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An Analysis Method of Fluid Flow Monitoring Using a Genetic Algorithm

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ABSTRACT

When estimating fluid flow behavior using a nonlinear least-squares method, appropriate initial guesses of the estimating parameters are required to solve the problem because the final estimates are often influenced by the initial guesses of the values of the estimates.

An objective analysis method has been developed which is independent of the initial guesses for the parameters. Applying the method to the analysis of field data obtained from a fluid flow monitoring survey, fracture distributions can be evaluated which are consistent with drilling results.

Introduction

An advanced geophysical technique has been developed for dynamic imaging of fluid flow behavior in reservoirs. In this method, changes with time of self-potential anomalies at the ground surface associated with production or injection operations are simultaneously and continuously measured by potential electrodes located surrounding a given well.

Recently, many kinds of soft-computing techniques, which are genetic algorithms, neural network, fuzzy reasoning, and so on, are applied to various inverse problems to obtain objective results. In reservoir evaluations, genetic algorithms are applied to reservoir modeling by Sen et al. (1995), to identifying reservoir properties using tracer breakthrough by Guerreiro et al. (1998) and Tanaka et al. (1999).

In this study, we apply a combination of a genetic algorithm and a nonlinear least-squares method to the analysis of fluid flow behavior to estimate objectively and accurately three-dimensional fracture distributions.

Analysis Method

Genetic Algorithm

Genetic algorithms are stochastic optimization and search algorithms based on the mechanics of natural selection and natural genetics (Goldberg, 1989). Comparing with a nonlinear least-squares method, genetic algorithms have many remarkable features: the initial guess for the values of the unknown parameters is not required, which can keep results objective; they can search simultaneously many estimates in an identical search space, which suggests the possibility of parallel computing. However, Boschetti (1996) pointed out that genetic algorithms are poor optimizers. Therefore, a number of authors have suggested hybrid techniques, which combines genetic algorithms with various search techniques. When the problem-specific information or the explicit objective function exists, it may be advantageous to consider a hybridized genetic algorithm (Goldberg, 1989).

The final estimates obtained from an analysis using genetic algorithms are not optimal solutions but discrete values close to them. A nonlinear least-squares method is available for improving the estimates obtained by genetic algorithms as quasi-optimal solutions. Since the convergence properties of the least-squares method can be quadratic in the convergence domain containing the quasi-optimal solution. Thus, we have developed a new analysis method to improve genetic algorithms, which has a two-step estimating procedure. It has been applied to the evaluation of fluid flow behavior to estimate fracture distributions.

Analysis Process

Figure 1 (overleaf) shows that the flow chart of an analysis procedure by the genetic algorithm and the least-squares method. In the first step of the procedure, estimates, which are objectively obtained as quasi-optimal solutions by the genetic algorithm, can be expected to be good initial guesses for the parameters for the second step. The obtained objective estimates are expected to be further improved by the nonlinear least-squares method to converge to the optimal final estimates in the second step. The simplest implementation of a genetic algorithm uses three gene operations, which are reproduction, crossover, and mutation.

First, the system is initialized with a population of N individuals that contain the binary bit strings for the encoded

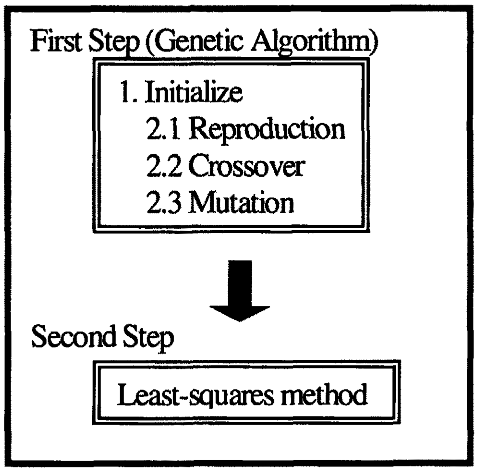
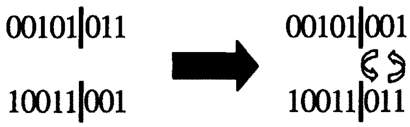
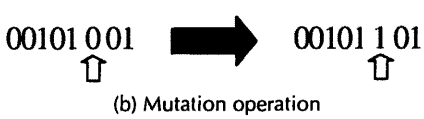


Figure 1. Flow chart showing the order of the analysis procedure with the genetic algorithm used to find the initial guesses for the second step and the least squares method to further improve the estimates.

unknown parameters to estimate. In genetic algorithms, the term "individual" is defined as a set of unknown parameters to estimate. The term "population" is defined as the total number of parameter sets. Reproduction is the next process after initialization in which two individuals are selected according to their objective values, called fitness or misfit values. The strings within an individual with a higher fitness or with a smaller misfit value has a higher probability of selection to reproduce a new population of offsprings. After reproduction, a crossover site is selected at random and bits are partially exchanged between two strings at the right side of the crossover site (Figure 2a). In this paper, we used a multi-point crossover in which there is crossed over between corresponding parameters of two strings. Mutation is simply the alteration of bits selected randomly in the parameter code shown in Figure 2b and carried out based on the specified mutation probability.



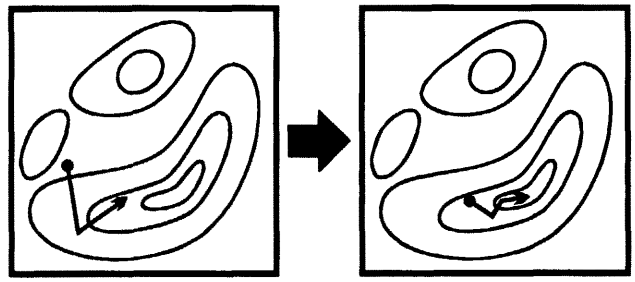
(a) Crossover operation



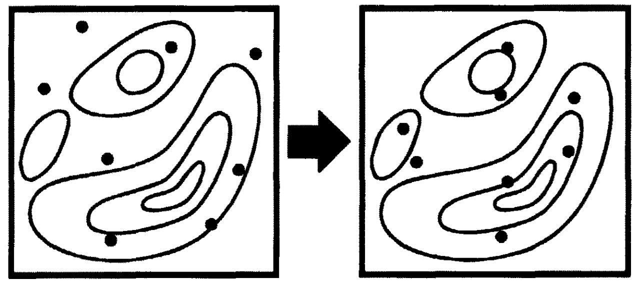
(b) Mutation operation

Figure 2. Schematic illustration of the gene operations of (a) a crossover and (b) a mutation.

Figure 3 shows the distribution changes of individuals based on an optimization process in a three-dimensional search space using the nonlinear least-squares method and the genetic algorithm. The conceptual contour map describes the distribution of the residual sum of squares with the both x and y-axes of the two unknown parameters as a three-dimensional search space. In the nonlinear least-squares method shown in Figure 3a, an appropriate initial guess is given and improved to the global optimum. In the genetic algorithm shown in Figure 3b, the distribution of individuals becomes denser around the global optimum and the local optima through the optimization process.



(a) Least Squares Method



(b) Genetic Algorithm

Figure 3. Distribution changes of individuals by (a) a nonlinear least-squares method and (b) a genetic algorithm with the optimization process in a conceptual search space, which describes a contour map of a residual sum of squares.

Fluid Flow Monitoring Survey for Fracture Evaluation

Self Potential

Many researchers have studied self-potential anomalies associated with pressure, temperature, and chemical potential gradients. Self-potential anomalies due to streaming potential effects can be expressed based on the theory of irreversible thermodynamics in inhomogeneous media. The cross-coupled equations between streaming potential and fluid flow distribution due to pressure gradient are defined as (Fitterman, 1979),

$$\begin{bmatrix} S_1 \\ S_2 \end{bmatrix} = \begin{bmatrix} L_{11} & L_{12} \\ L_{21} & L_{22} \end{bmatrix} \begin{bmatrix} -\nabla P \\ -\nabla \Phi \end{bmatrix} \qquad (1)$$

where $\mathbf{S_1}$ is the primary flow as the fluid flux vector, $\mathbf{S_2}$ the secondary flow as the electric current density vector, Φ the electric potential, P the fluid pressure, and L_{ij} the generalized conductivity. More specifically, L_{11} is the hydraulic permeability k, L_{22} is the electrical conductivity σ, L_{21}/L_{22} is the streaming potential coefficient C, and L_{12}/L_{11} is the osmotic coefficient. The Onsager reciprocal relation requires that $L_{12}=L_{21}$. When the effects of the secondary electric potentials on the primary flow are small, the primary flow equation can be decoupled and the resulting equations are

$$\mathbf{v} = -\frac{k}{\mu}\nabla P$$
$$\mathbf{I} = -\sigma(C\nabla P + \nabla\Phi) \qquad (2)$$

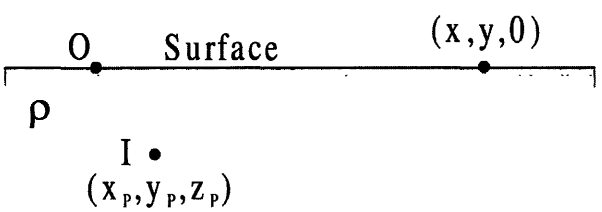
where **v** is the flow velocity vector and **I** the electric current vector.

Electric Potential Function

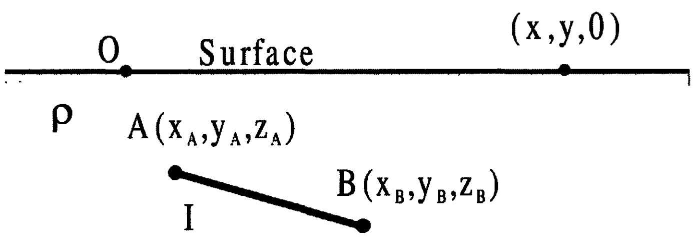
The distribution of the streaming current sources associated with the fluid flow cause the distribution of the self-potential anomaly on the ground surface. In this study, the distribution of these sources are assumed to be superposed on some simple-shaped electric current sources for the estimation. The distribution of the electric current sources obtained from the inverse analysis can be expected to suggest the distribution of the fluid flow.

Considering the homogeneous half-space as the ground, the electric potential on the ground surface at (x, y, 0) due to a buried point source of electric current located at (x_P, y_P, z_P) shown in Figure 4a is defined as

$$V = \frac{\rho I}{2\pi\sqrt{(x-x_P)^2 + (y-y_P)^2 + z_P^2}} \qquad (3)$$



(a) Point source



(b) Line source

Figure 4. Schematic diagrams of (a) a buried point source and (b) a buried line source of electric current.

where ρ is the resistivity of the ground and I the strength of the electric current source on condition that the potential is assumed to be zero at an infinite distance from the electric current source. The potential caused by a buried line source of electric current can be derived by a simple integration of equation (3) along the line source. When the line source is assumed to extend from point A (x_A, y_A, z_A) to point B (x_B, y_B, z_B) shown in Figure 4b, the electric potential at the point (x, y, 0) on the ground surface is given by

$$V = \begin{cases} \dfrac{\rho I}{2\pi L}\left|\log\dfrac{|\mathbf{b}|}{|\mathbf{a}|}\right| & (\beta - 4\alpha\gamma \neq 0) \\ \dfrac{\rho I}{2\pi L}\log\dfrac{(\mathbf{b}-\mathbf{a})\cdot\mathbf{b} + |\mathbf{b}-\mathbf{a}||\mathbf{b}|}{(\mathbf{b}-\mathbf{a})\cdot\mathbf{a} + |\mathbf{b}-\mathbf{a}||\mathbf{a}|} & (\beta - 4\alpha\gamma = 0) \end{cases} \qquad (4)$$

where

$$\mathbf{a} = (x_A - x, x_A - x, z_A)$$
$$\mathbf{b} = (x_B - x, x_B - x, z_B)$$
$$\mathbf{b} - \mathbf{a} = (x_B - x_A, x_B - x_A, z_A - z_B) \qquad (5)$$
$$\alpha = |\mathbf{b} - \mathbf{a}|^2$$
$$\beta = 2\mathbf{a}\cdot(\mathbf{b}-\mathbf{a})$$
$$\gamma = |\mathbf{a}|^2$$

Implementation of the Genetic Algorithm

We use a binary code to encode the value of each estimating parameter into the gene with discrete equal intervals between the maximum and minimum values. The value b_x, which is the part of the binary bit strings of length l and the integer value for the each parameter, is decoded to obtain the value of parameter according to the following equation

$$x = \frac{x_{\min} - x_{\max}}{2^l - 1} b_x + x_{\min} \qquad (6)$$

where x describes each parameter, such as the strength of the electric source of current I, and its coordinates (x, y, z). The subscripts *max* and *min* indicate the maximum and minimum values of each parameter, respectively.

In the reproduction process, the most basic selection method uses the ratio of the fitness value for an individual to the sum of them. To reproduce a new population of offsprings, two individuals are selected according to the probability P_{si}

$$P_{Si} = \frac{fitness_i}{\sum_{j=1}^{n} fitness_j} \qquad (7)$$

In this procedure, the correlation factor between measured and calculated values is used as the fitness value as follows:

$$fitness = \frac{\sum_{i=1}^{n}(V_{mi} - \overline{V}_m)(V_{ci} - \overline{V}_c)}{\sqrt{\sum_{i=1}^{n}(V_{mi} - \overline{V}_m)^2 \sum_{i=1}^{n}(V_{ci} - \overline{V}_c)^2}} \quad (8)$$

where n is the number of potential values, V_{mi} and V_{ci} are the measured and calculated electric potential anomaly at the i-th station, respectively. The bar denotes the average for the each potential. The mutation probability should be kept low, but nonzero, to maintain the diversity of the population. Therefore, in this study, the mutation probability is assumed to be 0.1.

Application of the Method to Field Data

To verify the usefulness of the genetic algorithm to estimate fluid flow behavior and fracture distribution, we analyzed the field data reported in Ushijima et al. (1999). A lost circulation zone was encountered during the drilling of an exploratory borehole in the Hatchobaru geothermal area, Japan. Sidetracks that were drilled twice to avoid the lost circulation zone. Unfortunately, these sidetracks were unsuccessful. Later, a fluid flow monitoring survey was carried out to characterize the geometry of the lost circulation zone and to determine the direction of the next sidetrack.

Potential electrodes P_1s were placed around the well to measure the changes with time of the self-potential anomalies at the ground surface, as shown in Figure 5. Another potential electrode P_2 is located far away from the well, as in the mise-à-la-masse method.

Self-potential anomalies associated with the fluid flow in fractures can be continuously monitored by a PC-controlled data acquisition system before and during injection operations at the target well. Step-wise increases in injection water are expected to be reflected by proportional increases in the self-potential anomaly. A typical measured distribution change in the electric potentials is shown in Figure 6 when the injection flow rate is at its maximum, assuming that the electric potentials before the start of the injection operation are back ground values.

There are sources of electric current wherever there are external or induced fluid flow sources, or wherever there are gradients of the cross-coupling coefficient parallel to the fluid flow (Sill, 1983). In the analysis of the field data, one negative point source of electric current can be located at the feed zone in depth about 160m of the well, and some positive line sources of electric current can be assumed based on the principle of the electrical natural. Then, the unknown parameters to be estimated in the analysis are the strength of the negative point source at the feed zone and the strengths and the locations of the line sources.

Figure 7 shows that the distribution of the self-potential anomaly calculated from the estimated electric current sources using the method of analysis described here. A close agreement between measured (Figure 6)and calculated self-potential anomalies (Figure 7) can be obtained.

Considering a variety of cross-coupling coefficients of natural fractures, the electric current sources can expected to occur along the fluid flow in fractures. Thus, estimated locations of the line sources of electric current indicate the distributions of fluid flow and fractures.

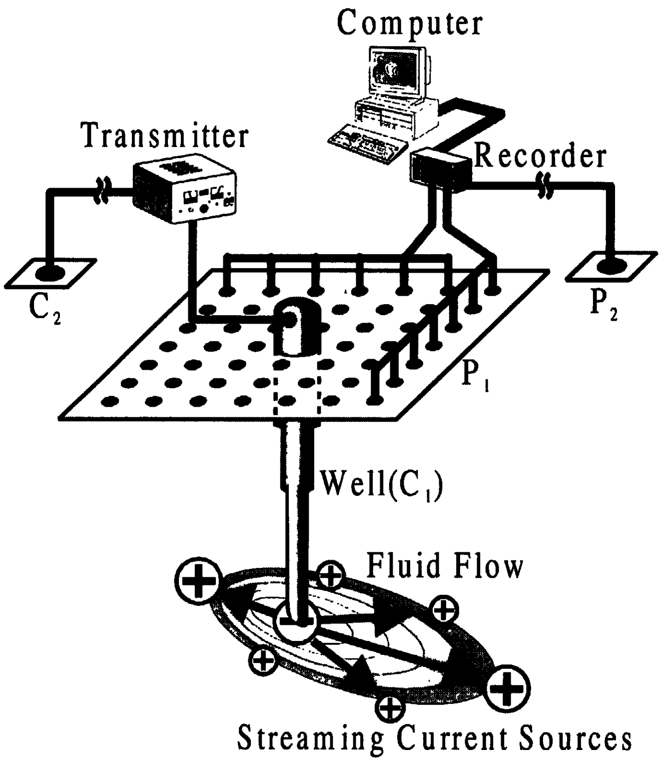


Figure 5. Electrode configurations of the fluid flow monitoring system

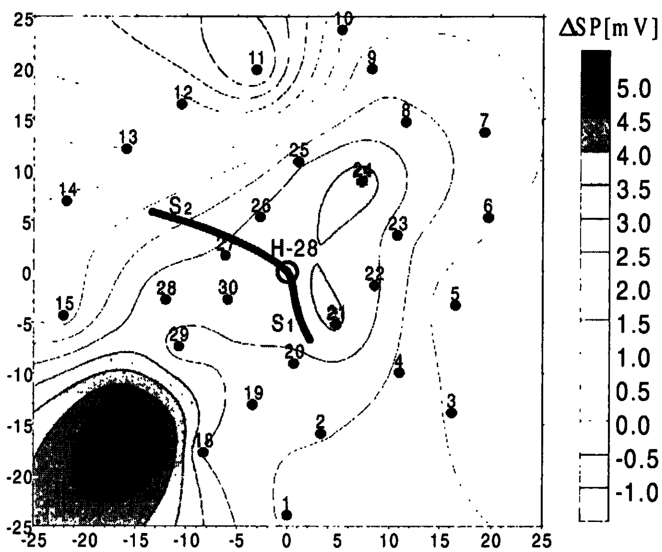


Figure 6. Distribution of the self-potential anomaly measured at 30 stations located around the well H28 when the injection rate is at its maximum. Open circle H28 and thick lines S_1 and S_2 indicate the target well and the two sidetracks, respectively.

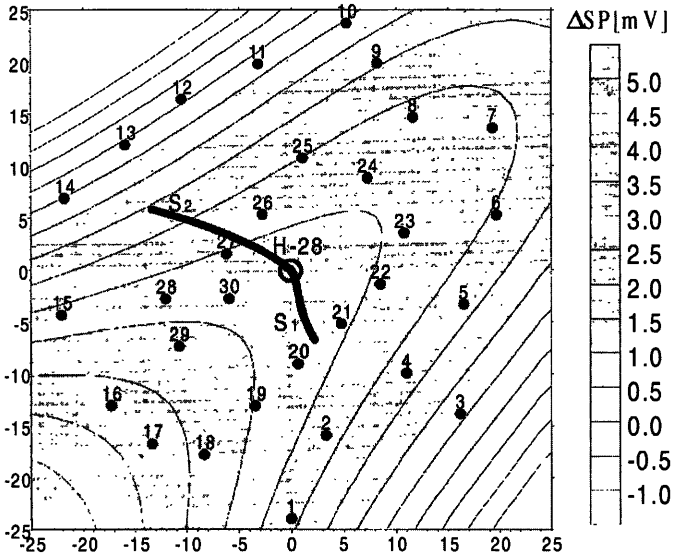


Figure 7. Distribution of the calculated self-potential anomaly resulting from the analysis.

Estimated strikes and dips of the fracture from the locations of the line sources and the drilling results are listed in Table 1. The estimated strike of N30°W from the analysis agrees with that of N39°W from the drilling results. While the estimated dip of 21°SW is one third of that of 64°SW from the drilling results. This is because the survey area, 50m x 50m, is so small that the depth resolution of the measured data may be lowered.

Table 1. Estimated strikes and dips from the analysis and the drilling results.

	Strike	Dip
This analysis	N39°W	21°SW
Drilling result	N30°W	64°SW

Conclusion

A new analysis method for the inverse problem of fracture evaluation using a genetic algorithm and a least-squares method has been developed. The results of field data analysis described here show the effectiveness of this new inverse method to characterize fractures. It is also concluded that the objective solution of the inverse analysis can be obtained independent of the skill of the person who analyzes the inverse problems. Since no initial guess for the parameter is required by the new analysis method.

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