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Optimal estimation of rock joint characteristics using simulated annealing technique – A case study

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Abstract: In this paper, simulated annealing technique was used to estimate the rock joint characteristics, RMR(rock mass rating) values, to overcome the defects of ordinary kriging. Ordinary kriging reduced the variance of data, so lost the characteristics of distribution. Simulated annealing technique could reflect the distribution feature and the spatial correlation of the original data. Through the comparisons between three times simulations, the uncertainty of the simulation could be quantified, and sufficient results were obtained.

1. Introduction

Rock mass classification method classifies rock mass into several groups showing similar mechanical behaviors and offers necessary standards which enable us to understand the characteristics of the groups as well as quantitative data for engineering design(Bieniawski, 1984).

Tunnel excavation and reinforcement designs are made according to the rock mass classification, and in order to classify the rock mass, engineers use borehole rock mass classification data and geophysical site investigation results. Since rock mass classification from borehole is the value at the specific point, however, it is essential to estimate rock mass class in which borehole investigation was not made using data from geophysical site investigation and geostatistics method such as kriging.

Kriging method has an advantage which is to reproduce the given data with minimum variance of errors as well as unbiased estimator. However, in case of which there is large amount of deviation, the values estimated by kriging tend to decrease the variance.

In order to overcome this problem, simulated annealing technique was used and rock mass class in the 13-4 section of works of Korea train express(Seoul-Pusan highspeed railway) was estimated.

Simulated annealing technique is a kind of combinatorial optimization technique, and it can produce variable which preserves the distribution of magnitude as well as the spatial correlation. Simulated annealing finds optima in a way that is analogous to the reaching of minimum energy configurations in metal annealing. Kirkpatrick et al.(1983) applied simulated annealing technique to optimization of login design and after that, simulated annealing technique was widely applied to many fields such as image processing(German and German, 1984), management(Ingber, 1984), and computational modeling(Ingber, 1989).

In this study, simulated annealing technique was used to estimate the rock joint characteristics, RMR(rock mass rating) values, to overcome the defects of ordinary kriging. Three times of simulated annealing were performed using RMR values from borehole data and geophysical site investigate results as input data. From these simulations RMR values at undrilled site were estimated, and comparisons were made between these results and ordinary Kriging results, finally the uncertainty of estimation was measured.

2. Simulated Annealing

Background of the Simulated Annealing

The simulated annealing algorithm was derived from statistical mechanics. Kirkpatrick et al.(1983) proposed an algorithm which is based on the analogy between the annealing of solids and the problem of solving combinatorial optimization problems(Pharm and Karaboga, 2000).

The energies of the states correspond to the values of the objective function computed at those solution, the minimum energy states corresponds to the optimal solution of the problem. In order to minimize the objective function, simulated annealing technique changes some variable arbitrarily or perturbs the data.

In the process of simulation, even if the difference between the objective function values of the current and the newly produced solution is larger than zero, the newly produced solution is accepted as the current solution by some probability process. So, the objective function gets out of the local minimum, and reaches the global minimum.

Simulated Annealing technique has three characteristics compared with kriging(Choi, 2002).

a. As the magnitude and distribution of the original data are maintained, the new values are generated.

b. Spatial correlation and heterogeneity of the data are reflected.

c. On the same simulation condition, the results are different but equi-probable, so the uncertainty of estimation can be measured.

Process of the simulated annealing

Fig. 1 shows the optimization process using simulated annealing.

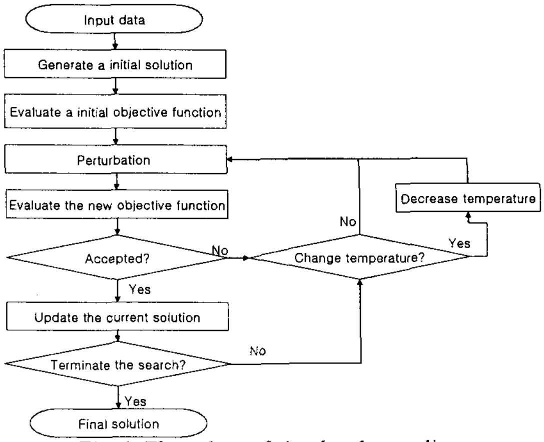

Fig. 1. Flow chart of simulated annealing.

The detailed process is shown below.

a. Generate a initial solution. An initial solution is created by relocating the conditioning data to the nearest grid nodes and then assigning random value from the histogram of the conditioning data to all remaining nodes.

b. Calculate experimental variogram and theoretical variogram in horizontal and vertical direction.

c. Evaluate a initial objective function. Objective function used in this study is given by equation (1).

$$O = \sum_h \frac{[\gamma^*(h) - \gamma(h)]^2}{\gamma(h)} \tag{1}$$

Here, $\gamma^*(h)$ is the experimental variogram of the simulated realization and $\gamma(h)$ is the theoretical variogram of the pre-specified input data.

d. The initial solution is perturbed by swapping pairs of nodal values chosen at random. And after each swap, the objective function is updated.

e. All swaps that reduce the objective function are accepted. If some swaps increase the objective function, the perturbations are accepted with an exponential probability distribution. For this, Metropolis algorithm(Metropolis, 1953) was used in this study. Metropolis algorithm is given by the following formula.

$$P\{accept\} = \begin{cases} 1, & if\ O_{new} \le O_{old} \\ e^{\frac{O_{old} - O_{new}}{t}}, & otherwise \end{cases} \tag{2}$$

Here, P is the acceptance probability distribution, O_{old} is the previous value of the objective function, O_{new} is the updated value of the objective function, and t is the temperature. The parameter t is analogous to the "temperature" in annealing.

f. After some numbers of iteration, temperature is cooling down.

g. Until the value of the objective function is converged, repeat the process ③-⑥. In this study, if the equation (3) is satisfied, then the simulation is terminated.

$$O = \sum_h \frac{[\gamma^*(h) - \gamma(h)]^2}{\gamma(h)} \leq 0.000001 \tag{3}$$

3. Simulation Results

RMR distribution by simulated annealing

In order to get the RMR distribution from borehole information, simulated annealing was performed in the 13-4 section of works of Korea train express(Seoul-Pusan highspeed railway) with the depth from 0 m to 900 m. The grid contained 240 zones in width, 50 zones in height, and the dimensions of one element were 22.3 m wide by 18.4 m high.

The results of simulated annealing were compared with that of ordinary kriging. And in order to examine the uncertainty of RMR estimation, simulated annealing was repeated three times with producing the equi-probable results using the same probabilistic input data, and each result was compared with the others.

Fig. 2 shows the RMR distribution of ordinary kriging, and Fig. 3 shows that of simulated annealing. Among three results of simulated annealing, first simulation result is presented typically.

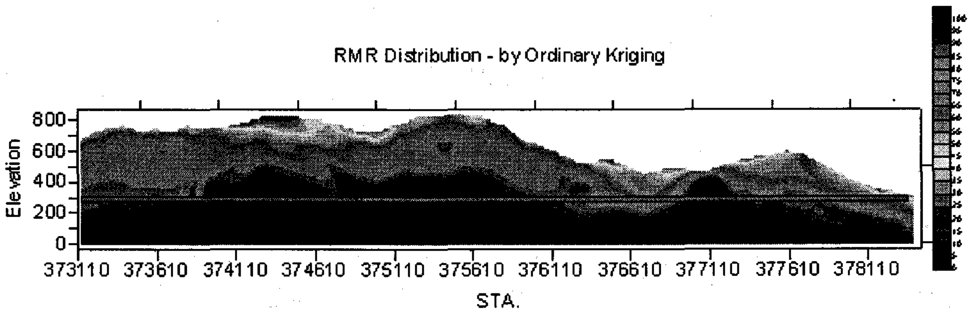

Fig. 2. RMR distribution using ordinary kriging.

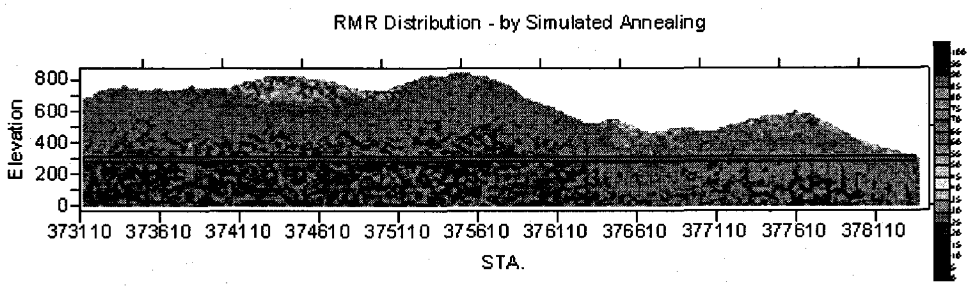

Fig. 3. RMR distribution using simulated annealing.

As the result shown on Fig. 3 is compared with that shown on Fig. 2, contour line is very smooth because of the reduction of variance, and in the interior of one contour line, only one value exists, no variation exists.

The results of simulated annealing shows that the generated RMR values satisfy the distribution curve of initial RMR values(borehole data) and the spatial correlation of RMR values by fitting the experimental variogram to the theoretical variogram.

Estimation uncertainty and reliability analysis

To estimate the uncertainty of the results of simulated annealing, comparisons were made between three simulation results that were simulated on the condition of equi-probability(same input parameters). RMR values along the elevation of the planned tunnel are shown on Fig. 4. RMR values have some deviations, but almost same trend.

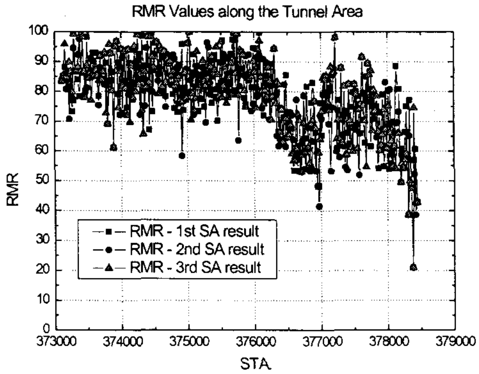

Fig. 4. Distribution of RMR values along the elevation of the planned tunnel.

As the same grid points, the variance of RMR values generated by three times simulated annealing were calculated and the results are shown on Fig. 5.

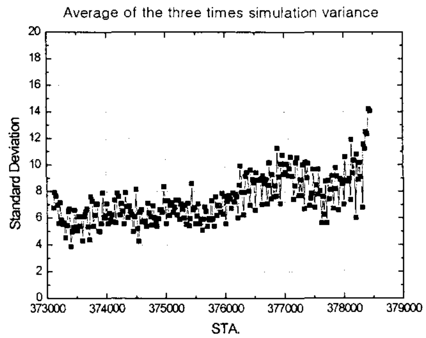

Fig. 5. Average of the three times simulation variance.

Standard deviations were ranged from 4 to 14, so the uncertainty of simulated annealing was small, and the un certainty of simulation could be quantified.

Fig. 6 shows the variation of the objective function as the number of iteration increase.

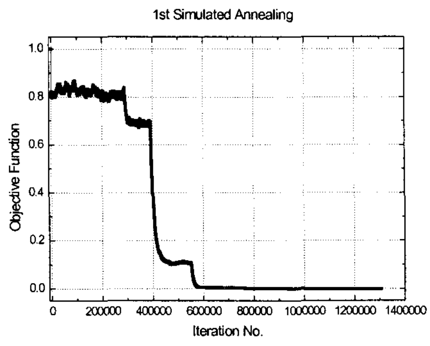

Fig. 6. Variation of the objective function as the number of iteration increase.

The number of iteration was greater than 1,000,000 times, the variation of the objective function was almost disappeared and the value of the objective function was converged to 0.

4. Conclusions

The objective of the study was to estimate rock joint characteristics(RMR values) optimally using simulated annealing technique. The results may be summarized as follows:

a. The trend of RMR values generated by ordinary kriging was similar to that by simulated annealing, but ordinary kriging reduced the variance of data and lost the characteristics of the distribution. Simulated annealing technique could reflect the distribution feature and the spatial correlation.
b. Comparisons between three simulation results that were simulated on the condition of equi-probability showed that the variance was sufficiently small and the value of objective function converged to 0, so the estimation uncertainty could be quantified.

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