated for every generation G in order to keep track of the progress that is made during the minimization process.

Extracting distance and direction information from the population to generate random deviations results in an adaptive scheme with excellent convergence properties

Particle Swarm Optimization : The particle swarm is an stochastic evolutionary computation technique (Kennedy and Eberhart, 1995) used in optimization, which is inspired in social behaviour of individuals (called particles) in nature, such as bird flocking and fish schooling. This has been successfully used in many different science and engineering fields including Geophysics (Shaw and Srivastava 2007). In a PSO, each particle samples the search space according to its own, l^k, and its companions, g^k, searching experience. The algorithm updates positions,

$\bar{x}^k$, and velocities, $\bar{v}^k$, of the individuals as follows:

$$v^{k+1} = wv^{k} + \alpha(x^k - g^k) + \beta(x^k - l^k)$$

$$x^{k+1} = x^k + v^{k+1}$$

$$\alpha = r_1 a_g \quad \beta = r_2 a_l \quad r_1 r_2 \in U(0,1) \quad w, a_g, a_l \in R$$

Constants, w a_g a_l constitute the tuning PSO parameters and are called respectively, inertia, global and local accelerations. In PSO, each particle of the swarm has two points of attraction: the global best, g^k, and its previous best position, l^k, and thus, the algorithm can be interpreted as a two discrete gradient method with random effects introduced in the global and local acceleration constants, a_g a_l by uniform random numbers r_1 , r_2 This algorithm is very intuitive and is easy to program.

Starting Model: We draw a starting model from a fractional Gaussian distribution described in Srivastava and Sen (2009 a, b) where the a priori probability density function is defined by three parameters, namely, the mean, the standard deviation and Hurst coefficient. The optimiztion method modifies the model based on the misfit between observed and synthetic data such that the statistic is honoured

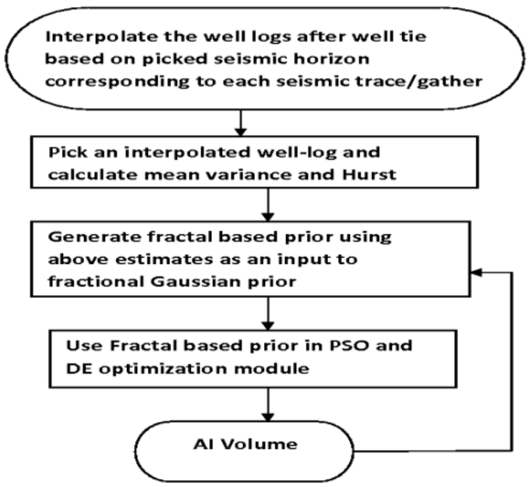

Figure 1:flowchart of Inversion Algorithm.

Examples

1. *Synthetic data* – we derived random reflectivity using a random generator and convolved it with 30 Hz Ricker wavelet to obtain a synthetic seismogram as our forward model; further we carried out inversion of the same model using PSO and DE in which we generate acoustic Impedance values. The data fit obtained by both the optimization methods is shown in Fig(2) and Fig(3) respectively

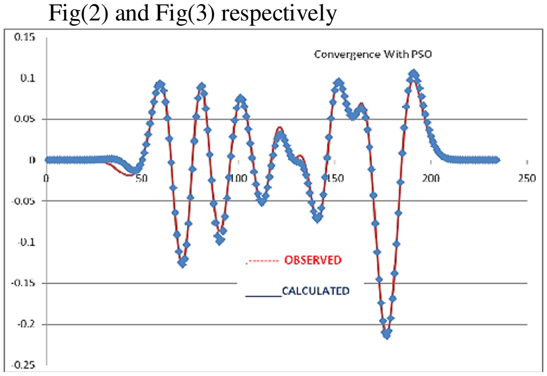

Figure 2:Data Fit by PSO

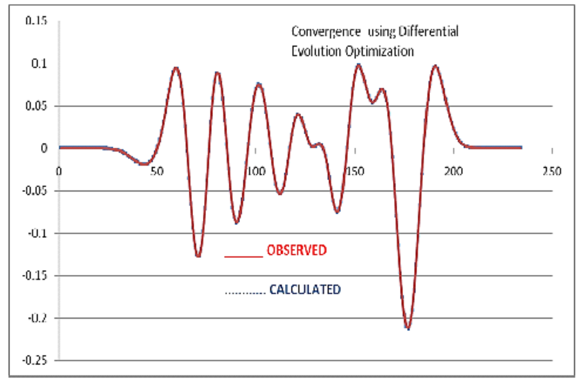

Figure 3: Data fit by DE

Real Seismic data Inversion: We also carried out inversion of field data (also used in Sen and Srivastava 2009a). We derived a particular log corresponding to trace number 27 xline number 42 of the seismic data and the acoustic impedance values thus generated were compared with the observed values from well-log data .The plots are shown in the figure 4 and 5. Respectively

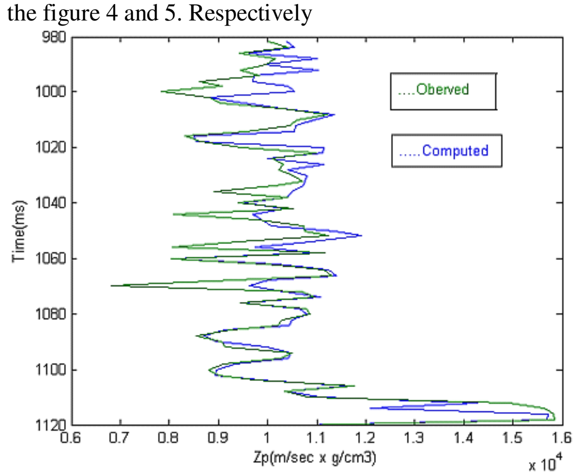

Figure 4: Acoustic Impedance Match for Computed and Observed values(for PSO)

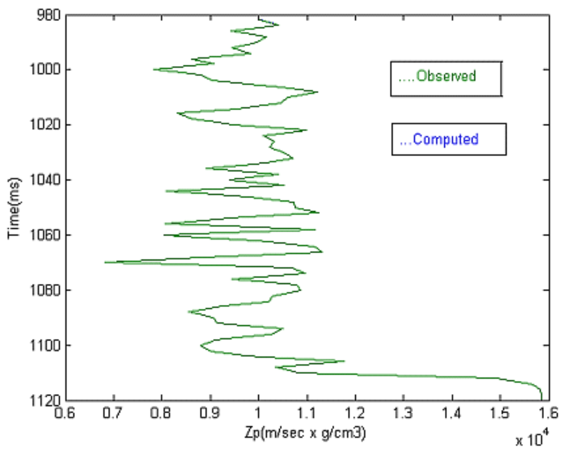

Figure 5: Same Match Using DE

Finally we carried out inversion for total of 119 traces using Differential Evolution; the plots are shown in figure 6. 2D Plots of Acoustic Impedance calculated by the inversion of section of seismic field data using PSO and DE are shown in figure 7; note the high resolution estimates

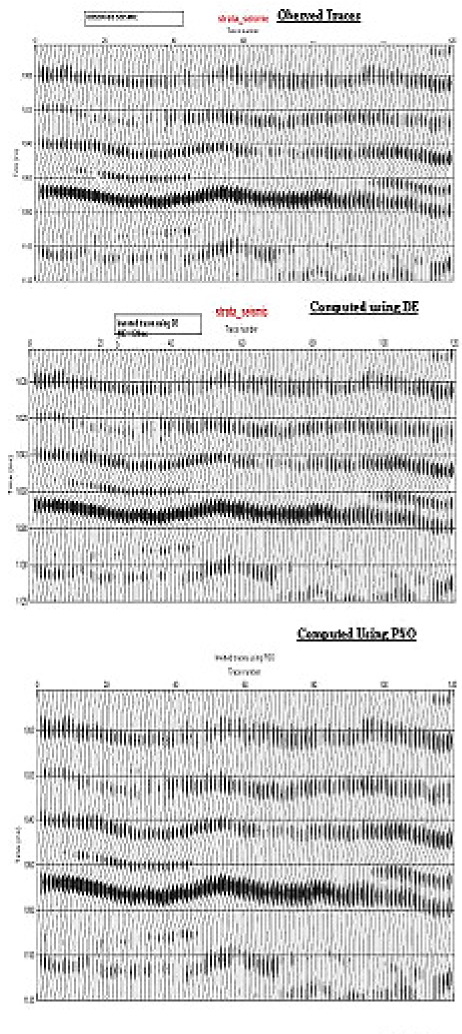

Figure 6 : Observed and Computed(by Inversion using PSO and DE) Traces of real field Data

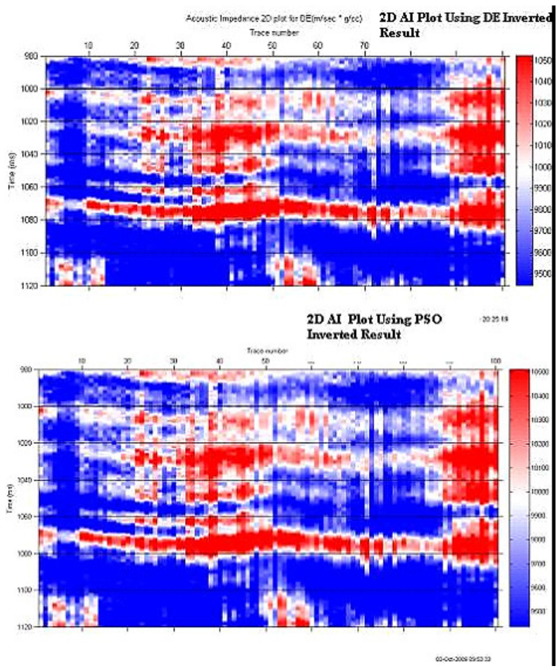

Figure 7:AI 2D plots

Conclusions/Discussions

We presented two new techniques for global optimization for geophysical inversion, namely Particle Swarm Optimization and Differential Evolution Optimization and applied for the inversion of post-stack seismic data and well-log data. In our research using PSO and DE , we generated fractal based a priori model for acoustic impedance values precisely. The results demonstrated the efficiency of two Evolutionary techniques (PSO and DE). PSO has been used previously for geophysical inversion, but to the best of our knowledge, this is the first application of DE fielding Geophysics.The objective function used matches seismic data and honors statistic of well-logs. The inversion process is fast - the results were obtained within 1000 iterations.

PSO and DE are both evolutionary algorithms and provided good data-fit with very low error approximately to the order of 10e-05 with appropriate time consumption though DE was comparatively faster than PSO with more accuracy and precision. These techniques require no prior knowledge of the bounds as the tasks were well accomplished with high bounds(±20%). Thus we feel that PSO and DE can be operated on a wide range of Geophysical problems and data sets with any number of unknowns to be determined accurately

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