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Influence of spatial variability of soil Young's modulus on tunnel convergence in soft soils

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ABSTRACT

Field data have shown the fact that soil spatial variability could aggravate the uncertainty of tunnel convergence ΔD (a key indicator for serviceability and safety of tunnels). This paper presents a detailed numerical analysis to investigate the probabilistic response of tunnel convergence in spatially varied soft soils. The soil Young's modulus E_s is highlighted and modeled with isotropic and horizontally stratified anisotropic random fields, respectively. The influence of scale of fluctuation (SOF) δ of the E_s on convergence ΔD is discussed in detail with respect to different directions, i.e., the vertical and horizontal directions both for δ and ΔD. It is observed that ignoring the spatial variability of E_s, i.e., disregarding the possibility of unfavorable soft soil (low stiffness soil) locally around tunnel, can underestimate the mean value of ΔD. The horizontally stratified anisotropic random field is more appropriate than isotropic random field in the sense of an accurate prediction, especially when extreme tunnel convergence occurs. In horizontally stratified anisotropic random fields, the influence of horizontal and vertical SOF is different on tunnel convergence. The surrounding soils near tunnel crown and invert or across tunnel horizontal diameter are very critical to the tunnel convergence. In addition, the effect of horizontal SOF δ_x on failure probability of the calculated ΔD exceeding the specified allowable ΔD_{lim} is limited when the δ_x is larger than 4.84 times of tunnel outer diameter.

1. Introduction

The ground deformation induced by tunneling in homogenous soil has been broadly analyzed during the past decades (Gurung and Iwao, 1998; Diais and Kastner, 2013; Zhang et al., 2015a). However, the ground condition in those studies is mostly treated in a deterministic manner which results in an averaged behavior of soils subjected to tunneling. The results of deterministic analyses may miss the true failure mechanisms and ignore the true shear bond that might pass through the weakest part of soils in the sense of randomness of soil properties (Griffiths et al., 2002). Furthermore, among various reasons to cause the discrepancy between estimated and actual performance of geotechnical system, the spatial variability of geo-material is known as a non-negligible one (Griffiths et al., 2002). Hence, probabilistic analysis considering spatial variability of soil properties is necessary and helpful to fully understand the tunneling mechanics.

The spatial variability is often modeled by random field theory. Studies about the influence of soil spatial variability on geotechnical systems using random field have been discussed for many years since the most prestigious work done by Vanmarcke (1977). Currently, the random field analyses largely focus on topics about the bearing capacity of footing, slope stability and foundation settlement (e.g., Fenton and Griffiths, 2008; Srivastava et al., 2010; Li et al., 2015a; Li et al., 2015b; Liu et al., 2015). The results show that ignoring the soil spatial variation can underestimate the failure possibility of these geotechnical systems by either underestimating the deformation or overestimating the bearing capacity.

However, the effect of soil spatial variability on structural behavior of tunnel linings has received little attention so far. Mollon et al. (2011) analyzed the face stability of a tunnel driven in anisotropic and non-homogeneous soils by considering the spatial variability of soil shear strength. Huang et al. (2015) presented that the longitudinal performance of shield tunnels in terms of differential settlement is significantly affected by the spatial variation of subgrade reaction coefficient in longitudinal direction. Nonetheless, less works have been dedicated to the influence of spatial variability on the convergence of tunnel lining though it is proved to be the most representative indicator for structural performance of tunnel lining (Yuan et al., 2012).

Among all soil properties, it is widely accepted that the Young's modulus E_s and Poisson's ratio v_s are the dominant parameters which greatly affect deformations of soils and embedded geo-structures (Fenton and Griffiths, 2008), e.g., tunnel lining convergence in this

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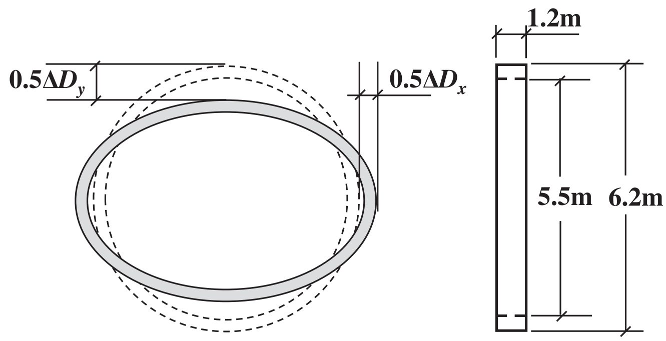

Fig. 1. Geometry for the segment ring and schematic diagram of maximum convergence in different direction for shield tunnel.

paper. Furthermore, the Poisson's ratio ν_s is believed to have less spatial variability and only a second-order importance to deformational analysis (Fenton and Griffiths, 2008). Hence, soil Young's modulus E_s is always specifically simulated by random field for deformational analysis of geotechnical system. Apart from the mean and coefficient of variance, one of the key measures for spatial variability is the scale of fluctuation (SOF). The SOF physically means the distance within which any two points of soil properties are significantly correlated. In addition, soils generally exhibit a stronger correlation in the horizontal directions due to the depositional process. It results in a larger SOF in horizontal direction than the value in vertical direction, which is also seen as the horizontally layered anisotropy (Firouzianbandpey et al., 2014).

Since the convergence of tunnel lining, as shown in Fig. 1, is regarded to be a significant indicator of tunnel deformational performance (Yuan et al., 2012), the aim of this paper is to investigate the influence of scale of fluctuation (SOF) of the soil Young's modulus on the convergence of tunnel lining in layered anisotropic soft ground. Both the isotropic and layered anisotropic random field for soil Young's modulus E_s is simulated. Other soil parameters that do not significantly affect soil deformation are treated deterministically. The layered anisotropic random field is modeled by making the horizontal SOF larger than the vertical SOF. This paper is structured as follows. Before a detailed modeling of the random field, a raw data analysis about the effect of investigated geological settings with spatial variability on the variation of measured lining convergence of shield tunnel is presented. Then, based on statistical results of SOF in soft soils from previous literature (Tang, 1979; Phoon and Kulhawy, 1999), two-dimensional random field for the Young's modulus are generated and further mapped into the finite difference analysis. Monte Carlo simulations (MCS) are then performed both in isotropic and anisotropic random fields to explore the influence of SOF on tunnel convergence both in vertical and horizontal directions. Discussion on the influence of both the horizontal and vertical SOF on the convergence is carried out eventually. Meanwhile, close attention is paid on the extreme (i.e., worst and best) realizations to capture the most unfavorable spatial distribution patterns (i.e., spatial variability mode) for tunnel convergence.

2. Spatial variability of soils and its effect on field data

Soil spatial variability inevitably aggravates uncertainty of performance of the underground structure embedded in the soil, especially when the structure is huge in dimension, such as the shield tunnel with thousands of lining rings installed longitudinally. For this reason, the deformational responses of shield tunnel lining buried in a spatially varied soft ground are collected. Based on those raw measured deformation data and the COVs of the soil CPT data, a correlation analysis is carried out as below before a detailed random field simulations.

Fig. 2 plots two typical longitudinal geological profiles of two interval tunnels of Shanghai metro line 10. Fig. 2 a shows that the interval tunnel from Hailun Road Station to North Sichuan Road Station is excavated through a single soil layer, i.e. the Silty sand (geological symbol ②$_{-3}$). It is observed from Fig. 2b that the central part of the tunnel from Guoquan Road Station to Wujiaochang Station is excavated through a multi-layered formation containing typical Shanghai soft clays, i.e. the muddy silty clay (geological symbol ④) and the clay (geological symbol ⑤$_{-1}$). In addition, a short part of the tunnel close to Wujiaochang Station passes through another multi-layered formation containing the Silty sand and the muddy silty clay. The elevation of tunnel crown and invert for the three selected part is marked by bold red lines in Fig. 2, i.e., Part I, Part II and Part III. As shown in Fig. 2, to avoid longitudinal stratigraphic variability, each selected part is relative short compared with the whole interval tunnel between two metro stations.

Three CPT tests are performed in those three typical soil formation areas respectively. Fig. 3 shows tip resistance data (p_s) against the depth from the three representative CPT tests. From Fig. 3a, three sets of data are acquired by extracting cone tip resistance p_s with a depth interval of 0.01 m from soil layer ②$_{-3}$, ④ and ⑤$_{-1}$. The coefficient of variation (COV) of the three set of p_s data are 0.38, 0.13 and 0.08 respectively. Each CPT curve of one soil layer in Fig. 3 can be reasonably deemed as one realization of random field for p_s. The intensively fluctuated CPT curves of the silty sand layer ②$_{-3}$ in Fig. 3 present a much rougher one-dimensional random field than the curve for underlying layers like muddy silty clay layer ④ and the clay layer ⑤$_{-1}$. Because relatively rough fields suggest small scale of fluctuation (SOF) and relatively smooth fields indicate large SOF (Fenton and Griffiths, 2008), the vertical SOF of silty sand layer ②$_{-3}$ should be smaller than the SOFs of the other two layers. To quantitatively verify this inference, the vertical SOFs of three soil layers (i.e., silty sand layer, muddy silty clay layer and clay layer) are obtained by fitting a theoretical correlation function to the sample autocorrelation function estimated from the three CPT curves shown in Fig. 3. It is important to select a reasonable correlation function before modeling the random field. Cao and Wang (2014) has adopted a Bayesian-based comparison method based on the CPT data to select the best correlation function among a pool of candidates, namely single exponential correlation function, binary noise correlation function, second order Markov correlation function and squared exponential correlation function. The results shown that the single exponential correlation function is the most probable correlation function among four candidates for the analysis of CPT data, which is thus used in this paper and shown as below:

$$\rho(\tau) = \exp\left(\frac{-2\ |\tau|}{\delta_y}\right) \tag{1}$$

where τ is the lag distance and δ_y is vertical scale of fluctuation (SOF). The fitting process is summarized as follows (Details can be referred to Firouzianbandpey et al., 2014): 1) Obtain cone tip resistance p_s versus depth data from CPT curve at a sequence of locations separated by certain distance $\Delta x = 0.1$ m; 2) Calculate the correlation coefficient $\rho_{sam}(\tau)$ of a lag distance $\tau = j\Delta x$ from data from the first step (the subscript "*sam*" means "sample", opposite to "theoretical"); 3) Plot the curve of $\rho_{sam}(\tau)$ versus the distance τ as the sample autocorrelation function curve; 4) Fit the theoretical correlation functions to the sample autocorrelation coefficient curve $\rho_{sam}(\tau)$.

Following the above procedure, each CPT curve provides one best-estimation of the SOF for each of the three layers. The calculated vertical SOFs for the silty sand layer ②$_{-3}$ from the three CPT curves ranges from 0.5 m to 1.6 m, the SOFs for muddy silty clay layer ④ ranges from 8.2 m to 10.3 m, and the SOFs for clay layer ⑤$_{-1}$ ranges from 10.1 m to 13.1 m, as listed in 6th column of Table 1. It is obvious that the vertical SOF of the silty sand layer is much smaller than that of the muddy silty clay layer and the clay layer. Thus, with a large COV and a small SOF, the spatial variability of silty sand layer ②$_{-3}$ can be quantitatively