O9-6 SQUENTIAL (HYBRID) USE OF GENETIC ALGORITHMS AND THE DAMPED LEAST-SQUARES INVERSION FOR THE ONE-DIMENSIONAL INTERPRETATION OF TEM AND VES DATA

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I performed GA and Levenberg- Marquardt inversion methods sequentially for TEM and DC data for 1-D subsurface models. The inherent problems of equivalence and suppression in transient electromagnetic (TEM) and direct current (DC) resistivity methods are studied.

Genetic Algorithms (GA) are the algorithms based on mechanics of natural selection and genetics. They combine survival of the fittest among string structures with randomized information exchange to form a search algorithm. This search algorithm consists of generations. Every generation is a new set of artificial creatures (strings) which is created using bits and pieces of the fittest of the old. An occasional new part is tried for good measure.

While randomized, GA is no simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance.

GA performs a multi-directional search by maintaining a population of potential solutions and encourages information formation and exchange between these directions. The population undergoes a simulated evolution: at each generation the relatively 'good' solutions reproduce, while the relatively 'bad' solutions 'die'. Misfit values are used to select a better model parameter sets. Here misfit plays the role of the environment.

GA use stochastic process to produce an initial population of models. Simple manipulations of operators (crossover and mutation) are applied to the model population. This process is repeated several times until suitable model or group of models evolves. The initial population is referred as parents, the new population as offspring.

Chromosomes are the main carriers of the hereditary information and genes, which presents the hereditary factors are lined up on chromosomes e.g. (00100100111). Each chromosome (genotype) represent a potential solution to the problems.

An evolution process runs on a population of chromosomes corresponds to search through a space of potential solutions. Such a search balances the two objectives; exploiting the best solution and exploring the search space. Local methods, exploits the best solution for possible environment, but it neglects exploration of search space. Random search methods (e.g. Monty Carlo Method) explores the search space ignoring exploiting of the promising regions of the space, thus; unlike random search, GA is not directionless.

Since the algorithm evaluates the fitness function from many parts of the model space in parallel and it compares between them, it is not likely that it will get trapped into a local maximum with a poor fitness function value when a proper choice is decided for the size of population and crossover and mutation probabilities.

GA is different from normal optimization and search procedures in four ways:
1- GA works with a coding of the parameter set, not the parameter itself.
2- GAs search from a population of points, not single point, thus; it could - almost- avoid being trapped in a local minimum, GA is also free of assumed starting point.
3- GAs use fitness information, not derivatives or other auxiliary knowledge.
4- GAs uses probabilistic (stochastic) transition rules, not deterministic rules.

The main limitation with GA is the dependence on the speed of the fitness function computation, since many models need to be generated before convergence.

Reproduction process of offspring - which is hoped to produce better parameters compared to the parents - is very slow compared to the local methods, because reproducing of offspring is confined only in each generation.

In this paper the sequential use of coincident loop TEM and Schlumberger DC data is performed over 1D H,K,Q, and A type three layer models, both with and without noise.

I found that, GA does not produce irrelevant (unimportant) parameters, because the probabilistic (stochastic) character of parameter assigning process in GA, this is in sharp contrast with local search methods where parameters corresponding to relatively very small singular values will be classed as irrelevant.

By implementing GA, it could be avoided having unreasonable parameters because search space for each parameter is assigned prior to the search. It was found that due to stochastic process in producing parameters, GA is less effected by noisy data compared with local search methods. I found also that the decision made for the optimal population number becomes more important if data is contaminated with noise.

Contrary to GA applications in other fields- such as reservoir simulations in Petroleum Engineering or GA related to chemical applications - I can not recommend that fixed values for population size, cross-over or mutation probabilities for a certain problem. The optimal values for population size, cross-over or mutation probabilities changes from one case to another, and one has to find these values by trial and error. Due to its undesirable effects, I recommend not to use mutation in GA -that is equal to say that mutation probability is zero- unless the parameters became over-zealous and the algorithm could not yield better parameters in spite of concatenated generations, in this case it could be recommended using mutation coefficient of low value. To minimise observed data misfit and to get better parameters, I recommend using two child as a result of the cross-over process. Finally, it was found that using offspring outputs of GA as initial guess parameters for Levenberg-Marquardt inversion method as an example for the local methods gives very satisfactory results as these initial guess parameters are very likely to be free of being trapped in a local minimum, and further iterations performed on these parameters by deterministic local methods will further enhance the parameters.

It is important to understand the nature of data to be interpreted to avoid building unrealistic initial models, GA could be a very useful tool to guide to the possible subsurface resistivity distribution, and this notion becomes more important in TEM data compared with DC data. Because it is much difficult to resolve subsurface resistivity distribution which leads to TEM data whereas it is not the case with DC data.

Using a hybrid scheme of both global and local search strategies gives us the advantage of that the search performed by GA is enhanced by a local search method to improve the convergence.