Application of interactive geological inversion techniques and grid computing to numerical modelling of geological processes

W. Potma[1&2], T. Poulet[1&2]

(1) Computational Geoscience for Predictive Discovery, CSIRO Exploration & Mining, ARRC Kensington, Western Australia 6151.
(2) Predictive Mineral Discovery CRC

Abstract

Numerical modelling of geological processes requires the quantification of a large number of (often unmeasurable) parameters in order to reproduce an observed physical behavior. Interactive geological inversion using genetic algorithms, grid computing and complex post processing can be combined with numerical-modelling to reverse engineer the key parameters which control the physical processes observed in the geological record. A series of customised tools and a workflow have been developed to perform this analysis and provide a quantified basis for predictive numerical modelling of geological processes to aid exploration geologists.

Keywords: Numerical Modelling, Interactive Geological Inversion; Genetic Algorithm; Grid Computing, Data Analysis.

Introduction

4D numerical modelling of geological processes requires the quantification of a large number of parameters in order to generate a valid result, or reproduce an observed physical behavior. Many of these variables cannot be directly measured, because they represent rock properties or speculated geometries at >10km depth, and must therefore either be inferred or tested as part of the numerical modelling process. Any given modelling scenario may require the testing of multiple geometries (fault orientations, rock layering etc.), physical rock properties (cohesion, tensile strength, friction angle, permeability etc.) and boundary conditions (pore pressures, deformation forces, fluid fluxes etc.). The potential parameter search space is infinitely large and even when individual variables are assigned only 8 possible values, parameter spaces as large as 15^8 may need to be searched in order to reproduce an observed mechanical deformation and fluid flow behavior in rock.

We employ interactive geological inversion techniques (Boschetti & Moresi 2001), grid computing and semi-automated data retrieval and post-processing to enable rapid visual ranking and analysis of results in 2D, 3D & 4D. The tools and workflow we have developed significantly reduce the time required to explore the vast parameter space associated with reverse engineering of complex geological processes (such as vein and shear zone formation in gold ore systems).

Interactive Geological Inversion

Interactive Geological Inversion techniques (Boschetti & Moresi 2001) are used to search, in an efficient way, the parameter space of the geological process being simulated. We generally use Genetic Algorithms (Goldberg 1989) to drive the search, however, some other algorithms are being investigated, such as Lipschitzian methods (Strongin & Sergeyev 2000), to try and limit the randomness of the process. Additional functions are included to optimise the search, such as reducing the parameter space with cutting equations. The inversion application generates different sets of parameters to test, and expects the user to provide some feedback about the quality model result for each set of parameters.

Grid Computing

Each simulation can take around 15 hours to run and it is therefore essential to be able to run many different simulations in parrallel. Grid computing is an elegant way to do so as it allows a user to benefit from the computing power of many distributed machines without having to manage each machine or job individually.

Visualisation

We also use Sammons Mapping (Sammon 1969) to visualise the relative similarity of the "N dimensional" parameter space in a 2D representation to help identify the locus (loci) of any emergent global minima (good model results). The aim of this process is to converge on a group(s) of model results which most closely represent the observed geological phenomena. We are then able to quantify the various parameter values (rock properties, boundary conditions etc.) which contribute to or control the observed mechanical and fluid flow behavior. These parameter values can then be applied to modelling what-if geological scenarios which can be used as a predictive tool to aid exploration geologists, rock mechanics engineers and geological process modellers.

The Next Problem

We are now able to run more models than we can reasonably analyse, interpret and rank, resulting in a severe data analysis and feedback bottle-neck which must be overcome. At this stage we are exploring two options to overcome this bottle-neck:

1) The implementation of automated 4D (x,y,z + time) image recognition applications. This method must be capable of ranking 4D raster and vector data based on a set of user defined rules. Effective ranking relies on assessing the interplay between the spatial distribution and absolute values of up to 10 data output types across multiple 3D visualisations (in the same physical space but potentially different time). This produces a composite ranking result which is only as good as its defining rules and the resolution/perspective of the images being assesed. This method would potentially enable the "bad" model results to be identified and binned, leaving the user to concentrate on only the good results which require more complex manual analysis and ranking.
2) A non-visual primary data analysis method which analyses the primary numerical outputs from the models. These data are attached to the nodes and centriods of a 3D finite difference mesh, and identify which models exhibit the required numerical characteristics in the correct spatial (and temporal) location within the mesh.

Both methods require significant user input to establish the "rules" which will constitute a good vs bad result, however, this process is already undertaken by the user as part of the manual ranking process. The challenge is to translate the data analysis process which is currently a completely manual task, to a partly (or potentially completely) automated process. The difficulty of this task is compounded by the need for both the user and the data anlysis tool to "learn" and adapt the interpretation/ranking rules (and potentially method) as unexpected modelling results are received.

References

F. Boschetti and L. Moresi. *Interactive inversion in geosciences*. Geophysics 66, 1226-1234. 2001

D.E. Goldberg. *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley Publ. Co., Inc. 1989.

J. W. Sammon, Jr. *A nonlinear mapping for data structure analysis*. IEEE Transactions on Computers, C-18(5):401-409, May 1969

R.G. Strongin and Y.D Sergeyev. *Global Optimization with Non-Convex Constraints, Sequential and Parrallel Algorithms*. Kluwer Academic Publishers. ISBN 0-7923-6490-2, October 2000.