LARGE NEAR-SURFACE ANOMALIES, SEISMIC REFLECTION DATA, AND SIMULATED ANNEALING

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ABSTRACT

Where the near-surface of the Earth is irregular, seismic signals reflected from the underlying subsurface are degraded. The most important effects of near-surface anomalies are often traveltime delays called statics. Large near-surface anomalies can cause large statics that grossly distort the apparent structure of the Earth in reflection seismic sections.

To estimate (and then remove) statics, traveltime delays are measured by crosscorrelating seismograms. When statics are large, however, the lag that yields the maximum value of a crosscorrelation function may be an unreliable indicator of the true time delay. Gross errors are common.

Statics estimation is usually posed as a linear inverse problem. However, because statics estimation is actually a *nonlinear* inverse problem, linear approaches to statics estimation rely implicitly on an initial guess. I present a method for the estimation of statics that is independent of an initial guess. Statics estimation is formulated as a nonlinear inverse problem in which the estimation of the optimal statics corrections requires locating the global minimum of a multidimensional objective function.

Global optimization must avoid entrapment in suboptimal local minima. To achieve this goal, I adapt the method of simulated annealing, a Monte Carlo method that mimics the physical process by which a crystal is grown from a melt. Geophysical parameters are treated as if they were the microscopic components of a physical system. The method randomly generates new values for these parameters in a way that simulates thermal equilibrium; a control parameter analogous to absolute temperature determines the freedom with which the parameters' values are changed. A non-zero temperature allows perturbations that can either decrease or increase the objective function.

The most efficient form of the new statics estimation algorithm also uses crosscorrelation functions. Instead of picking the peaks of crosscorrelation functions to estimate time delays, the new method transforms the crosscorrelation functions to probability distributions. Estimates of time delays are then randomly drawn from these probability distributions. This procedure is repeated iteratively until a stable solution is reached.

Results are demonstrated on synthetic data and field data from the Wyoming Overthrust belt. Further applications of the method are proposed.

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