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Geostatistical Integration of MT and Borehole Data for RMR Evaluation

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암반등급 평가를 위한 MT와 시추공 자료의 지구통계학적 복합해석

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Abstract : The geostatistical approach was applied to integrate MT (Magneto-telluric) resistivity data and borehole information for the spatial RMR (Rock Mass Rating) evaluation. Generally, resistivity of the subsurface is believed to be positively related to the RMR, thus the resistivity and borehole RMR information was combined in a geostatistical approach. To relate the two different sets of data, we take the MT resistivity data as secondary information and estimate the RMR mean values at unsampled points by identification of the resistivity to the borehole data. Two types of approach are performed for the estimation of RMR mean values. Then the residuals of the RMR values around the borehole sites are geostatistically modeled to infer the spatial structure of difference between real RMR values and estimated mean values. Finally, this geostatistical estimation is added to the previous means. The result applied to a real situation shows prominent improvements to reflect the subsurface structure and spatial resolution of RMR information.

Keywords : RMR, Resistivity, Geostatistical estimation, Residual RMR values

요 약 : 터널 등과 같은 대규모의 토목공사에서 암반등급 평가에 이용되는 RMR값의 효율적인 추정을 위해 지구물리 탐사자료인 MT 역산결과와 시추공에서 직접 얻어진 자료에 대해 지구통계학적 복합해석을 수행하였다. 일반적으로 물리 탐사를 통해 획득한 전기비저항 정보는 RMR 값과 정성적으로 양의 상관관계를 갖는 것으로 판단되지만, 직접적인 일대일 대응은 부정확한 결과를 내놓을 수 있다. 이러한 점을 극복하고, RMR값이 공간적 연속성을 갖는 다는 점을 고려하여 지구통계학적 추정 기술을 적용하였다. 본 연구에서는 MT 자료에 의한 전기비저항치와 시추공에서 얻어진 RMR값의 상관관계에 대한 평균 분포를 비선형적으로 구하고, RMR의 잔차에 대하여 공간적 해석을 적용하여 보다 실제적인 RMR의 분포를 얻고자 하였다. MT 탐사 결과의 비저항 분포를 2차 자료로 이용하여 1차 자료인 시추공에서 얻은 RMR값을 추정 해석하였다.

주요어 : RMR, 전기비저항, 지구통계학적 추정, RMR의 잔차

Introduction

RMR (Rock Mass Rating) is a very significant criterion to evaluate the stability of an area of interest for the planning and construction of large-scale engineering works like tunneling. In most cases, the RMR information is given only around the borehole sites, so the spatial information for RMR tends to be deficient. Geostatistics is largely based upon the random function model, whereby the set of unknown values is regarded as a set of spatially dependent random variables. Such presentation reflects the imperfect knowledge of the unsampled value $z(u)$ and more generally, of the distribution of z within the area (Goovaerts, 1997). The most frequent use of geostatistics for evaluation of RMR simply applies the Kriging technique to the 1-D borehole RMR data (Öztürk, 2002, Ryu *et al.*, 2003) to obtain a 2-D distribution of RMR values, which is dependent on the borehole RMR data alone. However, an estimation that depends only on spatially limited information may make that the interpreter misunderstands the situation or simplify it by exaggeration. Therefore, it is very natural to devise a combined interpretation between 1-D borehole data, which includes direct RMR information and resistivity data available from geophysical explorations like MT or DC (Direct

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current) surveys. The resistivity information generally reflects the subsurface structure well and is believed to be positively related to the RMR. To understand the degree of relation between the resistivity and RMR value, various statistical aspects are considered.

This study starts with inferring the similarity between the resistivity and RMR values around the borehole site to obtain a correlation trend for two types of information by simple regression and nonlinear transform. Geostatistical spatial modeling is then applied to the residual that is the difference between observed RMR values and inferred trend of RMR obtained by resistivity from the MT inversion result. Then the spatial-modeling result is added to the previous trend model to obtain a final RMR distribution map, reflecting subsurface geophysical characteristics and borehole information.

Application of this algorithm to a field site was performed at a mountainous area planned for a large-scale tunneling construction. The resistivity data inverted from MT exploration serve as secondary information of inferring primary RMR values outside the borehole sites. The identification of a relation between resistivity and RMR is performed by trend modeling, using two different approaches, and then geostatistical modeling is applied for the residuals.

Geology and plan of tunnels of study area

The objective of the project for the study area is to make a construction plan for an approximately 2-km long tunnel for a motorway through a rugged mountain with a 200-m depth at the center of the tunnel. Previous geological surveys for the project reported that the rocks are granite and andesite, but some weathered rocks are also found at the top and slopes. Fig. 1 shows the lineament obtained from visual interpretation of remote sensing images of the plan map of the tunnel. Three significant lineaments cross the target area and these seem to be related to low RMR values and resistivity.

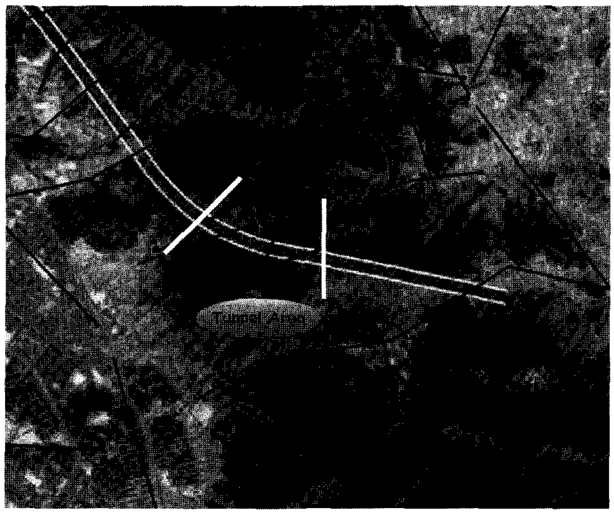

Fig. 1. The lineament obtained from visual interpretation of remote sensing image on the plan map of tunnel. The white bars indicate the tunnel area.

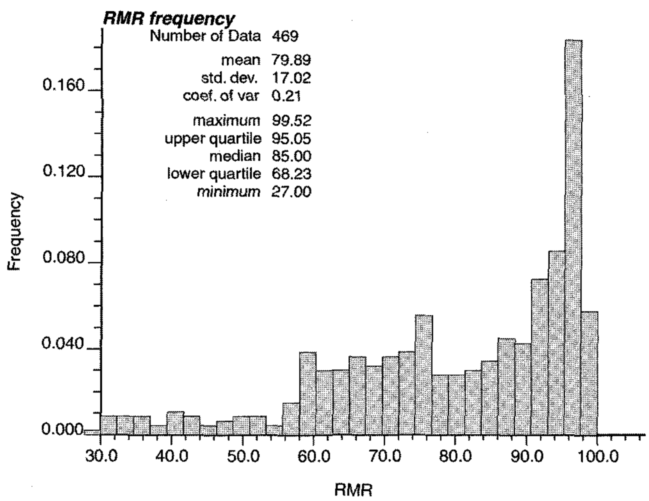

Fig. 2. Histogram showing the distribution of all RMR values directly measured from borehole sites.

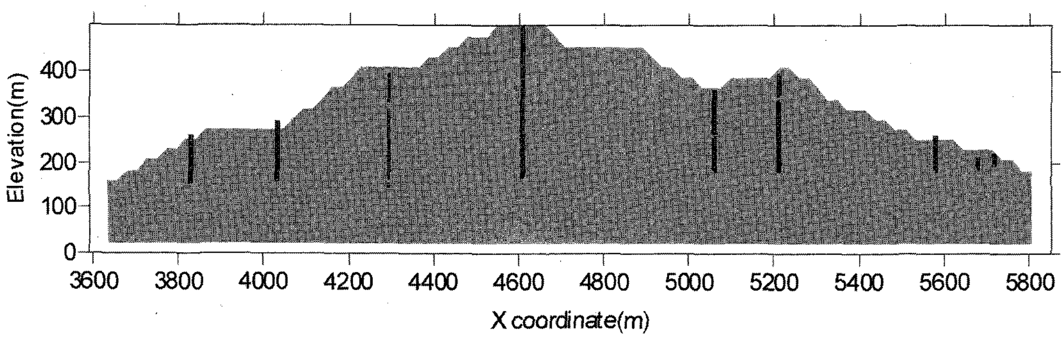

Fig. 3. Distribution of borehole sites and their drilling depths. A total of 10 borehole sites are drilled.

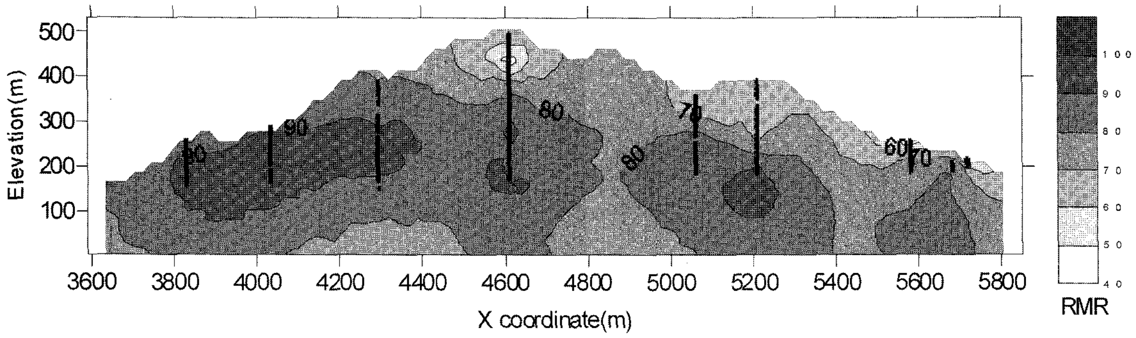

Fig. 4. Estimated RMR distribution based only on the RMR values observed at each borehole by Kriging method.

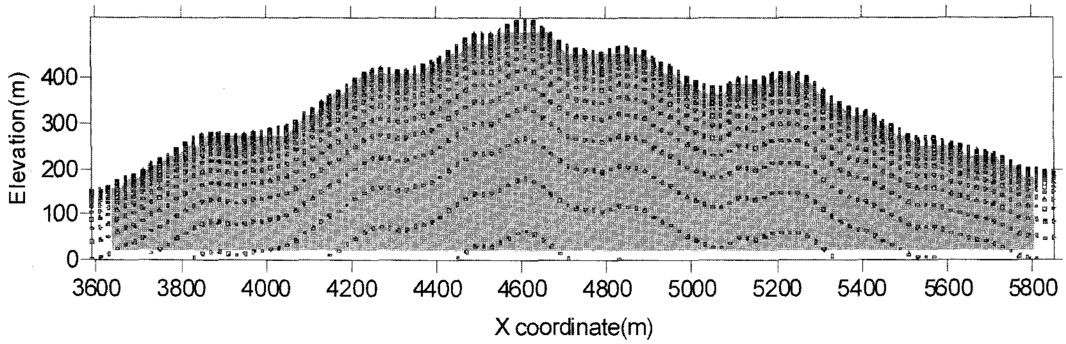

Fig. 5. Distribution of resistivity information calculated from 1-D MT soundings. The measurement was taken at every 50 m, following the level site.

RMR values at borehole sites

Fig. 2 is a histogram showing the distribution of RMR values directly measured from borehole sites. The RMR values are evaluated from a total of 469 points from 10 borehole sites, and Fig. 3 shows the position of borehole sites and the drilling depth. The deepest drilling borehole is at $x = 4610$ with a drilling depth of about 350 m and the most shallow hole is at $x = 5720$. As seen in the Fig. 2, three quarters of the RMR values are greater than 68, and seem to be somewhat fresh rocks. However, the remainder shows a wide range of RMR values lower than 68 and most of them seem to be moderately or slightly weathered rock.

Fig. 4 is an estimated RMR distribution based only on the RMR values observed at each borehole obtained by using Kriging technique. Due to the spatial limit of information, the distribution is very simple and shows some lack of resolution in the horizontal direction.

Geophysical investigation MT exploration

The MT sounding was conducted at every 50 m, keeping

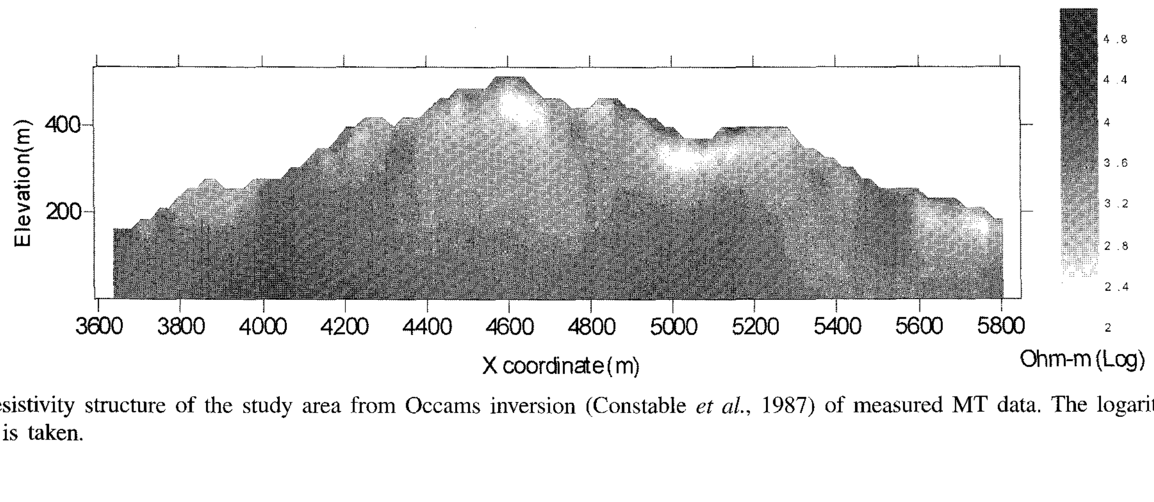

Fig. 6. Resistivity structure of the study area from Occams inversion (Constable *et al.*, 1987) of measured MT data. The logarithm of the resistivity is taken.

track of the level position. Fig. 5 shows the measurement points of MT exploration. Actually, because the measurement of MT depends on the frequency, it was converted to depth in the inversion process. Fig. 6 shows the resistivity structure of the study area obtained from Occam's inversion (Constable *et al.*, 1987) of measured MT data. For the convenience of calculation and stability, the logarithm of the resistivity was taken. Compared with Fig. 4, the structure roughly coincides with the RMR values at near surface, ignoring the spatial resolution.

Methodology

In the process of local estimation using geostatistical tools, direct measurements of the primary attribute of interest are often supplemented by secondary information originating from other related categorical or continuous attributes (Goovaerts, 1997). The estimation generally improves when this additional and usually denser information is taken into consideration, particularly when the primary data are sparse or poorly correlated in space. In the problem of estimation of RMR values, the primary information, RMR, tends to be constrained to the borehole region, and it is natural to incorporate secondary information to support overall distribution. Generally, RMR is evaluated by skilled experts, and the evaluation factors include the solidity, joint, etc. Qualitatively, these characteristics of RMR are positively related to the resistivity of geophysical exploration. This section describes the geostatistical integration process by the simple Kriging technique with a varying local mean value approach and shows how to obtain the varying local mean value with two different methods.

Simple Kriging with varying local mean values (SKlm)

In many geostatistics texts (Issaks and Srivastava, 1989), the simple kriging (SK) estimator is:

$$Z^*_{SK}(u) - m = \sum_{\alpha=1}^{n(u)} \lambda_\alpha^{SK}(u)[Z(u_\alpha) - m]\,. \tag{1}$$

$Z^*_{SK}(u)$ is the SK estimation of the RMR at point u, m is the SK mean value, and λ_α^{SK} is the SK weights determined from observed data $Z(u_\alpha)$. Under the decision of stationarity (Matheron, 1963), the mean m does not depend on location u but represents global information common to all unsampled locations. To account for the secondary information, resistivity, available at each location u, the known stationary mean m may be replaced by known varying means $m^*_{SK}(u)$, leading to the simple Kriging method with varying local means (SKlm) estimator:

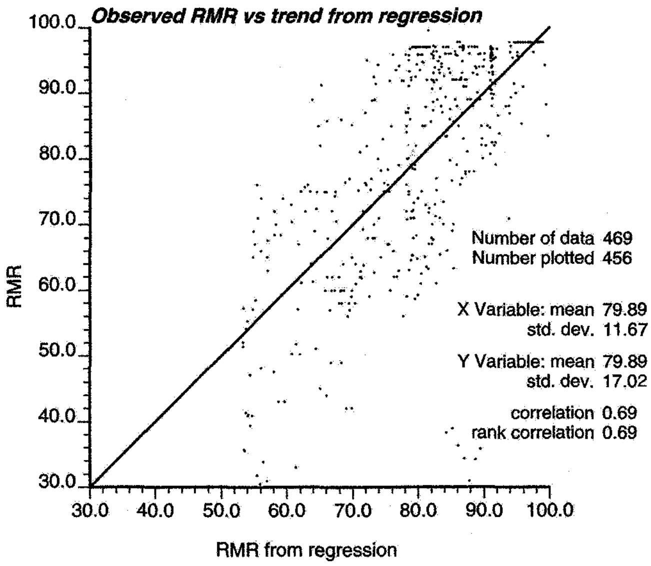

Fig. 7. A scattergram for all of the observed RMR values at boreholes versus corresponding MT resistivity values by simple regression.

$$Z^*_{SKlm}(u) - m^*_{SK}(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha^{SK}(u)[Z(u_\alpha) - m^*_{SK}(u_\alpha)]\,. \tag{2}$$

The Kriging weights $\lambda_\alpha^{SK}(u)$ in Eq. (2) are obtained by solving a simple Kriging system:

$$\sum_{\beta=1}^{n(u)} \lambda_\beta^{SK}(u) C_R(u_\alpha - u_\beta) = C_R(u_\alpha - u) \quad \alpha=1, ..., n(u) \tag{3}$$

where $C_R(h)$ is the covariance function of the residual random function $R(u)=Z(u)-m(u)$, not that of $Z(u)$ itself.

Here, two alternative methods may be used to estimate the $m^*_{SK}(u)$ values. The first is to simply estimate the regression line that reflects the correlation between resistivity and RMR. The second one is to determine the function $f(.)$ nonlinearly.

Simple regression for trend estimation

Fig. 7 shows a scattergram for all of the observed RMR values at boreholes versus estimated ones from MT resistivity by simple regression. Fig. 7 implies prospect and disappointment to adopt the resistivity as secondary information for RMR estimation. First, it shows kinds of correlation between two types of information, but also reveals significant deviation from it. As seen in Table 1, the correlation coefficient for simple regression is only 0.685. Fig. 8 shows the Q-Q (quantile-quantile) plot to compare the aspect of

Table 1. Regression parameters for RMR values at borehole versus resistivity data.

Parameter	Values
Equation	Y = 29.77* X − 16.85
Number of data points used	469
Average X	3.24
Average Y	79.89
Residual sum of squares	71962.4
Regression sum of squares	63819.7
Coef of determination	0.685

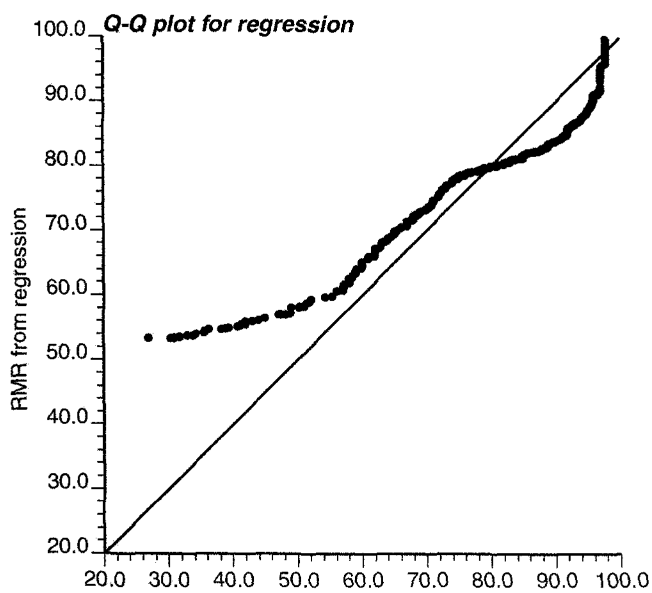

Fig. 8. Q-Q plot for all of the observed RMR values at boreholes versus corresponding MT resistivity values by simple regression.

each distribution. Especially at low RMR values, the Q-Q plot is skewed to the regression value, meaning that the RMR is overestimated at this range. To overcome this phenomenon, simple Kriging with the varying local means (Goovaerts, 1997) technique was adopted. For a more flexible identification of RMR values, a nonlinear transform technique using the indicator approach was applied.

Nonlinear indicator transform of resistivity

Although it may be expected that any trend cannot fully describe the relation between RMR and resistivity, a more flexible method than the simple regression would be helpful to obtain more plausible results. The nonlinear indicator transform approach consists of discretizing the range of variation of the resistivity into K classes $(y_k, y_{k+1}]$. The primary local mean $m(u)$ is then identified with the mean of RMR

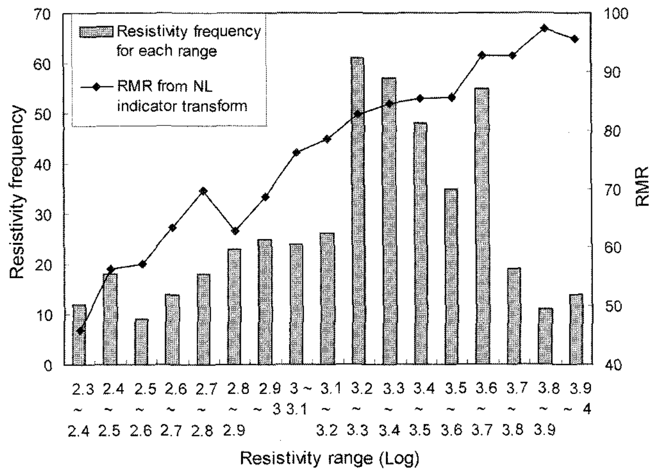

Fig. 9. Resistivity frequency for each range and its RMR value by nonlinear indicator transform around the borehole sites. Resistivity frequency is indicated on the left axis and RMR on the right axis.

values with collocated resistivity values falling into class $(y_k, y_{k+1}]$:

$$m^*_{SK}(u)=m_{|k} \quad \text{with} \quad y(u) \in (y_k, y_{k+1}],$$

where $y(u)$ means the MT resistivity value at point u. The conditional mean $m_{|k}$ is computed as

$$m_{|k}=\frac{1}{n_k}\sum_{\alpha=1}^{n} i(u_\alpha;k)\cdot z(u_\alpha).$$

The number of primary data $z(u_\alpha)$, such as $y(u_\alpha) \in (y_k, y_{k+1}]$, is n_k, and the y-indicator variable $i(u_\alpha;k)$ is defined as

Table 2. The conditional mean $m_{|k}$ and the number of primary data $z(u_\alpha)$, such as $y(u_\alpha) \in (y_k, y_{k+1}]$, for a given resistivity range of the nonlinear indicator transform.

Resistivity range (Log)	$m_{\|k}$	n_k
2.3~2.4	45.93	12
2.4~2.5	56.40	18
2.5~2.6	57.07	9
2.6~2.7	63.39	14
2.7~2.8	69.71	18
2.8~2.9	62.87	23
2.9~3	68.70	25
3~3.1	76.16	24
3.1~3.2	78.53	26
3.2~3.3	82.57	61
3.3~3.4	84.51	57
3.4~3.5	85.43	48
3.5~3.6	85.55	35
3.6~3.7	92.64	55
3.7~3.8	92.63	19
3.8~3.9	97.26	11
3.9~4	95.60	14

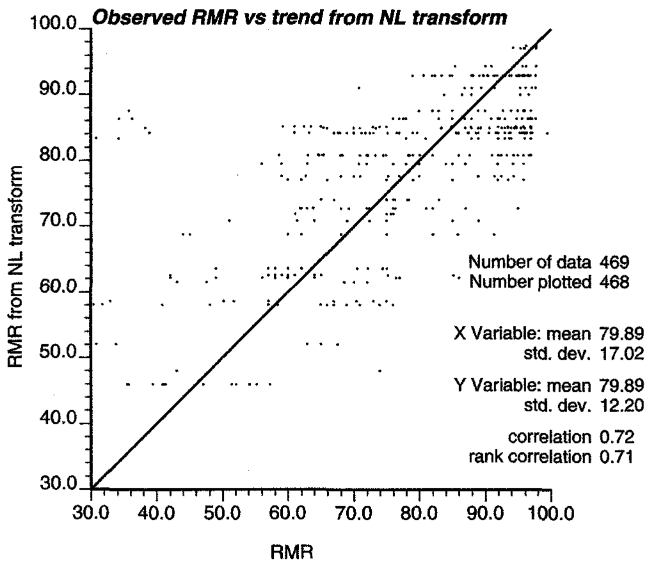

Fig. 10. A scattergram for all of the observed RMR values at boreholes versus corresponding MT resistivity values by nonlinear indicator transform.

$$i(u_\alpha;k)=\begin{cases}1 & \text{if } y(u_\alpha)\in(y_k, y_{k+1}] \\ 0 & \text{otherwise}\end{cases}$$

Fig. 9 displays the resistivity frequency for each range around the borehole sites and its corresponding RMR value from the nonlinear indicator transform. In this study, the interval of resistivity was set as linearly 0.1 with 17 separations from 2.3 to 4.0. Table 2 shows the conditional mean m_{lk} and the number of primary data $z(u_\alpha)$, n_k, for each

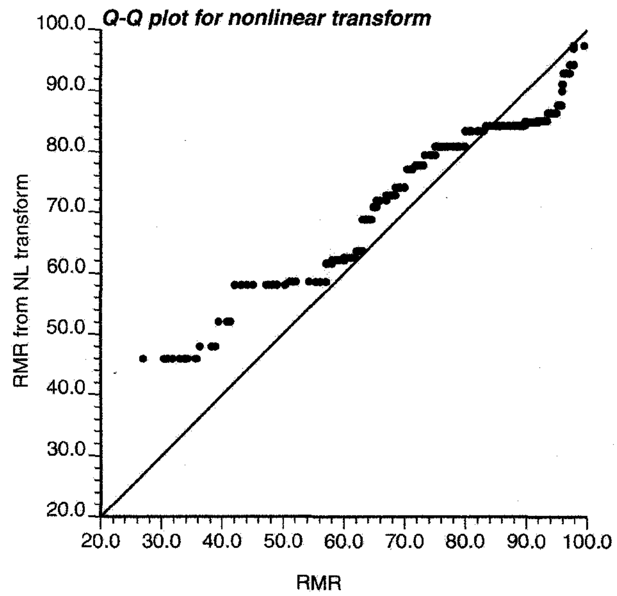

Fig. 11. Q-Q plot for all of the observed RMR values at boreholes versus corresponding MT resistivity values by nonlinear indicator transform.

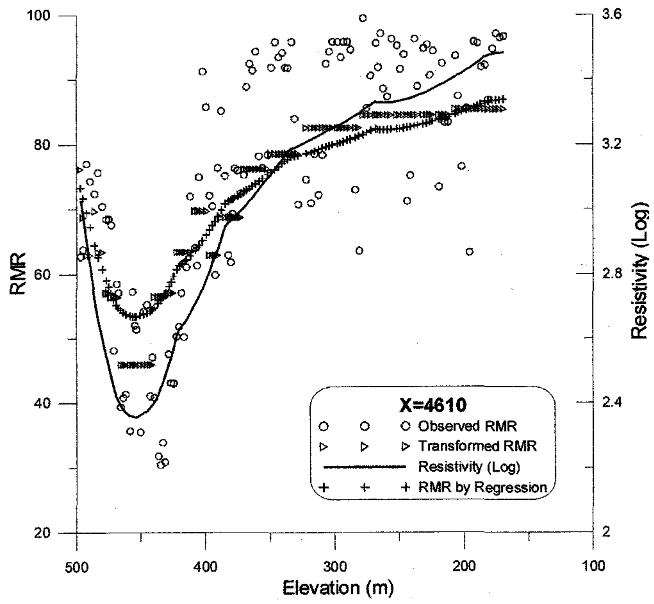

Fig. 12. Identification of RMR values at borehole position $x=4610$ (Fig. 3) using resistivity from MT data by simple regression and nonlinear transform method. Resistivity values are indicated on the right axis.

range for the nonlinear transform information.

Fig. 10 shows a scattergram for all of the observed RMR values at boreholes versus estimated ones from MT resistivity by nonlinear indicator transform. The overall pattern is not significantly different from that of regression. However, the correlation coefficient is better and as shown in Fig. 11, the q-q plot is more clearly identified than that of regression around the low RMR values. This effect can easily be shown for each borehole site.

Fig. 12 shows the identification of RMR values at borehole position x=4610 (Fig. 3) using resistivity from MT data by simple regression and the nonlinear transform method. The nonlinearly transformed RMR values seem to be more similar to the observed RMR values. For the high value region, both of the methods are underestimating at the same degree. However, for low value regions, the nonlinear transform shows a more flexible match to RMR values. Compared with results of the simple regression, a little improvement is seen in the correlation coefficient. However, the importance is simply not in the value of coefficient, but in the flexibility and robustness of the nonlinear transform method. A user may control the range of variation of parameters depending on the interest or robustness of data. However, both of the identification methods show a difference in the observed values; therefore, it requires more processes to infer the RMR distribution at unsampled positions.

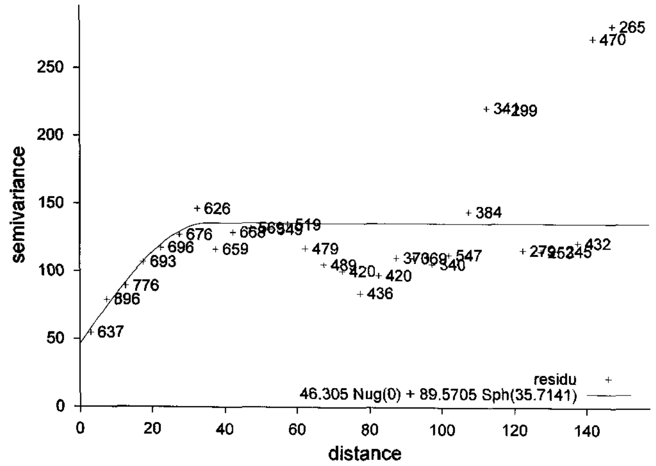

Fig. 13. Variogram model for residuals.

Results

Geostatistical modeling of residual

Seen from previous sections, it is impossible to perfectly identify the RMR value with resistivity data only by a trend model of the simple regression or nonlinear transform. Eq. (3) is a way to overcome this difference by geostatistical spatial modeling of the residuals. Fig. 13 is a variogram modeling result for residual of RMR values. A residual is calculated by subtracting the converted RMR trend of resistivity from observed RMR values at borehole sites. The variogram model matches well with the traditional spherical model (Deutsch and Journel, 1998). Some extreme variances at distances farther than 100 m seem to be related with a lack of horizontal continuity of borehole data. Seen in the variogram model equation, because the range is small as 50 m, the limit of residual information should be considerate. Then the Kriging technique is applied to the residual, and estimated residual values are added to the previous trend value. Fig. 14 shows the overall schematic for the geostatistical integration of MT resistivity and borehole data for spatial RMR evaluation.

RMR distribution by SKlm method

Fig. 15 shows RMR distributions obtained by SKlm method with two different trend modeling methods. The overall pat-

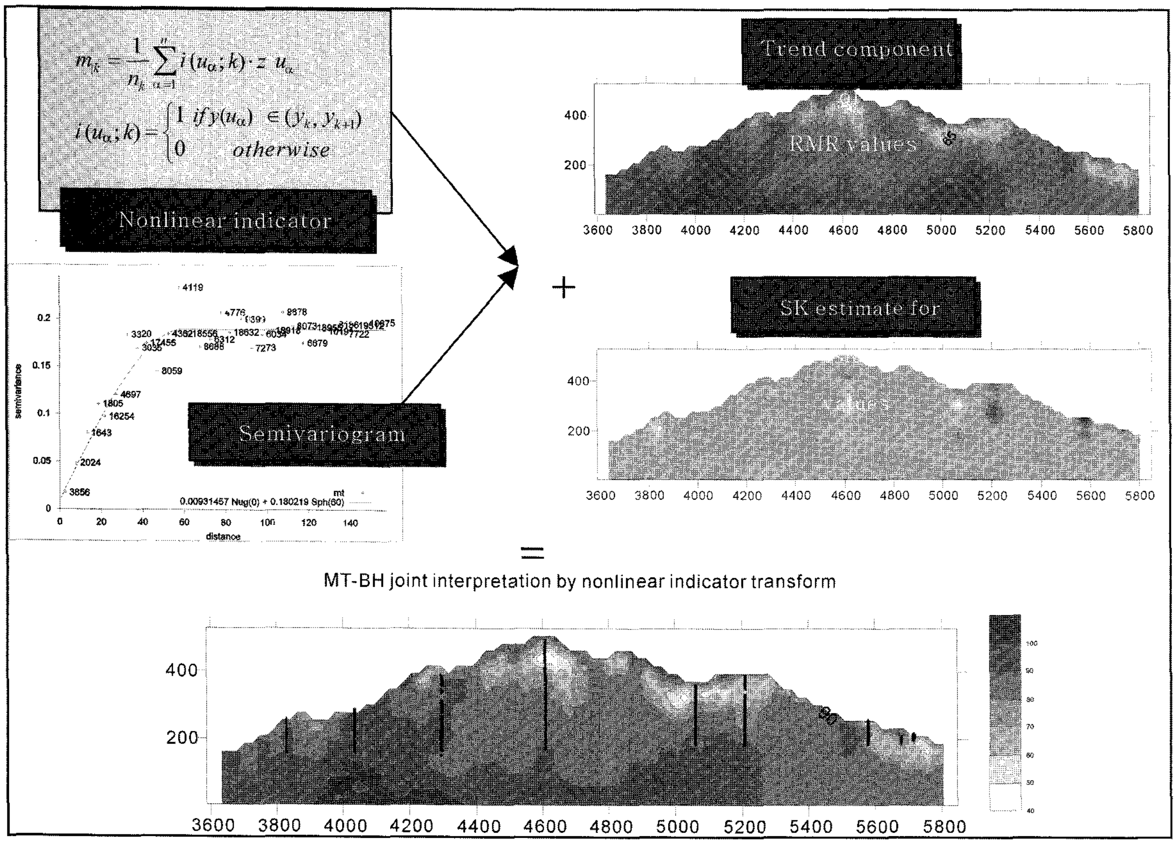

Fig. 14. The schematics of joint interpretation of resistivity data and borehole RMR information. Nonlinear transform or simple regression is applied to get trend component of RMR at unsampled position, then the simple Kriging estimation for the residual values are added to the trend obtained by geostatistical modeling.

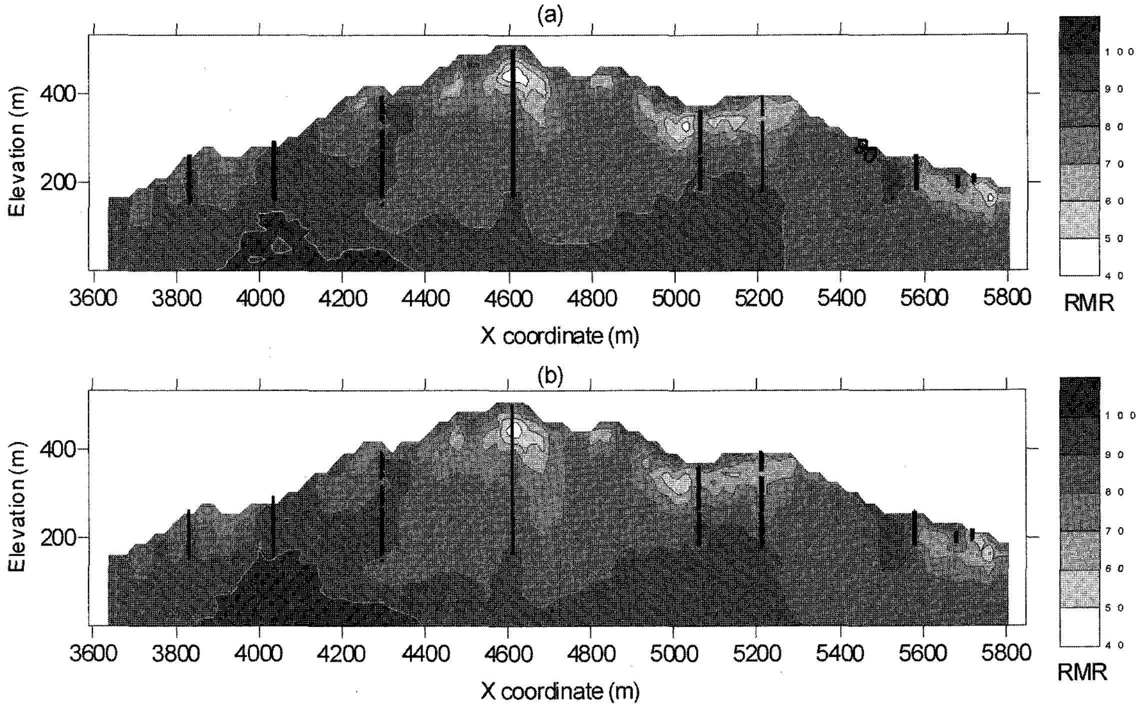

Fig. 15. RMR distribution estimated by simple Kriging with local varying means methods. (a) determines the mean by nonlinear indicator transform and (b) uses a simple regression.

tern of the RMR values is not significantly different between the two results. However, as expected in Q-Q plot analysis, the aspect of RMR values near low values is somewhat different. The RMR distribution from the trend of the nonlinear transform method showed more enhanced low value zones around $x = 4200$, $x = 4500$ to 4700, $x = 5000$ to 5200, and x

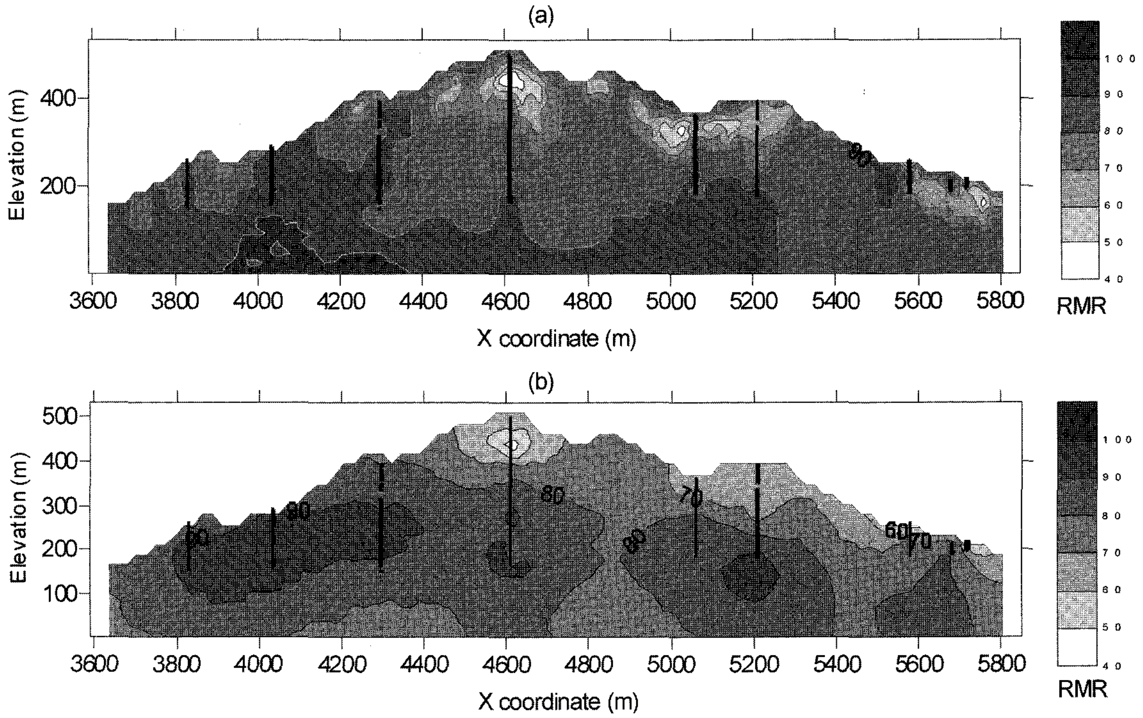

Fig. 16. Difference between combined result using (a) MT resistivity and borehole information, and (b) using RMR data only with the Kriging results.

= 5700, while the medium range of RMR, 60 to 70, is narrower especially around $x = 4600$ to 4700 than that of the trend of the regression model. This phenomenon seems to mean the nonlinear transform provides more dynamic ranges to describe the RMR values.

Fig. 16 explains how the integrated estimation by the algorithm of this study and Kriging results, using only RMR values obtained at boreholes are different to each other. The former reflects the subsurface structure well and improves the spatial resolution of RMR values.

Conclusion and Discussion

Geostatistics is a very useful tool to estimate spatially distributed data at unsampled regions or points. For the spatial estimation of RMR values generally obtained at limited region, the simple Kriging technique with the local varying means technique was applied. This approach takes the resistivity data as exhaustive secondary information, and then integrates it with the spatially limited borehole data. This method is very simple and powerful to reflect the subsurface characteristic into the RMR evaluation, which also depend on the geological structure of the targeted area. Two types of approach were used to obtain a trend model for RMR values at unsampled points from resistivity data. The nonlinear indicator transform method was found to be more robust and flexible than the regression technique.

However, because the geostatistical spatial modeling depends only on the spatial continuity of obtained data, if the range of limit of spatial continuity is narrower than the space of the borehole sites, it would not reflect the information of the borehole. Therefore, geostatistical estimation should have its confidence limit, and the interpreter always should not ignore it.

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