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A dynamically approach based on SVM algorithm for prediction of tunnel convergence during excavation

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ABSTRACT

The use of urban underground spaces is increasing due to the growing world population. Iran's capital is no exception, traffic in Tehran is an annoying problem and Amirkabir tunnel is being excavated as a motor way to improve this situation. The excavation of this tunnel started in 2010 using New Austrian Tunneling Method (NATM). Since this tunnel lies in shallow depths of maximum 12 m in a residential area, a careful monitoring of the convergence mode is necessary to avoid instability, surface subsidence and unexpected incidents. This research intends to develop a dynamically model based on Support Vector Machines (SVMs) algorithm for prediction of convergence in this tunnel. In this respect, a set of data concerning geomechanical parameters and monitored displacements in different sections of the tunnel were introduced to the SVM for training the model and estimating an unknown non-linear relationship between the soil parameters and tunnel convergence. According to the obtained results, the predicted values agree well with the in situ measured ones. A high conformity (R^2 = 0.941) was observed between predicted and measured convergence. Thereby the SVM provides a new approach to predict the convergence of the tunnels during excavation as well as in the unexcavated zones.

1. Introduction

Nowadays, underground facilities in urban areas such as tunnels have a significant importance on the daily life of commuters as they provide fast and safe transportation services. The use of underground spaces is being expanded due to the growing world population and our increasing demand of transportation. Over population and increase in the traffic congestion in Tehran have led to an inevitable rise in the construction of underground structures. Traffic congestion is chronic in the city center due to the concentration of several major shopping centers. To solve this issue an underpass consisting of 2200 m long route, namely Amirkabir tunnel, is being constructed to help to reduce transportation problems.

The main issue of tunneling in urban environment, typically by a low overburden thickness and presence of surface infrastructure, is the control of movements caused by tunnel excavation. In this respect, the first step for designing any protective measure, reducing the tunnel impact on surrounding buildings, is an accurate prediction of the tunneling-induced displacements. Therefore, instrumentation and monitoring the behavior of the excavation during and after construction is the best way to provide the means for a realistic judgment of the tunnel stability.

Hence tunnel convergence monitoring will provide data that can be used to determine whether the tunnel is in a stable or unstable structural situation. Fig. 1 shows conceptually five typical plots of rate of convergence. As shown in this figure, curves A and B represent decreasing convergence, indicating an eventual stable situation. Curves C, D and E with increasing convergence rates, generally demonstrate unacceptable performance.

Various methods for prediction in engineering applications were suggested by others. SVM is one of the methods of tackling this problem, which is a supervised machine learning method based on the statistical learning theory.

In this research, a SVM model is designed to be involved to identify dependencies between the convergence and the geological and geotechnical conditions encountered to estimate the unknown non-linear relationship between geomechanical parameters and monitoring results as real values. For this purpose, Amirkabir tunnel was selected as a case study for testing the SVM model.

Prior to the excavation, related and practicable data should be collected to have a realistic view of the zone to be excavated. This data can be used to predict the convergence as well using the suggested model. It is not out of place to mention that this method can

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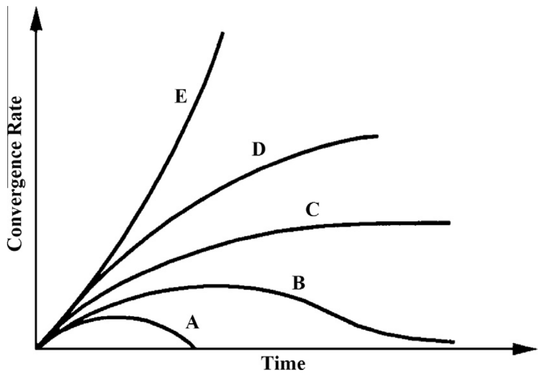

Fig. 1. Five typical curves of tunnel convergence rate (Engineer manual, 1997).

be used for prediction of the convergence of the other underground spaces than tunnels such as mines and caverns.

2. Literature review

Tunnel convergence is one of the issues that affects the performance of the tunnels both during the excavation and afterwards. Review of the literature shows that this problem has been investigated from different points of view by many researchers, some of which are as follows.

The convergence confinement method (Deere et al., 1970; Carranza-Torres and Fairhurst, 2000; Oreste, 2003) that is used for a circular tunnel in a hydrostatic stress field, gives the tunnel convergence and the load acting on the support through the intersection of the ground reaction curve of the tunnel and the support reaction line, is part of the rational approach and uses an analytical type calculation (Oreste, 2009). Another method based on analytical functions was proposed by Sulem et al. (1987). They suggested that the closure must be expressed as a function of the two parameters, distance to the face and the time-dependent properties of the ground.

A method was proposed by Grossauer et al. (2005) concluding that parameters can be back-calculated from case histories using curve fitting techniques. Also, a method based on statistical functions, exponential function and linear function was suggested by Kim and Chung (2002). Pan and Dong (1991) considered the tunnel convergence as a function of the rheological properties and the stress state of rock mass. Mahdevari and Torabi (2012) developed a method based on artificial neural network for prediction of convergence in tunnels.

This study aims at applying as many geotechnical parameters as practicable to predict the convergence using a SVM model. These parameters can usually be obtained by laboratory and in situ tests. Recently, SVM has been shown to give good performance for a wide variety of non-linear regression problems. There have been many studies of the application of SVM in geotechnics, some of which are as follows.

Zhang et al. (2009) proposed a SVM model to estimate the prediction parameters for the probability-integral method of mining subsidence prediction. Feng et al. (2004) modeled non-linear displacement time series of geo-materials using evolutionary SVM and found accurate results. Yao et al. (2010) predicted tunnel surrounding rock displacement using SVM method. Liu et al. (2004) used SVM approach to design the tunnel shotcrete-bolting support. Khandelwal (2010) predicted the blast induced ground vibration using SVM and found better results as compared to vibration predictor equations. Zhao (2008) presented a SVM model for slope stability analysis and explained that the SVM based first-order second-moment method reliability analysis can be used successfully for slope reliability analysis. Tan et al. (2009) presented a method to calculate subsidence coefficient based on SVM. Finally, Zhao et al. (2009) predicted gas leakage in coal mines using SVM.

3. Function regression techniques

3.1. Multi-variable regression

The goal of regression analysis is to determine the values of parameters for a function that cause the function to best fit a set of data observations provided. In other words, the purpose of a regression analysis is to build a model that relates the independent variables to dependent variables with minimum possible error (Liitiainen et al., 2009). In statistics, Multi-Variable Regression (MVR) is a simple approach to model the relationship between a dependent variable and a set of independent variables. The purpose of the MVR is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The MVR attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data (Kutner et al., 2004; Yilmaz et al., 2007). In MVR, data can be modeled using linear functions and unknown model parameters are estimated from the data. When there are i independent variables $X_1, X_2,\ldots, X_i$, the MVR equation is in the general form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_i X_i \quad (1)$$

where Y is the dependent variable; $X_1, X_2,\ldots, X_i$ are the independent variables; β_0 is the constant, where the regression line intercepts the Y axis, representing the amount the dependent Y will be when all the explanatory variables are zero; $\beta_1, \beta_2,\ldots, \beta_i$ are the regression coefficient, representing the amount the response variable Y changes when the explanatory variable changes one unit.

In linear regression, the function is a linear equation. When there is more than one independent variable, then MVR analysis is used to get the best-fit equation. The MVR solve the data sets by performing least squares fit. It constructs and solves the simultaneous equations by forming the regression matrix and solving for the coefficient using the backslash operator.

3.2. Support vector machines regression

The SVM is a universal approach for solving the problems of high-dimensional function estimation. It is based on the Vapnik–Chervonenkis (VC) theory (Cortes and Vapnik, 1995; Vapnik et al., 1997). Concisely, VC theory characterizes properties of learning machines, which enable them to generalize properly unseen data. Support Vector Regression (SVR) employs the SVM to tackle with problems of function approximation and regression estimation by introducing an alternative loss function.

The SVR is also implementing the Structural Risk Minimization (SRM) inductive principle for obtaining strong generalization ability on a limited number of learning patterns. The SRM involves simultaneous attempt to minimize the empirical risk and the VC dimension (Basak et al., 2007).

Suppose that we are given a training set $\{(x_1, y_1),\ldots,(x_n, y_n)\} \subset R^d \times R$ where R^d is the space of the input features x_i, and y_i is the phenomenon under investigation. In SVR, the main objective is to find a function $f(x)$, that has almost ε deviation from the actual targets y_i given by the training data and at the same time, is as flat as possible (Vapnik, 1995). In other words, there is no care of errors as long as they are less than ε, but any deviation larger than this will not be accepted.

Concept of ε-insensitive loss function is depicted graphically in Fig. 2. Only the samples out of the $\pm\varepsilon$ margin (shaded region known as ε-insensitive tube) will have a nonzero slack variable. Normally,