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Probabilistic estimation of ground condition and construction cost for mountain tunnels

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A B S T R A C T

An innovative methodology for the probabilistic estimation of ground condition and construction cost is proposed in this article, which is an integration of the geology prediction approach based on Markov process and the cost variance analysis based on work breakdown structure. The former one provides the probabilistic description of ground classification along tunnel alignment according to the geology information revealed from boring holes. The latter one provides the probabilistic description of expected cost for each interested operation according to the survey feedbacks among practitioners. Then an engineering application to Chuanshi Tunnel is well presented to demonstrate how the ground condition and the construction cost are estimated in a quantitative and probabilistic way. It facilitates both the owners and the contractors to be aware of the risk they should carry before construction, and it is meaningful for both tendering and bidding.

1. Introduction

Geological condition is the primary source of uncertainty in the construction of mountain tunnels. The construction cost and period fluctuate dramatically corresponding to the varying geological conditions, and both the owner and the contractor are facing with huge risks of cost overspending and period delaying. Therefore, many hard methods and soft methods have been employed to mitigate the geology-related uncertainty during survey, design and construction phases. Hard methods, such as subsurface boring, pilot drilling and advanced geophysical prospecting, utilize in situ equipments to detect the geology information in some specific locations along the tunnel alignment (Alimoradi et al., 2008; Kuroda et al., 2009; Lee et al., 2010; Carrière et al., 2013). Soft methods, such as time series approach, neural network approach and random process approach, utilize mathematical models to predict the geology information in a continuous and dynamic way along the tunnel alignment (Ioannou, 1987; Jeon et al., 2005; Ching and Chen, 2007; Leu and Adi, 2011; Guan et al., 2012). These hard and soft methods are developed complementarily, and many successful engineering applications have been well reported.

On the other hand, variance in direct-cost is the secondary source of uncertainty in the construction of mountain tunnels. The construction cost is generally divided into direct-cost (i.e. labor, material and machinery) and indirect-cost (e.g. overhead, tax and so on). The indirect-cost has little variance in tunnel construction, while the direct-cost is often influenced by the market fluctuation, as well as the different proficiency of working skill. The construction cost can be estimated roughly from historical data (Rostami et al., 2013; Paraskevopoulou and Benardos, 2013), or on the other hand, be analyzed directly based on work breakdown structure (Jung and Woo, 2004; Chua and Godinot, 2006; Jung and Kang, 2007; Chen, 2008). And some norms and quotas have been regulated to specify the average level of direct-cost in tunnel construction.

Based on these achievements presented above, an innovative methodology, which is an integration of the geology prediction approach based on Markov process and the cost variance analysis based on work breakdown structure, is proposed in this article to estimate the ground condition and construction cost in a quantitative and probabilistic way. The geology prediction approach, which is mainly referred to Ioannou (1987) and Guan et al. (2012), is briefly presented in Section 2. The cost variance analysis, which is mainly referred to MTPRC (2007), is briefly presented in Section 3. Then an engineering application to Chuangshi Tunnel in Songjian Expressway is well presented in Section 4.

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2. Geology prediction approach based on Markov process

2.1. Single geological parameter as a continuous-space discrete-state Markov process

The spatial variability of a single geologic parameter can be described by the transition in or out of its states, each of which has a certain length of persistence. Therefore, a single geologic parameter can be regarded as a random process $X(t)$, whose state probability is a function of location t. In practice, Markov process with its distinguishing characteristic of one-step memory is often employed to describe this random process. The continuous-space discrete-state Markov process for a single geological parameter is completely determined by its transition intensity matrix $\boldsymbol{A}$, as shown in Eq. (1).

$$\boldsymbol{A} = [a_{ij}], \quad \text{where } a_{ij} = \begin{cases} -c_i; & i = j \\ c_i p_{ij}; & i \neq j \end{cases} \quad i, j = 1, 2, \ldots n \tag{1}$$

In the above, transition probability p_{ij} is the probability that the next state of X will be j given the present state is i; transition intensity coefficient c_i is the expected distance over which the parameter X will remain in a particular state i.

The probabilistic behavior of a Markov process $X(t)$ over interval is defined by the interval transition probability matrix $\boldsymbol{V}$, as shown in Eq. (2). Due to the one-step memory characteristic, the interval transition probability matrix $\boldsymbol{V}$ satisfies the Kolmogorov differential equation, and thus can be linked with its transition intensity matrix $\boldsymbol{A}$ by Eq. (3).

$$\boldsymbol{V} = [v_{ij}], \quad \text{where } v_{ij} = P[X(t_z) = j | X(t_q) = i] \tag{2}$$

$$\boldsymbol{V}(t_z - t_q) = e^{(t_z - t_q)\boldsymbol{A}}, \tag{3}$$

If the state probability at location t_q is known and denoted as row vector $\vec{s}(t_q)$, one can infer the state probability at new location t_z by Eq. (4).

$$\vec{s}(t_z) = \vec{s}(t_q)\boldsymbol{V}(t_z - t_q) \tag{4}$$

As presented above, a Markov process is totally determined by its transition intensity matrix $\boldsymbol{A}$. In general, the estimation of p_{ij} and c_i can be accomplished by either subjective assessment or statistical procedure. If the geology profile along tunnel alignment and the geology map for a large area are available, c_i can be estimated by computing the inverse of average length of each state i, while p_{ij} can be estimated by computing the ratio between the number of transitions from states i to j and the total number of transitions out of state i.

2.2. Bayesian updating for transition intensity matrix

The likelihood matrix $\boldsymbol{L}$ for a particular exploration method at a certain location is defined by Eq. (5), where l_{jk} denotes the likelihood of observation result k given that the true parameter state is j. The likelihood matrix $\boldsymbol{L}$ reflects the engineers' confidence about the observation results. In generally, it is assessed subjectively and varies from different exploration methods and different locations.

$$\boldsymbol{L} = [l_{jk}], \quad \text{where } l_{jk} = P[Y(t_b) = k | X(t_b) = j] \tag{5}$$

When new geological information is available (e.g. a new face logging or a new boring hole is revealed), the interval transition probability matrix $\boldsymbol{V}$ should be updated sequentially according to this new information. Suppose that a new location t_n is revealed towards the direction of a known location t_q. Considering the interval from location t_n to location t_q, the prior interval transition probability matrix $\boldsymbol{V}(t_n – t_q)$ is calculated by Eq. (3), using the prior transition intensity matrix $\boldsymbol{A}$. Then according to Bayes' theorem, the posterior interval transition probability matrix $\boldsymbol{V}'(t_n – t_q)$ is updated by Eq. (6), when a certain observation result k is revealed at location t_n.

$$\boldsymbol{V}' = [v'_{ij}], \quad \text{where } v'_{ij} = \frac{v_{ij} l_{jk}}{\sum_{j=1}^{n} v_{ij} l_{jk}} \text{ for a certain observation result k at a new location} \tag{6}$$

Then the posterior transition intensity matrix $\boldsymbol{A}'$, which reflects the "average" transition probability and the "average" transition intensity coefficient within the interval from location t_n to location t_q, can be computed inversely by Eq. (7).

$$\boldsymbol{A}' = \frac{\log \boldsymbol{V}'(t_n - t_q)}{t_n - t_q} \tag{7}$$

With the updated transition intensity matrix $\boldsymbol{A}'$, one can infer the state probability at any interested location t_z within the interval from location t_n to location t_q, just by using Eqs. (3) and (4) again.

2.3. Ground condition as a function of 4 geological parameters

As presented above, the state probability for a single geological parameter can be described by Markov process and updated by Bayes' theorem. In practice, however, the ground condition is classified into grades according to the different combination of several geological parameters. As one example, the *BQ* system specified by Chinese Codes for Design of Road Tunnel (2004) is presented in Appendix A.

In accordance with the *BQ* system, 4 geological parameters are selected and described by the Markov processes independently in this article. Rock hardness (H) corresponds to the parameter of R_c (uniaxial compression strength) in *BQ* system. Index 1 or 2 denotes that the revealed intact rock is relatively hard or relatively soft. Joint intensity (I) partially corresponds to the parameter of K_v (coefficient of integrity) in *BQ* system. Index 1, 2 or 3 denotes that the joint number accounted within unit area is relatively less, medium or relatively more. Joint quality (Q) partially corresponds to the parameters of K_v and K_2 (occurrence of major joint) in *BQ* system. Index 1, 2 or 3 denotes that the joint quality revealed is relatively good, medium or relatively poor. Water content (C) corresponds to the parameter of K_1 (inflow of underground water) in *BQ* system. Index 1 or 2 denotes that the location revealed is relatively dry or relatively humid. Notice that, the indices of geological parameters merely describe the relative relationships and should be defined case by case. The definitions of 4 geological parameters presented above provide one good example, which is employed in the engineering application of Chuanshi Tunnel (see details in Section 4).

After the definition of 4 geological parameters, a geology table should be established to specify which kinds of geological parameter combination belong to which grade of ground condition. As consequence, the ground condition can be regarded as a function totally determined by these 4 geological parameters. Notice again that, the definition of geology table is also case by case, one good example is presented in the engineering application of Chuanshi Tunnel (see details in Section 4). When the probabilistic characteristic of each geological parameter is determined, the state probability of ground condition can be calculated in accordance with the geology table.

3. Cost variance analysis based on work breakdown structure

3.1. The work breakdown structure due to budgetary norms

Since the indirect-cost has little variance, only the direct-cost is focused in this article and abbreviated as cost henceforth. In