Tunnelling and Underground Space Technology 43 (2014) 453–458

Contents lists available at ScienceDirect

Tunnelling and Underground Space Technology

journal homepage: www.elsevier.com/locate/tust

A novel groutability estimation model for ground improvement projects in sandy silt soil based on Bayesian framework

Min-Yuan Cheng [a,1], Nhat-Duc Hoang [b,*]

[a] Dept. of Civil and Construction Engineering, National Taiwan University of Science and Technology, Taiwan, ROC
[b] Institute of Research and Development, Duy Tan University, Viet Nam

ARTICLE INFO

Article history:
Received 30 October 2013
Received in revised form 17 April 2014
Accepted 2 July 2014
Available online 24 July 2014

Keywords:
Groutability prediction
Microfine cement
Bayesian framework
K-nearest neighbor
Machine learning

ABSTRACT

In construction engineering, permeation grouting with microfine cement is a widely utilized approach for soil improvement. Hence, estimating groutability is a very important task that should be carried out in the planning phase of any grouting project. This research aims at establishing a novel method for groutability prediction with the utilization of microfine cement in sandy silt soil. The newly proposed approach integrates the Bayesian framework and the K-nearest neighbor (K-NN) density estimation technique. The Bayesian framework is used to achieve probabilistic groutability estimations. Meanwhile, the K-NN method is employed to approximate the conditional probability density functions. Moreover, to establish the new approach, 240 in-situ grouting cases have been recorded during the progress of Mass Rapid Transit and highway projects in Taiwan. Experimental results point out that the proposed method can deliver superior prediction accuracy. Hence, the new groutability estimation approach is a promising alternative to help construction engineers in grouting process assessment.

1. Introduction

In geotechnical engineering, permeation grouting is a widely employed ground improvement approach for reducing the permeability of granular soils (Huang et al., 2007; Zebovitz et al., 1989). Especially for underground construction projects, inflows of groundwater have always brought about critical issues for geotechnical engineers. Incidents of inflow often lead to undesirable consequences such as construction delays, serious damages for the quality of the underground structures, and catastrophic damages for the quality of the surface structures. Therefore, permeation grouting is a crucial task needed to be accomplished in a majority of ground improvement projects.

Among the approaches for permeation grouting, microfine cement grouts have been increasingly utilized in the industry. It is because this approach usually provides improved groutability for the target geomaterial and it does not cause groundwater pollutions in the surrounding environment (Perret et al., 2000; Zebovitz et al., 1989). Furthermore, the microfine cement grouts are demonstrated to possess the ability of filling cracks with small openings as well as penetrating fine soils with very low permeability (Perret et al., 2002).

Although there are several formula-based methods for groutability prediction reported in literature, an accurate prediction of grouting activity using microfine cement is an immensely challenging task. The reason is that the validity of conventional predictive formulas (Akbulut and Saglamer, 2002; Incecik and Ceren, 1995), which are mostly based on the grain-size of the soil and the grout, is unreliable for semi-nanometer scale grout (Liao et al., 2011).

Various studies have dedicated in investigating groutability estimation. Akbulut and Saglamer (2002) and Ozgurel and Vipulanandan (2005) point out that in addition to the size of the soil and the grout, the water-to-cement ratio of grout (w/c), the void size in soil, and the fines content (FC) of the total soil should be taken into account (Akbulut and Saglamer, 2002). Liao et al. (2011) found that the inclusion of soil gradation information, namely the coefficient of uniformity (C_u), which measures the particle size range, and the coefficient of gradation (C_z), which characterizes the particle size curve, can boost the overall predictive performance. Needless to say, it is beneficial to take into account these factors for estimating the grouting process (Tekin and Akbas, 2011).

Because the site condition is highly uncertain and inherently context-dependent, artificial intelligence (AI) methods may

* Corresponding author. Address: P809 - K7/25 Quang Trung, Danang, Viet Nam. Tel.: +84 0916677916.

E-mail addresses: myc@mail.ntust.edu.tw (M.-Y. Cheng), ducxd85@yahoo.com (N.-D. Hoang).

[1] Address: #43, Sec. 4, Keelung Rd., Taipei 106, Taiwan, ROC. Tel.: +886 2 27336596; fax: +886 2 27301074.

http://dx.doi.org/10.1016/j.tust.2014.07.001
0886-7798/

provide viable alternatives for the groutability prediction problem. AI techniques can be utilized to derive new facts from historical data (Cheng et al., 2013). Moreover, the prediction process may change adaptively in response to new information obtained from the data. Notably, the problem of groutability prediction can be modeled as a classification task that contains two class labels ('success' and 'failure'). Therefore, AI based classifiers can be promising solutions for coping with the problem at hand.

Artificial Neural Network (ANN) methods have been proved to be a feasible alternative for groutability prediction as well as for other problems in construction field (Chen et al., 2009; Kalinli et al., 2011; Liao et al., 2011; Tekin and Akbas, 2011). Nonetheless, the implementation of the ANN is exposed to several drawbacks. This method suffers difficulties in selecting a large number of controlling parameters such as the number of hidden layers, the number of neurons, and the learning rate (Bao et al., 2005). Furthermore, one major disadvantage of the ANN approach is that its training process is achieved through a gradient descent algorithm on the error space, which can be very complex and may contain many local minima (Kiranyaz et al., 2009). Thus, training process is likely to be trapped into a local minimum and this unquestionably hampers the predictive performance. Another disadvantage of ANN models lies in their knowledge representation. The black box nature of the ANN makes it unmanageable for construction engineers to comprehend how the approach predicts groutability.

On the other hand, classifiers based on the Bayesian framework are effective probabilistic approaches for solving classification problems (Agrawal and Bala, 2008). Bayesian Classifiers, relying on the principle of the Bayes decision theory, provides a fundamental methodology for dealing with statistical classification tasks when the probability distribution of the pattern is known (Duda et al., 2001). This approach features a number of advantages, such as flexibility in modeling, capability of coping with uncertainty, and resilience to noise (Langley and Sage, 1994). In addition, experiments from previous researches have revealed that Bayesian methods can deliver competitive prediction performances compared with ANN models (Domingos and Pazzani, 1997; Kononenko, 1993; Sebastiani, 2002). Nevertheless, none of previous studies has investigated the capability of Bayesian approaches in groutability prediction. Thus, our research is an attempt to fill this gap.

The objective of this study is to put forward a novel groutability prediction approach relying on the Bayesian framework, named as Bayesian Classifier for groutability prediction (BCGP). In the new model, Bayesian inference is used to derive the posterior probability of groutability given an input pattern. Meanwhile, the K-nearest neighbor (K-NN), a simple yet effective approach for density estimation, is employed for approximating the class-conditional probability. The rest of the paper is organized as follows. The second section of this paper review the methodology employed to establish the BCGP. The third section provides the detailed description of the new approach. Experimental results are reported in the fourth section. Conclusion of this study is addressed in the last part of the article.

2. Methodology

2.1. Bayesian framework for classification

In the field of machine learning, the goal of classification is to assign an object to one of M discrete classes C_m where $m = 1,\ldots, M$. Thus, the input space is separated into several decision regions by the decision boundaries (Bishop, 2006). To classify the object based on the evidence provided by the feature vector X, it is mandatory to obtain the conditional probability $P(C_m|X)$, which expresses how likely the input X belongs to the class C_m. Based on that information, the object will be assigned to the class with largest conditional probability.

Within the context of Bayesian theorem, the conditional probability $P(C_m|X)$ is calculated as follow (Bishop, 2006; Duda et al., 2001):

$$P(C_m|X) = \frac{P(X|C_m) \times P(C_m)}{P(X)} \tag{1}$$

where $P(C_m|X)$ represents the posterior probability of the class C_m. Meanwhile, $P(X|C_m)$ is called the likelihood which is the class-conditional probability density function of the feature X. $P(C_m)$ denotes the prior probability of the class C_m. And $P(X)$ represents the evidence factor.

The evidence factor $P(X)$ can be viewed as a scale factor used to ensure that the posterior probabilities sum to one (Duda et al., 2001). It can be is computed in the following manner:

$$P(X) = \sum_{m=1}^{M} P(X|C_m) \times P(C_m) \tag{2}$$

As can be seen from Eq. (1), the structure of Bayesian classification relies upon the prior probabilities $P(C_m)$ and the conditional densities $P(X|C_m)$ (Theodoridis and Koutroumbas, 2009). The first quantity can be estimated directly from the distribution of the training samples among classes (Clark and Niblett, 1989). If N is the total number of available training cases and N_m is the number of cases belonging to the class C_m, then the prior probability of this class is calculated as $P(C_m) = N_m/N$. The next step is to derive the class-conditional density $P(X|C_m)$. The $P(X|C_m)$ describes the distribution of the feature vector X in each class. This conditional density is also known as the likelihood function of C_m with respect to X.

Herein, we consider the problem in which the pattern X represents a D-dimensional vector, and each attribute of X is denoted as X_j where $j = 1, \ldots, D$. Thus, to derive the likelihood function $P(X|C_m)$, the common approach is to assume that the probability distributions of attributes X_j, within each class, are independent of each other. In this case, the classification approach is known as the Naïve Bayesian Classifier (Bishop, 2006). Accordingly, the class-conditional density can be computed as follows:

$$P(X|C_m) = \prod_{j=1}^{D} P(X_j|C_m) \tag{3}$$

where $P(X_j|C_m)$ denotes the probability distribution of the attributes X_j within each class C_m. In addition, the density $P(X_j|C_m)$ is often assumed to be a Normal distribution.

Obviously, the assumption that the probability distributions for attributes are independent of each other can be unrealistic. It is because correlations among attributes are not unusual in real world circumstances. Additionally, a Normal distribution may not be the most appropriate approximation. It is because the true probability density function can possibly be multi-modal and the function can also take an arbitrary form. When the aforementioned assumptions are violated, the performance of the Bayesian Classifier can be undoubtedly degraded (Greco et al., 2012). Therefore, this research proposes to utilize the K-NN approach for estimating the class-conditional density $P(X|C_k)$.

2.2. K-nearest neighbor for Density Estimation

Generally, density estimation is the task of modeling a probability density function when only a finite number of data instances are available. This task can be challenging because the data points are in high dimensional space and the true probability distribution is oftentimes unknown (Scott, 1992). Among the methods for