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Wavelet prediction method for ground deformation induced by tunneling

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ABSTRACT

A wavelet intelligence prediction system (WIPS) is presented herein to predict the ground deformations induced by tunneling. In this method, the solution is comprised of three parts: wavelet analysis, model identification and system prediction. Based on the sensitivity analysis of influencing factors, ground deformation is decomposed into the trend deformation and the wave deformation. Wavelet analysis is introduced to filter the residual error and extract the actual deformations, which is similar to de-noising in signal processing. In addition, the identification model is established by using Elman neural network based on modified PSO (named EMPIM), with which one can approximate the actual deformations. The prediction system (i.e.; WIPS) developed with two identifiers enable one to map all influencing parameters to ground deformations, which helps avoid complex theoretical analysis of rock-soil mechanisms and mathematical descriptions of ground deformations. Later, WIPS is applied to estimate future deformations. The validation use cases show that the WIPS is an effective tool for predicting ground deformations dynamically under difficult and uncertain conditions, and can be widely applied to practical subway projects.

1. Introduction

Tunnel excavation inevitably disturbs the rock-soil masses and modifies the existing stress–strain field, which may lead to ground deformation. When large ground deformations occur on the limited land of urban areas, nearby structures and utilities may be serious damage. To ensure the safety of tunnel engineering and structures nearby, numerous scholars and experts have assessed and predicted ground deformations with different methods, such as the empirical method, the analytical method, the numerical method. Some representative studies are listed below.

Empirical methods are mainly used to describe the tunneling-induced ground settlement profile based on field observations. Schmidt (1969) and Peck (1969) proposed the Schmidt–Peck method to anticipate ground settlement by approximating the normal probability curve in the clay. Later, Attwell (1978) and Kimura and Mair (1981) proposed the semi-empirical methods to calculate ground settlement based on engineering experience. However, as the database and soil parameters considered are limited, the application of empirical methods is restricted to certain cases using shield driven tunneling in homogenous and soft soil (Eisenstein et al., 1981). The pragmatic approaches are insufficient for most practical applications (Liu and Hou, 1991).

Sagaseta (1987) presented an analytical method with the assumption of an elastic half-space, and applied it to calculate soil settlement induced by tunneling or extraction in soft soil. Based on Sagaseta's analytical solution, Verruijt and Booker (1996) introduced approximate analytic solutions in an elastic soil at arbitrary points of the half plane for ground deformation. Later, Loganathan and Poulos (1998) incorporated the equivalent ground loss concept into the analytical solution for tunnels in clays. However, the analytical methods are based on simplified assumptions of constitutive models, homogeneous ground layers, and definition of the boundary and initial conditions (ITA, 2006). With these methods it is most difficult is to obtain the gap parameters, which will vary as abundant layer patterns change (Chou and Bobet, 2002).

Numerical methods, such as finite element models (FEM), the boundary element method (BEM), and the discrete element method (DEM) have been exploited to calculate ground deformation profiles. Abu-Farsakh and Voyiadjis (1999) employed a 2D/3D FEM model to predict ground settlement above tunnels which are constructed in soft ground. Kasper and Meschke (2004) adopted a 3D FEM simulation model for shield-driven tunnel excavation. Callari (2004) presented an enhanced FEM to analyze the shallow tunneling in poor-elastoplastic media. Nunes and Meguid (2009) performed the finite element analyses to explain the role of

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the relative stiffness between the overlying layer and the soft soil deposit.

However, the problem in modeling the behavior of tunnel excavation, by whatever numerical method, is that the tunneling construction is significantly affected by a number of factors, such as tunnel geometry, geological conditions, shield operation and underground water conditions (Suwansawat and Einstein, 2006; Cheng et al., 2008). Moreover, under stress and dynamic movements of tunnel excavation, these factors are generally complex, vague, and uncertain. Thus, choosing an affective numerical method or presenting an explicit analytic expression to calculate the ground deformation profiles is especially difficult (Ding et al., 2011).

Because of parameter uncertainties and the fact that factors cannot simultaneously be taken into consideration with the above methods, they are unable to provide a satisfactory prediction of actual measured settlements profile in general soil conditions (Karakus and Fowell, 2005).

In the last two decades, computational intelligence (CI) techniques (Madjid and Lars, 1999), such as artificial intelligence (AI), evolutionary algorithm (EA), swarm intelligence (SI), and expert control, have rapidly developed and widely used in different fields (Kennedy et al., 2001). These approaches can model the behaviors of complex systems as well as simulate human brain behaviors (Li et al., 2005). They are effective for identifying dynamic systems, and accurately predict changes without any complicated mathematical analyses.

For these reasons, researchers in a wide range of disciplines have been interested in investigating intelligence algorithms (IA), such as particle swarm optimization (PSO) (Eberhart and Kennedy, 1995), genetic algorithm (GA) (Holland, 1992) and artificial neural network (ANN) (Yegnanarayana, 1999). The main advantages of these algorithms are:

- They can approximate the nonlinear input–output mapping of a dynamic system.
- They can tackle nonlinear behaviors without a priori information about the structures of a system.
- They can deal with the complexity and nonlinearity problems, and have great potential for identification and prediction applications.

Hence, due to its unique characteristics, CI is the best way to overcome the difficulties in analyzing variation parameters, expressing time-variant systems and explaining uncertain knowledge (Pham and Oh, 1992; Ku and Lee, 1995; Chiang and Hao, 2003).

Recently, AI has been introduced in the fields of rock-soil engineering and applied in tunnel engineering. Goh et al. (1995), Celestino et al. (2000) and Santos and Celestino (2008) have successfully employed ANN to analyze ground settlement during tunneling, while Suwansawat and Einstein (2006) used ANN to determine the correlations among TBM operational parameters, ground mass characteristics and surface movements.

In addition, wavelet analysis (WA) (Mallat, 1989) is becoming an attractive tool for analyzing localized behavior of unknown signals within a time series. By decomposing a time series into time–frequency domains, one is able to determine both the dominant modes of variability and how these modes vary over time. The wavelet transform has been applied in different fields of research, such as hydrogeology (Salerno and Tartari, 2009), meteorology (Janicke et al., 2009), physiology (Anderson et al., 2006), tropical convection (Weng and Lau, 1994) and the dispersion of ocean waves (Meyers et al., 1993).

An intelligence analysis method based on WA was developed and applied for approximating and predicting the ground deformations herein. This method is comprised of three parts: wavelet analysis, system identification and prediction control. First, wavelet transformation is utilized to decompose the measured deformations into extracting trend deformations and wave deformations from actual ground deformations (AGD). Later, the residual error similar to white noise is filtered to obtain AGD. Then, the identifier formed by Elman neural network, based on modified PSO (ENMP) algorithm, is trained and tested to fit AGD. Based on the two identifiers, the prediction system will be established to estimate the trend of future deformations.

The discussions of this approach are arranged as follows: Jiangji Tunnel of Wuhan subway and its geotechnical characteristics are introduced in Section 2. The major factors affecting dynamic ground deformations are discussed in Section 3. The composition of the actual deformation is gained and described based on the influencing factors in Section 4. Wavelet transformation is introduced in Section 5. AGD is extracted from the measured deformation in Section 6. The prediction system is developed in Section 7. Then, the prediction system, which is established by the identification model, applied for predicting all the deformations in Jiangji Tunnel, and the reliability of the proposed approach is verified by case studies in Section 8. Finally, the conclusions of this study are proposed in Section 9.

2. Jiangji Tunnel of Wuhan subway

Wuhan lies in the middle and lower reaches of Yangtze River. Its topography is low and flat, approximately 25–26 m above sea level. The Wuhan tunnel project line 2 is subdivided into the north section and the south section. Jiangji Tunnel from Jiyuqiao Station to Wuchang Airshaft is a twin tunnel (Fig. 1). Tunnel depth varied from 10.3 m to 26.5 m. The geological profiles through which the tunnel passes (seen in Fig. 2) are: silty sand, mucky soil, silty clay–fine sand and fine sand. The tunnel is mostly located within the mucky soil layer and silty clay–fine sand layer (i.e., about 10–28 m below ground surface), with some parts of the route in the fine sand layer.

According to the geological surveys report, situ tests have been used to define the geotechnical characteristics of the formations found along Jiangji Tunnel given in Table 1. In addition, large numbers of deformation markers are installed above the tunnel mostly center line with intervals ranging from 10 m to 50 m along the tunnel alignment, which are utilized to measure the ground deformations during excavation (Fig. 3).

The deformation data, which is gathered regularly before shield approaching and after shield passing, are used to investigate the process of ground deformation. The relative measurements are taken once a day on the marked sections, while the measurements of the shield operational parameters are taken several times per day. Therefore, the average value of each shield operational parameter between the two neighboring measurements is used as input data for shield operational factors.

This study focuses on the left line in the picture. By comparing between prediction and measurement data, certain data samples are trained and tested to validate the relationship established by making comparison between prediction and actual measurement.

3. Factors analysis

3.1. Factors of ground deformation

During tunnel excavation, the rock-soil masses are inevitably disturbed by tunnel excavation and their stabilities are affected by numerous factors. And the ground deformation happens, which can be highly nonlinear system when developing from a steady