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Design of tunnel supporting system using geostatistical methods

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ABSTRACT: Rock mass classification provides a guideline for a tunnel excavation and reinforcement design. The borehole data and geophysical site investigation results have been popularly used for rock mass classification, but the locality and limited information from the borehole data and qualitative characteristics of geophysical data have been problematic. A geostatistical method such as kriging can be an alternative to solve these problems. This paper describes a design of tunnel supporting system based on geostatistical tools. Korean tunnel supporting system is typically composed of six different types of combination of shotcrete, rockbolts, and concrete lining based on rock mass rating (RMR). Ordinary kriging (OK), indicated kriging (IK), and sequential indicator simulation (SIS) were used to estimate RMR around the tunnel. Kriging methods could estimate RMR with the best linear unbiased estimator. Using SIS, RMR was presented in the probabilistic term such as mean, variation, and confidence interval. Reliability of the estimated values was verified by split-sample validation and compared with the real RMR obtained from the side wall of the tunnel while excavating carried out. Based on 100 equally probable simulations, RMR could be presented in the form of a probability distribution function and the uncertainty of estimation could be successfully quantified.

1 INTRODUCTION

Tunnel excavation and reinforcement design are made according to the rock mass classification. Engineers have been using the borehole data of rock mass classification and geophysical site investigation results. Due to the locality and limited information from the borehole data and qualitative characteristics of geophysical data, geostatistical method such as kriging should be considered for the rock mass classification.

Kriging is one of the most widely used interpolation methods in geostatistics. There has been considerable researches conducted using this technique (Taboada et al., 1997; Facchinelli et al., 2001; Marinoni, 2003; Pardo-Igúzquiza and Dowd, 2005). Despite its wide use, the kriging map flattens out the local details of the spatial variation with the overestimation of small values and underestimation of large values. This type of selective bias is a serious shortcoming because of the loss of the distribution features of the original data.

Kriging is focused on the estimation of unknown points by one deterministic value, whereas sequential simulation is on the stochastic simulation by probabilistic form. Juang et al. (2003) showed the spatial distribution of soil contamination by the sequential indicator simulation, and Feng et al. (2006) proposed an improved sequential indicator simulation.

This paper describes a design of tunnel supporting system based on geostatistical tools. Typical Korean tunnel supporting system was composed of six types of combination of shotcrete, rockbolts, and concrete lining based on the rock mass rating (RMR). Ordinary kriging (OK), indicated kriging (IK), and sequential indicator simulation (SIS) were used to estimate RMR around the tunnel. For IK, we estimated the three-dimensional distribution of RMR with the field data of borehole logging and geophysical data. And this result was compared with the results using OK and SIS. Using SIS, an equally probable simulation was performed 100 times to quantify the uncertainty of estimation. The accuracy of estimation was checked by split-sample validation.

2 ESTIMATION PROCESS

2.1 *Ordinary kriging*

1 Construct a variogram from the scatter point set to be interpolated.

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}[z(x_i) - z(x_i + h)]^2 \quad (1)$$

where h = lag distance; $z(x)$ = value of position x; and n = number of total data.

2 Define a theoretical variogram. Spherical model was used in this study.
3 Calculate the weights for each point and estimation value is the linear combination of weighted known values.

$$z_0{}^* = \sum_{i=1}^{n} \lambda_i z_i \tag{2}$$

with a constraint

$$1 - \sum_{i=1}^{n} \lambda_i = 0 \tag{3}$$

$$\begin{pmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1n}^2 & -1 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2n}^2 & -1 \\ \cdots & \cdots & \cdots & \cdots & -1 \\ \sigma_{n1}^2 & \sigma_{n2}^2 & \cdots & \sigma_{nn}^2 & -1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \cdots \\ \lambda_n \\ \omega \end{pmatrix} = \begin{pmatrix} \sigma_{01}^2 \\ \sigma_{02}^2 \\ \cdots \\ \sigma_{0n}^2 \\ 1 \end{pmatrix} \tag{4}$$

where σ_{ab}^2 is the covariance between a and b.

2.2 *Indicator kriging*

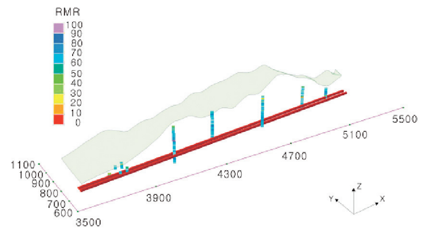
1 Determine thresholds of borehole data and seismic data. Because borehole data is quantitative and seismic data is qualitative regarding to RMR, both borehole and seismic data changed into the indicators between 0 and 1. The thresholds were RMR 20, RMR 40, RMR 60, and RMR 80 for borehole data, and 800 km/s, 1500 km/s, 2400 km/s, and 3600 km/s for seismic velocity.

$$I(v_t, x) = \begin{cases} 1, & if \;\; V(x) \le v_t \\ 0, & if \;\; V(x) > v_t \end{cases} \tag{5}$$

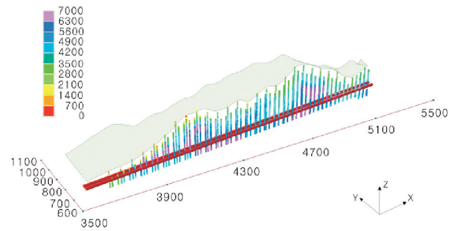
where v_t = indicator value; $V(x)$ = data function.
2 Calculate an indicator of unknown nodes with the same process of ordinary kriging.
3 Convert an indicator into RMR using cumulative probability distribution function of estimated four indicators for four thresholds.

2.3 *Sequential indicator simulation*

1 Determine the thresholds (1st quartile, medium, and 3rd quartile) and divide the data into indicators. The indicator function is given by equation (5).
2 Calculate the experimental variogram and determine the theoretical variogram for each threshold.
3 Select an unsampled node using a random path and calculate the indicator values at the selected node by ordinary kriging.
4 Calculate the CDF (Cumulative probability Distribution Function) using three thresholds and sampling from the CDF.
5 Include the calculated value as conditioning points.
6 Go back to random path selection until all unknown nodes are calculated.



(a) Borehole data



(b) Seismic velocity data

Figure 1. Borehole and seismic velocity data in the research area.

3 EXAMPLES AND RESULTS

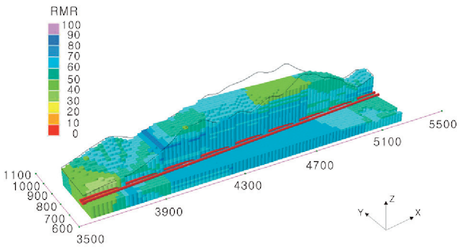
3.1 *Estimation of three-dimensional RMR*

Estimation of three-dimensional RMR distribution was performed in the highway project from 'Sosa' to 'Noksan'. It was 1700 m in length from STA 3k600 to STA 5k300, with a depth from −40 to 200 m. The grid was 86 zones in length (x-direction), 16 zones in width (y-direction) and 25 zones in height (z-direction). The dimensions of one element were 20 m in length, 20 m in width and 10 m in height. RMR estimation was performed by borehole logging data and seismic data. Borehole location and seismic data were presented in Figure 1(a) and Figure 1(b), respectively.

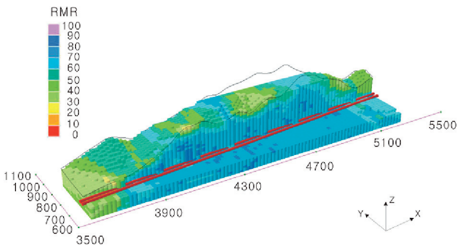
The results of ordinary kriging, indicator kriging, and SIS are shown in Figure 2. Ordinary kriging used a borehole logging data as input data, and indicator kriging used both borehole logging data and seismic survey data. Figure 2(c) shows the first result of 100 SIS results. The RMR distribution around the planned tunnel is presented in Figure 2(d). Korean tunnel supporting system was composed of six types based on the RMR. Five grades of RMR are matched with the five types of support system and sixth support system is for the portals of a tunnel. Therefore, the most important issue in the design of tunnel support system can be a determination of reliable RMR values.

3.2 *Reliability analysis of estimated RMR*

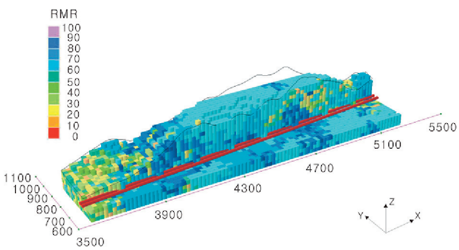
Split-sample validation was performed to verify the accuracy of the GA (Genetic Algorithm) simulation. A subset that was composed of 100 data points from



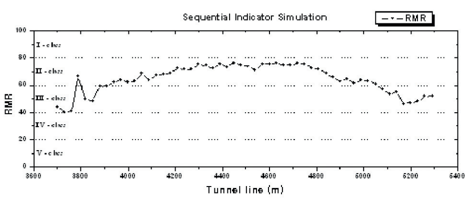
(a) RMR estimation using OK



(b) RMR estimation using IK



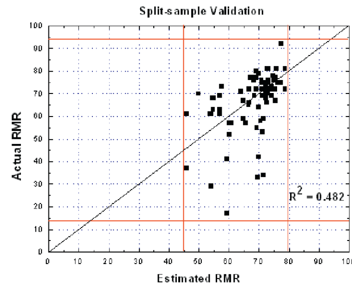
(c) RMR estimation using SIS



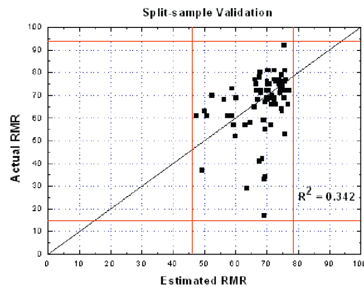
(d) RMR distribution around the tunnel using SIS

Figure 2. Estimation results and RMR distribution abound the tunnel.

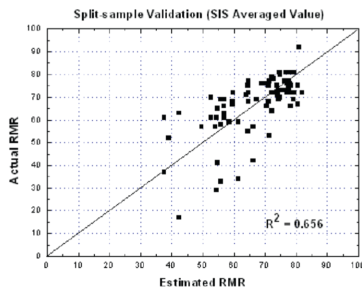
the original borehole-logging data was set aside as test data; the reminder was training data. And the results of split-sample validation are presented in Figure 3. The perfectly estimated result is presented as a straight line inclined at 45°. The result of split-sample validation shows dots located around the 'perfect estimate' line. The dots in the upper and lower parts of the line are approximately random, and their numbers are almost identical.



(a) Split-sample validation using OK



(b) Split-sample validation using IK



(c) Split-sample validation using SIS

Figure 3. The results of split-sample validation.

The coefficient of variation was 0.482 and 0.342 for ordinary and indicator kriging, respectively. These values are very sensitive to local area. With the same borehole input data, SIS was performed to 100 equally probable times. Through these analyses of results, RMR could be presented in the form of a probability distribution function, and the uncertainty of estimation could be successfully quantified.

As shown in Figure 3(a) and Figure 3(b), the original input RMR ranged from 15 to 95, whereas the output RMR ranged from 45 to 80 by both ordinary and indicator kriging. Distribution features of original geological data were disappeared by kriging in the process of minimizing the error variation, and this phenomenon is called as 'smoothing effect'. The coefficient of variation for averaged SIS result was 0.656 as shown in Figure 3(c).

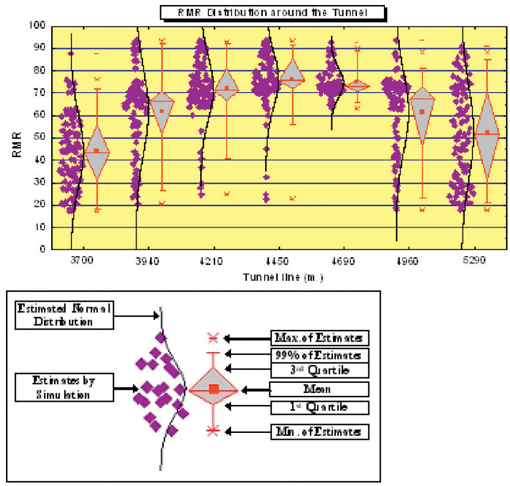


Figure 4. Box chart and probability distribution function of RMR distribution in the planned tunnel area using SIS.

Table 1. Variation of RMR in the planned tunnel area.

Station	Mean	Standard deviation
3k700	44	16.3
3k940	62	18.7
4k210	72	13.4
4k450	76	12.5
4k690	75	6.5
4k960	62	17.6
5k300	52	21.1

In order to investigate the reliability of the estimation, an equally probable simulation was performed 100 times in order to quantify the estimation uncertainty. The RMR distribution around the planned tunnel is presented in Figure 4. The left dots and distribution curve represent the RMR realizations, and the right box chart presents their normal distribution. In the figure, X, the vertical line, the diamond shape box chart, and the center dot represent the maximum and minimum values of 1% and 99% respectively, the box range from 25% and 75% of the CDF, and the mean value, respectively. The mean and standard deviation of the 100 simulations are presented in Table 1. As the reliability of the estimation increases, the variance decreases.

4 CONCLUSIONS

The objective of this study was to estimate reliable RMR values and correctly design a tunnel support system. The results may be summarized as follows:

1 Kriging and sequential indicator simulation have its special characteristics and sequential indicator simulation could estimate RMR effectively.
2 Estimation values could be shown in the form of a probability using the 100 stochastic simulations that were simulated on the condition of equi-probability. The estimation uncertainty could be quantified by a variance of RMR.
3 Reliability analysis was performed by split-sample validation. The differences between true values and estimation values could check the precision of the estimation.

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