An evolutionary approach to thermal history modelling with fission track data

K. Gallagher

School of Geological Sciences, Kingston University, Kingston, KT1 2EE, England

Introduction

Recent advances in our understanding of fission track annealing have led to empirical predictive models such that, given various assumptions, it is possible to predict the expected fission track parameters (age, track length distribution) for a given thermal history (Laslett *et al.* 1985; Green *et al.* 1989; Carlson 1991). In practice, however, it is the fission track parameters that are measured, and the thermal history is unknown. In sedimentary basins, the thermal history is intimately linked to the burial history and a reasonable reconstruction of both is often possible when a suite of downhole samples is used. However, in situations where only surface samples are analysed, the thermal history and cooling/exhumation rates must often be constrained from the fission track data alone. In principle, analytical inversion methods could be used to determine the thermal history directly from the data, but the mathematical formulations are non-linear. This non-linearity can lead to computational problems with analytical methods (e.g. instabilities in matrix inversions and partial derivative calculations, an initial guess very close to the true thermal history). The resulting method may be unstable and a rigorous resolution analysis of the solution is difficult. Alternatively, more robust optimisation methods which avoid many of these pitfalls can be used.

Random Monte Carlo

Random Monte Carlo methods have been applied to this problem (e.g. Lutz and Omar 1990). The basis of this approach is that a temperature history is selected at random from within specified bounds and fission track parameters are calculated for this temperature history. This process is repeated until either a temperature history is found which predcits the data to a satisfactory level, or the user decides to go home. The advantages of this approach are that all that is required are the specification of the forward problem (i.e. how to calculate fission track parameters for a given thermal history) and how to determine how well the predicted paramaters fit the observations. We readily avoid problems with numerical stability and linearising assumptions. However, one of the drawbacks of random Monte Carlo simulation is that every model thermal history is completely independent of the others. Thus, we may find the best data fitting thermal history after 1, 10 or 1 $\times$ 10^6 simulations - there is no guarantee or sense of convergence. In other words, Random Monte Carlo is very stable and safe, but inefficient.

Genetic algorithms

Unlike the more conventional random Monte Carlo methods, genetic algorithms actually learn the form of the better data-fitting thermal histories and the progressive sampling is geared to finding the more optimal thermal histories. Gallagher and Sambridge (1994) give a recent overview of genetic algorithms and their applications in the Earth Sciences. Their implementation is initially very similar to Random Monte Carlo. Bounds on possible values of temperature and time are specified and points selected randomly from within these bounds. However, after an selection of initial number of random thermal histories (i.e. starting population), these are allowed to breed. The breeding is biassed so the better data fitting models stand more chance of being parents, the idea being that the better parents will lead to better children, i.e survival of the fittest (the fittest being the best thermal history). Having generated a population of children, these can in turn can become parents and have offspring. This procedure is repeated until a satisfactory thermal history is found. However, because genetic algorithms use the information gained by this population sampling to generate better models, they are considerably more efficient than random Monte Carlo.

Fig. 1 shows 200 thermal histories generated using both random Monte Carlo and a genetic algorithm using synthetic fission track data as input, generated from a simple heating-cooling thermal history. The genetic algorithm clearly exhibits more efficient sampling of the possible thermal history models (more than $2x10^7$ in this case), and, for much the same amount of computational effort, achieves a better thermal

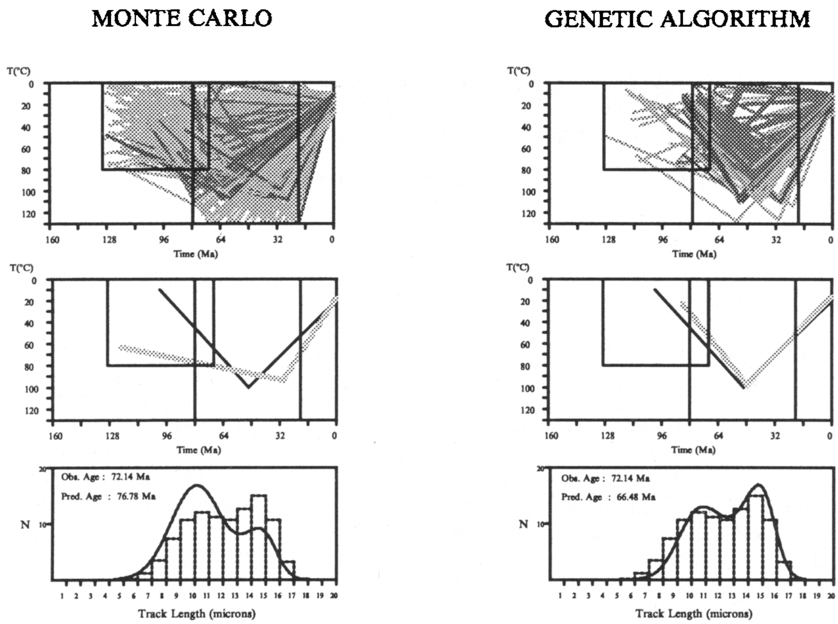

FIG. 1. Performance of random Monte Carlo and a genetic algorithm, using synthetic data (fission track age and track length distribution). 200 simulations were run in each case, with 10 iterations (20 models in each) of the GA. The upper panel shows all simulations with time:temperature points selected from within the 2 boxes shown, and the lighter lines generally represent better models. The true answer is shown in the middle panel (dark line) and the best thermal history (light line) for each method. Notice how the spread in solutions is reduced for the GA and most are similar to the true solution. The predicted and 'observed' data are summarised in the lower panel.

history. The overall spread in the resultant thermal histories is also an indication of the resolution of this best models.

It has been shown elsewhere (Gallagher *et al.* 1991, Sambridge and Gallagher 993) that as the number of unknowns increases (i.e., number of time:temperature points) the performance of genetic algorithms over random Monte Carlo increases exponentially. However, that does not mean that we should then always use many time:temperature points. The best philosphy is to use the minimum number required to achieve an adequate fit to the data.

Summary

Genetic algorithms provide an extremely efficient method to assess the information on the thermal history contained in measured fission track data.

An overview of the methodology will be given, using both synthetic and real data examples. The fact that many (> 1000) thermal histories can be tested rapidly allows the spread in good data fitting solutions to be examined directly to assess the characteristics required to fit the observed data. The methodology may be applied to any type of thermochronological data, although fission track data are particularly useful because of the information on cooling rates contained in the length distribution.

References

Gallagher, K, Hawkesworth, C.J. and Mantovani. M.S.M (1994) *J. Geophys. Res.*, in press.

Gallagher, K., and Sambridge, M. S. (1994) *Comp. Geosci.*, in press.

Gallagher, K., Sambridge, M. S. and Drijkoningen, C. (1991) *Geophys. Res. Letts.*, **18**, 2177–80.

Green, P. F., Duddy, IR., Laslett, G.M., Hegarty, KA., Gleadow, A.J.W., and Lovering, J.F. (1989) *Chem. Geol., (Isot. Geosci. Sect.)*, **79**, 155–82.

Laslett, G.M., Green, P.F., Duddy, I.R., and Gleadow, A.J.W. (1987) *Chem. Geol. (Isot. Geosci. Sect.)*, **65**, 1–13.

Lutz, T.M., and Omar, G. (1991) *Earth Planet. Sci. Lett.*, **104**, 181–95.

Sambridge, M. S., and Gallagher, K. (1993) *Bull. Seis. Soc. Amer.*, **83**, 1467–91.