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CPT-based subsurface soil classification and zonation in a 2D vertical cross-section using Bayesian compressive sampling

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Abstract

A novel method is developed in this study for soil classification and zonation in a two-dimensional (2D) vertical cross-section using cone penetration tests (CPT). CPT is usually performed vertically, and the number of CPT soundings in a site is often limited in geotechnical engineering practice. It is, therefore, difficult to properly interpret CPT results along horizontal direction or accurately estimate the horizontal correlation length of CPT data. The method proposed in this study bypasses the difficulty in estimating horizontal correlation length and provides proper identification of subsurface soil stratification (i.e., soil layer number is constant along horizontal direction) and zonation (i.e., soil layer number varies along horizontal direction) in a 2D vertical cross-section directly from a limited number of CPT soundings. The proposed method consists of three key elements: 2D interpolation of CPT data using 2D Bayesian compressive sampling, determination of soil behavior type (SBT) using SBT chart at every location in the 2D section, including locations with measurements and unsampled locations, and soil layer/zone delineation using edge detection method. Both simulated and real data examples are used to illustrate the proposed method. The results show that the method performs well even when only five sets of CPT soundings are available.

Keywords: Site investigation, Spatial interpolation, Bayesian methods, Compressive sensing, Geostatistics
Introduction

Delineation of subsurface soil stratification (i.e., soil layer number is constant along horizontal direction) and zonation (i.e., soil layer number varies along horizontal direction) is an essential element in site investigation as required in geotechnical design and analysis. The effect of subsurface soil stratification and zonation on geotechnical structures has been well-recognized in literatures (e.g., Lu et al. 2005; Padrón et al. 2008; Lee et al. 2013; Salimi Eshkevari et al. 2018). Subsurface soils may consist of different geological units or layers that were formed during various geological processes, such as weathering, erosion, transportation, and metamorphic processes. As a result, both soil properties and the boundary that separates geological units varies spatially (e.g., Clayton et al. 1995; Mayne et al. 2002).

The subsurface soil stratification and zonation can be identified from borehole drilling and various in-situ tests, e.g., standard penetration test (SPT) and cone penetration test (CPT). Although soil samples can be obtained during SPT for visual inspection, SPT is commonly performed with a measurement interval of at least 1 m. In contrast, CPT pushes a cylindrical steel probe into the ground and provides nearly continuous measurements (e.g., 2-5cm interval) of penetration tip resistance and sleeve friction to evaluate the stratification of subsurface soil. It has been a popular tool to assess the engineering properties of subsurface soils (e.g., Robertson and Wride 1998; Fenton 1999; Juang et al. 2003; Wang et al. 2010; Cao and Wang 2013; Cai et al. 2018; Jamshidi Chenari et al. 2018) because of its convenience, repeatability and economic efficiency. In CPT, subsurface soil properties are generally reflected in the CPT data profiles (e.g., variations of cone resistance $q_c$, sleeve friction $f_s$, and pore water pressure $u$ with depth) recorded by the embedded electronic sensors without taking out core samples (e.g., Lunne et al. 2014). When the cone penetrates through different soil layers, the apparatus records distinct CPT readings. Therefore, the subsurface soil layer boundaries can be identified
from CPT results in geotechnical engineering. In literatures, CPT has already been used for subsurface soil classification and stratification (e.g., Robertson 1990&2009; Zhang and Tumay 1999; Hegazy and Mayne 2002; Phoon et al. 2003; Das and Basudhar 2009; Wang et al. 2013; Ching et al. 2015; Cao et al. 2018).

Note that these methods mentioned above are only applicable to one-dimensional (1D) analysis, i.e., along the depth. In engineering practice, however, two- or three-dimensional (2D or 3D) geotechnical analysis is often performed in which 2D or 3D information on subsurface soil stratification and zonation are needed. Li et al (2016) used a Kriging-based method to characterize soil zonation in a 2D horizontal plane from CPT data. Their study focused on a 2D horizontal plane and assumed horizontal stationarity and isotropy for the CPT data. They do not consider the auto-correlations over vertical and horizontal directions simultaneously. In geotechnical engineering practice, however, a 2D vertical cross-section profile is commonly used to characterize geological conditions in a site, e.g., spatial variations of soil types along both vertical and horizontal directions.

In addition, subsurface soil stratification is often delineated through linear interpolation between CPT profiles, i.e., connecting the boundaries that separate different soil layers in adjacent CPT profiles by straight lines to form a 2D vertical cross-section (e.g., Mayne et al. 2002), as shown in Fig. 1. However, the actual soil layer boundaries are not necessarily linear. More importantly, the linear interpolation method cannot be used when different number of soil layers are observed in different CPT profiles, a scenario that is frequently encountered in engineering practice. Consider, for example, CPT1 and CPT2 in Fig. 1. Four soil layers (i.e., clay, silt mixtures, sand mixtures and sand) are observed from CPT1, while only three soil layers (i.e., clay, sand mixtures and sand) are found from CPT2. It is therefore difficult to determine the soil type for the triangle zone filled with question marks in Fig. 1 and its associated boundaries, because three sides of the triangle have three different soil types. The
example in Fig. 1 underscores the need of a rational method to identify subsurface soil zonation in a 2D vertical cross-section from limited CPTs or boreholes. It is worth noting that, although Kriging has been applied in various fields, especially in geosciences (e.g., Isaaks and Srivastava 1989; Webster and Oliver 2007), it might not be suitable for direct interpolation of CPT results in this study. This is because Kriging generally requires an assumption of stationarity for the data (e.g., Webster and Oliver 2007). The CPT data in this case are obviously non-stationary because different soil types are involved in a 2D vertical cross-section (see Fig. 1). Furthermore, accurate estimation of semi-variogram function and associated parameters along horizontal direction requires extensive data, while the number of CPT soundings available is often limited in geotechnical practice (e.g., Wang et al. 2017; Wang et al. 2018a). If the semi-variogram over two directions are considered simultaneously, it is very challenging to determine the isotropic or anisotropic characteristics in the 2D vertical cross-section from limited data.

This study addresses the above challenges and proposes a novel method for soil classification and zonation in a 2D vertical cross-section from limited CPT soundings. The proposed method properly considers the non-stationary spatial variability in both vertical and horizontal directions. The proposed method is illustrated using both simulated and real data.

**The proposed method**

In this Section, framework and detailed procedures of the proposed method are introduced. The proposed method consists of four components: (1) collection of a series of normalized CPT soundings data within a 2D vertical cross-section; (2) interpolation of normalized CPT soundings data in horizontal direction using 2D Bayesian compressive sampling (2D BCS); (3) soil behavior type (SBT) classification at each location using the interpolation results and SBT chart (e.g., Robertson 1990); and (4) delineation of soil layer or zone boundaries using an edge detection method. The last three components are introduced briefly as follows.
2D interpolation of normalized CPT data using Bayesian compressive sampling

The 2D interpolation of normalized CPT soundings data is performed using 2D Bayesian compressive sampling/sensing (2D BCS). 2D BCS is an application of compressive sampling or sensing (CS) in a 2D space. CS is a novel sampling theory in signal processing (e.g., Candès et al. 2006; Candès and Wakin 2008; Ji et al. 2008; Wang and Zhao 2016), and it can reconstruct a spatially varying signal (e.g., a CPT profile along depth) from sparse sampling points (e.g., Wang and Zhao 2016). In the context of 2D BCS, a 2D signal \( F \) (e.g., CPT profiles in a 2D vertical cross-section), which is spatially varying along coordinates \( x_1 \) and \( x_2 \) (e.g., depth direction and horizontal direction), is represented by a matrix of \( N_{x_1} \times N_{x_2} \). Fig. 2 shows two 2D cross-section examples of normalized CPT data (i.e., normalized friction ratio \( F_R \) and normalized cone resistance \( Q_t \)) in a vertical cross-section. The colormap in Fig. 2 can be treated as the 2D signal \( F \) in BCS. Mathematically, \( F \) is expressed as weighted summation of a series of orthonormal 2D basis functions (e.g., Fang et al. 2012; Zhao et al. 2018):

\[
F = \sum_{i=1}^{N_{x_1} \times N_{x_2}} B_{i}^{2D} \omega_{i}^{2D}
\]

where \( B_{i}^{2D} \) is 2D basis function; \( \omega_{i}^{2D} \) is the corresponding weight coefficient. Note that for many natural signals (e.g., spatially autocorrelated geotechnical properties), most \( \omega_{i}^{2D} \) have negligibly small values except for a limited number of non-trivial ones with significantly large magnitudes (e.g., Zhao et al. 2018). Therefore, \( F \) can be approximated properly as \( \hat{F} \) if the non-trivial components of \( \omega_{i}^{2D} \) are identified and estimated using sparse measurements data \( Y \) in the context of CS/BCS. \( Y \) is a sub-matrix of \( F \) with a dimension of \( M_{x_1} \times M_{x_2} \) (\( M_{x_1} \leq N_{x_1} \), \( M_{x_2} \leq N_{x_2} \)). The relation between \( Y \) and \( \omega_{i}^{2D} \) is expressed as (e.g., Fang et al. 2012; Zhao et al. 2018):
(2) \[ Y = \Psi_{x_1} F \Psi_{x_2} = \sum_{t=1}^{N_x \times N_y} A_t^{2D} \omega_t^{2D} \]

in which \( \Psi_{x_1} \) and \( \Psi_{x_2} \) are problem-specific measurement matrices with dimensions of \( M_{x_1} \times N_{x_1} \) and \( N_{x_1} \times M_{x_2} \), respectively, reflecting the positions of rows and columns of measured data \( Y \) in \( F \). \( \Psi_{x_1} \) and \( \Psi_{x_2} \) can be adapted from an identity matrix. \( A_t^{2D} \) is a submatrix of 2D basis function \( B_t^{2D} \), i.e., \( A_t^{2D} = \Psi_{x_1} B_t^{2D} \Psi_{x_2} \) and has the same dimension as \( Y \). Consider, for example, \( M=5 \) CPT soundings (i.e., dashed lines M1-M5 in Fig. 2) are performed vertically in the 2D vertical cross-section shown in Fig. 2. Fig. 3 shows 1D \( F_R \) and \( Q_t \) profiles of these five CPT soundings. Two \( Y \) matrices are constructed for \( F_R \) and \( Q_t \) respectively (e.g., one for \( F_R \) data in Figs. 3(a)-3(e), and the other for \( Q_t \) data in Figs. 3(f)-3(j)). Using the Eq. (2), the non-trivial coefficients can be estimated through maximum likelihood estimation (e.g., Ang and Tang 2007) for \( F_R \) and \( Q_t \) respectively. To distinguish from the underlying true coefficients \( \omega_t^{2D} \), \( \hat{\omega}_t^{2D} \) is used to denote the estimated ones. The best estimate of the \( \hat{\omega}_t^{2D} \) vector is derived under Bayesian framework and expressed as (e.g., Wang and Zhao 2017; Zhao et al. 2018):

(3) \[ \mu_{\omega^{2D}} = (J + D)^{-1} V_{\omega} \]

where \( J \) is a matrix with element \( J_{t,s} = \text{tr}[A_t^{2D}(A_s^{2D})^T], \) \( (t, s = 1, 2, \ldots, N_{x_1} \times N_{x_2}) \). “tr” represents trace operation in linear algebra. \( D \) is a diagonal matrix with diagonal elements \( D_{t,t} = \alpha_t \) \( (t = 1, 2, \ldots, N_{x_1} \times N_{x_2}) \) in which \( \alpha_t \) are non-negative parameters to be determined by maximum likelihood algorithm (e.g., Tipping 2001). \( V_{\omega} = \{ \text{tr}[Y(A_1^{2D})^T], \text{tr}[Y(A_2^{2D})^T], \ldots, \text{tr}[Y(A_{N_x \times N_y}^{2D})^T] \}^T \) is a column vector with a length of \( N_{x_1} \times N_{x_2} \). Using the best estimate of \( \hat{\omega}_t^{2D} \) together with corresponding 2D basis function, the
best estimate of 2D signal $F$ can be obtained as $\mu_\widehat{F}$ (e.g., complete 2D cross-section of $F_R$ and $Q_t$), which is expressed as (e.g., Zhao et al. 2018):

$$\mu_\widehat{F} = E(\widehat{F}) = \sum_{i=1}^{N_x \times N_y} B_i^{2D} E(\hat{\omega}_t^{2D}) = \sum_{i=1}^{N_x \times N_y} B_i^{2D} \mu_{\hat{\omega}_t^{2D}}$$

in which $\mu_{\hat{\omega}_t^{2D}}$ is the best estimate or expectation of $\hat{\omega}_t^{2D}$. Detailed derivation of the Bayesian formulation is referred to Zhao et al. (2018).

When compared with Kriging, BCS method is non-parametric, and it does not require estimation of semi-variogram function form or parameters before interpolation. The autocorrelations over two directions are also considered simultaneously in BCS. More importantly, BCS method is capable of directly dealing with non-stationary data (e.g., Wang et al. 2017; Wang et al. 2019; Zhao et al. 2018).

**Classification of soil behavior type (SBT) using SBT chart**

Once the 2D vertical cross-sections of normalized CPT data are interpolated using 2D BCS, soil classification at each location can be carried out using the SBT classification chart. SBT chart has been a popular tool in past decades to identify in-situ soil type and soil stratification based on behavior characteristics, as it conveniently links the cone parameters with soil types (e.g., Robertson 1990&2009). An example of SBT chart is shown in Fig. 4. The horizontal and vertical axis are $F_R$ and $Q_t$, respectively. The expressions of $F_R$ and $Q_t$ are given as below (e.g., Robertson 1990; Robertson and Wride 1998):

$$F_R = \frac{f_s}{q_t - \sigma_{v_0}} \times 100\%$$

$$Q_t = \frac{q_t - \sigma_{v_0}}{\sigma_{v_0}}$$
where \( \sigma_{v0} \) and \( \sigma'_{v0} \) are vertical total stress and vertical effective stress respectively; \( q_t \) is corrected cone resistance, expressed as:

\[
q_t = q_c + (1 - a)u
\]

where \( a \) is cone area ratio. The whole chart is divided into nine areas, corresponding to nine SBTs ranging from sensitive, fine-grained to very stiff fine-grained soils, indexed as number 1 to 9, respectively. SBT at each location can be determined using the \( F_R \) and \( Q_t \) data pair from their respective interpolated 2D cross-sections at the same location. By checking which area the \( F_R \) and \( Q_t \) data pair is located on the SBT chart (see, for example, Fig. 4), the SBT at the corresponding location is determined. In a similar fashion, the SBT at every location in the 2D vertical cross-section is obtained, leading to a 2D SBT map for the vertical cross-section.

**Delineation of soil layers or zone boundaries**

To clearly define the stratification and zonation of subsurface soil, boundaries of different soil layers and zones should be delineated. In general, the locations where the SBT index changes abruptly in the SBT map may be interpreted as the boundaries of different soil units. For example, if two adjacent elements in the SBT map are classified as 5 (i.e., sand mixtures) and 6 (i.e., sands) respectively, the line between these two elements may be interpreted as the boundary between sand mixtures and sands zones (see, for example, red bold line in Fig. 5a). In other words, determination of soil layer or zone boundaries is to locate the abrupt change of SBT values in an SBT map.

In image processing, locating abrupt change may be achieved through edge detection (e.g., Ziou and Tabbone 1998), which mathematically is to find the locations where the first order derivative of the image intensity (e.g., SBT value in this case) is greater than a threshold (e.g., Canny 1986; Lim 1990). In this study, first order derivatives along both vertical and horizontal directions at each location are calculated by convolving the SBT map with an edge.
detection operator, such as a Canny filter (e.g., Canny 1986). The convolution results in a 2D SBT gradient map, where those locations with gradients larger than a pre-specified threshold are interpreted as the boundary. A binary matrix with the same dimension as the SBT map can be obtained after the thresholding, with “Y” representing the locations of boundaries and “N” for elsewhere. Using the above edge detection method, soil layer or zone boundaries can be delineated automatically from the SBT map. The edge detection process described above can be implemented conveniently using commercial software, such as the “edge” function in image processing toolbox of MATLAB. Note that the Canny filter adopts a Gaussian kernel and its first order derivative to compute intensity gradient of the image. Variance of Gaussian kernel and filter threshold are key parameters of the Canny filter. When these parameters are properly specified, noises in the SBT map may be removed, and clear edges or boundaries may be obtained.

Figure 5a shows an illustrative example of SBT map with two SBT values, i.e., 5 (i.e., sand mixtures) and 6 (i.e., sands). The true boundaries between these two SBTs are shown by a red bold line in the figure. Figure 5b shows the SBT gradient map obtained and the boundary determined by edge detection method. Locations of the boundary are marked by the letter “Y” in Fig. 5b. The boundary determined by the edge detection method is consistent with the true boundary (i.e., the red bold line).

Figure 6 briefly shows a flowchart summarizing four-step procedures of the proposed method. In Step 1, a series of normalized CPT data (i.e., $F_R$ and $Q_t$) within a 2D vertical cross-section is collected, and $Y$ matrices respectively for $F_R$ and $Q_t$ are constructed accordingly. Then dimension of the target 2D CPT vertical cross-sections (i.e., $N_{n_1} \times N_{n_2}$) is specified, and 2D interpolation of the normalized CPT data is performed using Eq. (4) in Step 2, leading to complete 2D vertical cross-sections of $F_R$ and $Q_t$. In Step 3, the SBT at each location is classified using the interpolated $F_R$ and $Q_t$ results and SBT chart, leading to an SBT map.
Finally the boundaries of soil layers and zones on SBT map are concisely delineated using edge detection method in Step 4. The proposed method is demonstrated using a simulated example in the following section.

Simulated example

This Section aims to illustrate the proposed method and explore its performance. To facilitate the illustration, a 2D vertical cross-section with four different soil types is simulated, as shown in Fig. 7. The four soil types simulated are clay, silt mixtures, sand mixtures and sand, with the corresponding SBT value of 3 to 6, respectively. Note that the subsurface condition is unknown in practice, and the simulated cross-section in Fig. 7 is for validation purpose only in this study. In this example, normalized CPT data, including $Q_t$ and $F_R$, are first simulated within each soil unit with a resolution of 0.1m along both depth and horizontal direction using a 2D random field generator (e.g., Dietrich and Newsam 1993). The random field simulation produces 2D cross-sections of $Q_t$ and $F_R$, respectively, each of which is stored in a matrix with a dimension of 128×256, representing a 2D vertical cross-section with a thickness of 12.7m and a width of 25.5m. Table 1 summarizes the parameters used for random field simulation of each soil unit. The random field parameters include mean $\mu$, standard deviation $\sigma$, and correlation lengths, and vertical and horizontal correlation lengths, $\lambda_v$ and $\lambda_h$, of ln$Q_t$ and ln$F_R$, where ln$Q_t$ and ln$F_R$ are logarithms of $Q_t$ and $F_R$ respectively. ln$Q_t$ and ln$F_R$ are taken to follow normal distributions respectively, so $Q_t$ and $F_R$ follow lognormal distributions. In this example, an exponential correlation structure is adopted and expressed as:

$$
\rho = \exp \left( -2 \sqrt{\frac{(\Delta x_v)^2}{\lambda_v^2} + \frac{(\Delta x_h)^2}{\lambda_h^2}} \right)
$$

(8)
in which \( \Delta x_v = x_v - x_{v_m} \) and \( \Delta x_h = x_h - x_{h_n} \) represent the distances between locations \( (x_v, x_{v_m}) \) and \( (x_h, x_{h_n}) \) in vertical and horizontal directions, respectively. The 2D \( F_R \) and \( Q_t \) shown in Fig. 2 are one example of the 2D vertical cross-sections simulated using the random field parameters mentioned above. The 2D vertical cross-sections in Fig. 2 simulate subsurface conditions at a site, considering not only the spatially varying soil properties but also the spatially varying soil layer boundaries. Note that the CPT data exhibit markedly different spatial variability along vertical and horizontal directions. Normalized CPT data profiles at M1-M5 (e.g., see Fig. 3) will be used as input to the 2D BCS interpolation; whereas the complete \( F_R \) and \( Q_t \) data over the 2D vertical cross-section (i.e., Figs. 2a&2b) are used for comparison and validation only.

**2D Interpolation of CPT data**

To implement 2D interpolation from the five sets of CPT data using 2D BCS, firstly it is required to construct two measurement data matrices \( Y \), respectively (i.e., one matrix for \( F_R \), and the other for \( Q_t \)). In vertical direction, the M1-M5 profiles take all data points and have a length of 128, the \( \Psi_{x_v} \) is therefore taken as a 128\( \times \)128 identity matrix. In horizontal direction, the M1-M5 profiles are respectively located at the 1\( st \), 65\( th \), 129\( th \), 192\( th \) and 256\( th \) column of the simulated 2D cross-sections, the \( \Psi_{x_h} \) is therefore a 256\( \times \)5 matrix with columns being the 1\( st \), 65\( th \), 129\( th \), 192\( th \) and 256\( th \) column of a 256\( \times \)256 identity matrix. After that, two \( Y \) matrices with a dimension of 128\( \times \)5 are constructed by Eq. (2) (i.e., one for \( F_R \), and the other for \( Q_t \)).

2D basis function \( B_{2D} \) with a dimension of 128\( \times \)256 is constructed based on Kronecker product of discrete cosine function. Discrete cosine basis function can be obtained readily using “dctmtx” function in MATLAB. After inputting the above information, 2D interpolations are performed for \( F_R \) and \( Q_t \), respectively, using BCS, and the best estimate \( \hat{\mu}_F \) for the 2D \( F_R \) and
vertical cross-section (i.e., see Eq. (4)) are obtained. Note that resolution of the interpolated 2D cross-section is $128 \times 256$. The remaining 251 CPT data columns are interpolated from the five available CPT soundings.

The interpolation results of $F_R$ and $Q_t$ are demonstrated in Figs. 8a&b respectively. The 2D colormap in Fig. 8 are generally consistent with that in Fig. 2. The 2D BCS provides reasonable interpolation results for the non-stationary and anisotropic CPT data. It can also be observed that at the vicinity of available soundings, the interpolation results are more accurate than those far away from any of the five CPT soundings. Fig. 9 compares the original CPT data profiles at four unsampled locations (i.e., U1-U4 in Fig. 8) and those interpolated from five soundings. The locations of U1 to U4 are marked in Fig. 8 by dotted lines, and they are far away from any of the five CPT soundings. In each subplot of Fig. 9, the original and interpolated profiles are shown by black solid line and red dotted line, respectively. Fig. 9 shows that the global trends of the CPT data interpolated by BCS are very consistent with the original ones, although some details or abrupt changes are not obtained accurately. The BCS interpolation results have a dimension of $128 \times 256$, and they will be used to determine the SBT at each of the $128 \times 256$ points in the 2D vertical cross-section, as described in the next subsection.

**Soil classification using SBT chart**

As described in the Section 2, the SBT at each location in the 2D vertical cross-section can be determined using SBT chart (see Fig. 4) and $F_R$ and $Q_t$ data at that location. Similarly, SBT at all $128 \times 256$ locations are determined, leading to an SBT map. Fig. 10a shows the 2D SBT map obtained from the BCS interpolation results. The underlying soil layer boundaries are also plotted by red solid lines in Fig. 10a. Figure. 10a shows that most SBTs in the 2D vertical cross-section obtained from the proposed method agree well with the original cross-section.
(see Fig. 7). Four different types of soils are properly identified. To investigate the performance of the proposed method at unsampled locations, four 1D profiles at unsampled locations (i.e., U1-U4 in Fig. 10a) are plotted in Fig. 11. Fig. 11 compares SBT values obtained from the proposed method with their corresponding original SBT values. The original SBT versus depth in these four profiles are shown by black crosses, and the SBT values obtained from proposed method are shown by red diamonds. Fig. 11 shows that most crosses are overlapped with red diamonds. The SBT values obtained from the proposed method with 5 CPT soundings are in good agreement with the original ones at the unsampled locations.

In addition, the accuracy on the SBT values obtained from the proposed method is evaluated quantitatively. The accuracy for each soil layer is quantified by a ratio between the number of points with correctly obtained SBT values over the total number of points in the soil layer. The ratio ranges from 0% to 100%. For example, in the original zonation shown in Fig. 7, there are 6696 points representing the clay zone (i.e., Layer 1), among which SBT values are correctly obtained at 6527 points when using the proposed method. Therefore, the accuracy is calculated as 6527/6696 = 97.5%. Table 2 summarizes the accuracy calculation results for the four layers shown in Fig. 7. The second column in Table 2 gives numbers of data points within each of the four layers, while the third column summarizes the corresponding number of SBT values correctly obtained from the proposed method with five CPT soundings. The accuracies are calculated as 97.5%, 76.9%, 94.0% and 94.8% for Layer 1 to 4, respectively, with a total accuracy of 93.1% for four soil layers together. The classification and zonation results obtained from the proposed method are accurate and reasonable.

Note that the results summarized in third column of Table 2 above are from one set of random field realizations of \( F_R \) and \( Q_t \) (i.e., Fig. 2). To examine the robustness of the proposed method, 100 sets of random realizations of 2D \( F_R \) and \( Q_t \) cross-sections are generated using the same zonation geometry (i.e., Fig. 7) and the same set of random field parameters as
summarized in Table 1. This leads to 100 sets of \( F_R \) and \( Q_t \) cross-sections, each of which is similar to those shown in Fig. 2. Then, the procedures described in the previous subsection and this subsection are repeated for each set of 100 cross-sections, leading to 100 sets of accuracy ratios in total. Table 3 summarizes statistics of these 100 sets of accuracy ratios. The mean accuracy ratios for those four layers vary from 81.2% to 96.7%. The mean accuracy ratio for total cross-section is 93.0%. The relatively high mean accuracy ratio indicates that the proposed method performs well. In addition, the standard deviation of the accuracy ratio varies from 1.0% to 4.8%, with the corresponding coefficient of variation, COV, varying from 1.0% to 5.9% for those four soil layers. The standard deviation of accuracy for total cross-section is 0.8%, with a COV of 0.9%. The standard deviation and COV are relatively small, suggesting that the proposed method is robust and reliable. Note that these results are estimated from only \( 5/256 \approx 2\% \) (i.e., 5 CPT soundings) of the underlying information. The proposed method is robust and provides accurate estimation of subsurface soil classification and zonation from a limited number of CPT soundings.

*Boundary delineation using edge detection method*

As described in the previous Section, boundaries separating different soil layers or zones may be delineated using an edge detection method. A Canny filter is used in this study to estimate an SBT gradient map from the SBT map shown in Fig. 10a. By convolving a Canny filter with the SBT map in both directions, the SBT gradient map is obtained, which is colored coded and shown in Fig. 10b. Then, a threshold is used to delineate soil layer/zone boundaries, as shown by black crosses in Fig. 10b. The black crosses in Fig. 10b divide approximately the cross-section into five zones, and the SBT values for each zone are labeled accordingly in Fig. 10b. The original boundaries are also shown by red solid lines in Fig. 10b. In general, the black crosses are consistent with the red solid lines. The boundaries and zonation obtained from the
proposed method with 5 CPT soundings properly identify the spatially varying patterns (e.g., fluctuating boundaries of the clay zone and the sand zone) of the underlying 2D cross-section. For example, there is an abrupt change of SBT from 3 (i.e., clay) to 5 (i.e., sand mixtures) at the middle part of the original 2D cross-section (see Fig. 7). This abrupt change has been identified properly by the proposed method. More importantly, the interpolation difficulty described in Fig. 1 is solved properly. For example, different numbers of soil layers were observed in CPTs M1 and M2 (see Fig. 10a), and it is therefore difficult to perform linear interpolation of soil layers/zones boundaries between M1 and M2. In contrast, the proposed method properly interpolates the CPT data and provides reasonable stratification and zonation results between M1 and M2. However, some local differences are observed between the true soil layer boundaries and those obtained from the proposed method (e.g., see Fig. 10). This is because of the considerate statistical uncertainty imbedded in the interpolated results when number of CPT soundings is quite small (e.g., 5 soundings). In addition, the SBT chart classification system (e.g., see Fig. 4) adopted may contains uncertainty, including CPT data normalization error and uncertainty in soil classification criteria. Although such uncertainty may be modelled explicitly through probabilistic analysis, quantification of the CPT data normalization error and uncertainty in soil classification criteria is needed for the modelling. Such quantification is not available currently, and it is beyond the scope of this study for incorporating the uncertainty in the SBT chart classification system. Nevertheless, the results above are reasonable, and they are obtained in a data-driven and non-parametric manner without assumption of auto-correlation function type or parameters along horizontal direction. These observations indicate that the proposed method can delineate subsurface soil stratification and zonation from a limited number of CPT soundings (e.g., 5 CPT soundings in this example).
Effect of the number of CPT soundings

It is well-recognized that sample size has important effect on characterization of subsurface soils (e.g., Wang et al. 2018b). In general, more investigation logs or soil samples lead to more accurate and reliable site characterization results. In this Section, the effect of the number of CPT soundings on subsurface soil stratifications and zonation is explored using the illustrative example in the previous Section. Three more scenarios of CPT sounding schemes, i.e., M=8 soundings, M=15 soundings and M=50 soundings, are performed for the case shown in Fig. 2. In each scenario, M CPT soundings are obtained with an equal sampling interval along the horizontal direction, i.e., M corresponding F_R and Q_t profiles are taken from Fig. 2 with equal horizontal spacing and used as input to the proposed method for each added scenario. Then, following the same procedures described in the previous Section, three more sets of SBT zonation results are obtained.

Figure 12 shows an evolution of the SBT map obtained as M increases from 5 to 50. The original layer boundaries are also shown by red solid lines in Fig. 12. When only five CPT soundings are available as data input (see Fig 12a), considerable differences are observed between the SBT zonation obtained from the proposed method and that shown by the red solid lines. The result improves significantly when M increases from 5 to 8 (see Fig. 12b). The fluctuating boundaries of layer 1 and layer 4 are properly identified in Fig. 12b. When M further increases to 15 and 50 (i.e., Figs 12c&d), the soil layer/zone boundaries obtained from the proposed method vary smoothly and almost overlap with the red solid lines, particularly when M = 50.

Figures 13a-d show the effect of M on the estimated SBT profiles at the four unsampled locations U1-U4, respectively. The legends used in Fig. 11 are also used in Fig. 13. As M increases, more and more black crosses are overlapped by red diamonds. When there are 50 CPT soundings, the estimated SBT profiles at these four locations are almost identical to the
original SBT, and even some thin layers are detected properly. As M increases, result obtained from the proposed method gradually converges to the underlying cross-section.

To quantitatively evaluate the results, Table 2 summarizes the accuracy for the four M scenarios studied. As M increases, the accuracy for each layer improves as well. For example, the accuracy ratio for layer 1 increases from 97.5% at M = 5 to 99.9% at M = 50%. Layer 1 has been virtually completely identified by the proposed method with 50 CPT soundings. A similar trend is observed for all four layers. When M = 50, the accuracies for all layers, except layer 2, reach at least 99%, and the total accuracy for the 2D cross-section is 98.4%. The subsurface classification and zonation obtained from the proposed method become increasingly accurate and reliable as the number of CPT soundings increases.

**Real data example**

In this Section, the proposed method is illustrated using a group of real CPT data in a 2D vertical cross-section at a site in Christchurch, New Zealand. This group of CPT data is obtained from the New Zealand Geotechnical database (NZGD, https://www.nzgd.org.nz/), and it includes 10 CPT soundings in a 2D vertical cross-section, as shown by a plan view in Fig. 14. Locations of the 10 CPT soundings are shown by yellow triangles and labeled with their corresponding CPT ID number used in NZGD. Projection of the 2D vertical cross-section of interest to the plan view is marked by a black dashed line. The 2D vertical cross-section to be studied along horizontal direction starts from the CPT_104974 to CPT_104641, covering a width of around 540m. Along the vertical direction, the CPT data were recorded from a depth of 3.00m to 8.10m with a vertical resolution of 0.02m. Therefore, the 2D vertical cross-section has area of 5.1m×540m. The proposed method is applied to these 10 CPT soundings to obtain subsurface soil classification and zonation within this 2D vertical cross-section, following the four-step procedures in Fig. 6.
The normalized CPT data, i.e., $F_R$ and $Q_t$ profiles for the 10 soundings, are shown in the Fig. 15 (Step 1). Subplots (a)-(j) in Fig. 15 correspond to the 10 CPT soundings from CPT_104974 to CPT_104641 in Fig. 14. $F_R$ and $Q_t$ profiles are denoted by blue dotted lines and red solid lines respectively. For each sounding, both $F_R$ and $Q_t$ profiles have 256 data points, and they are plotted together in the subplot, in which the $F_R$ profile is referred to the top axis and the $Q_t$ profile is referred to the bottom axis.

The vertical dimension (i.e., $N_{z_1}$) of the 2D cross-section is set to 256, with a resolution of 0.02m. The horizontal dimension (i.e., $N_{z_2}$) is set to 270, with a resolution of 2m. Using 2D BCS, 2D vertical cross-sections of $F_R$ and $Q_t$ are then interpolated, respectively, for the 2D cross-section (i.e., Step 2). Then SBT values at all locations are determined using SBT chart and the interpolation results. The estimated SBT map with resolution of $256 \times 270$ for this 2D vertical cross-section is shown in Fig. 16a (i.e., Step 3). Locations of 10 CPT soundings are also marked in this figure by dashed lines. In this case, seven soil behavior types (i.e., SBT index from 1 to 7) are classified in this 2D cross-section. The SBT classification in Fig. 16a can be roughly described as a cross-section containing clay and sand. Majority of the points in the upper part of the 2D cross-section are estimated as clay or silt. For the lower part, most points are estimated as sand or gravelly sand. Using the edge detection method, the boundaries of soil layers/zones are delineated (i.e., Step 4). In this real case, a Canny filter is used to obtain the SBT gradient map as shown in Fig. 16b. The points on soil layer/zone boundaries are marked by black dots. The delineated boundaries follow a pattern reasonably similar to the SBT map in Fig. 16a. Types of soil in local regions are labeled by text in Fig. 16b. A clear and nearly continuous boundary has been identified to distinguish sand/gravel strata and clay/silt mixtures strata. Note that this boundary is spatially varying, and it has the shallowest depth at a horizontal coordinate of around 175m. Several local soil zones are delineated, e.g., sand mixtures zones at depth of around 3.5m, sand zones at depth of around 5.5m and 7m.
To compare the results from the proposed method, results from a nearby borehole (i.e., BH-104515 in Fig 14) is also added to Fig. 16b. Because the borehole is not exactly within the cross-section (see Fig. 14), the borehole location is projected to the 2D cross-section, as shown by arrow in Fig. 16. The logging of BH-104515 is labeled as bold texts, and it contains three layers, i.e., a silt to peats layer at depths from 3m to 4.4m, followed by a gravel layer at depths from 4.4m to 5.8m and a sand layer at depths from 5.8m to 8.1m. The classification and stratification from the borehole are generally consistent with the results from the proposed method at the projected location of the borehole. Further comparison between CPT and SBT profiles at the projected borehole location are shown in the Fig. 17. The Fig. 17 consists of five subplots, including the interpolated profiles of $F_R$ and $Q_t$ at the projected borehole location, SBT profiles, borehole stratification and descriptions of borehole logging. Since the location of CPT-104548 is close to BH-104515 (see Fig. 14), interpolated CPT profiles at the projected borehole location are also compared to the measurement data from CPT-104548, and they are shown in Fig. 17 by black solid lines and red dotted lines, respectively. These two sets of $F_R$ and $Q_t$ profiles are quite similar. The SBT profile obtained from the proposed method shows that soils at depths of 3m-4.8m are mainly clay (clay to silty clay), and soils at depths of 4.8-6.5m and 7.2-8.1m are gravelly sand to sand, and soils at depths of 6.5m-7.2m are sand. The results from the proposed method are in general consistent with results from the nearby CPT sounding and borehole logging, although there may be some differences between SBT boundaries and the boundaries obtained from borehole. This may be attributed to: 1) the borehole is not exactly within the 2D vertical cross-section, and the soils may be different between the borehole location and the projected location on the 2D vertical cross-section; 2) the stratification methods of CPT and borehole are different, i.e., the CPT stratification is based on sounding data while borehole stratification is obtained through visual inspection of core samples (e.g., Robertson 1990; Mayne et al. 2002).
In general, these results indicate that the proposed method is effective for subsurface soil classification and zonation from limited CPT soundings in engineering practice. SBTs at all locations on a 2D vertical cross-section are obtained. The soil layers/zones delineation results obtained from the proposed method provide an objective basis for subsequent geotechnical analysis. Note that the proposed method can also be applied to CPT data at different sites, such as those reported by CANLEX project (e.g., Robertson et al. 2000), United States Geological Survey (USGS) Earthquake Hazard Program (https://earthquake.usgs.gov/research/cpt/data/) and the Pacific Earthquake Engineering Research Center (https://peer.berkeley.edu/).

Summary and conclusion

A CPT-based method was developed in this paper for subsurface soil classification and zonation in a 2D vertical cross-section. The proposed method is data-driven and non-parametric. It does not require selection of a parametric form of semi-variogram functions, or estimation of semi-variogram parameters, for CPT data along either vertical or horizontal directions. Different soil layers are analyzed simultaneously, bypassing the stationary assumption for geostatistical analysis of CPT data. The framework of the proposed method was described in detail and summarized into a flowchart. Normalized CPT data (e.g., $F_R$ and $Q_t$) profiles are firstly interpolated, respectively, within a 2D vertical cross-section using 2D BCS. Then, SBT at every location is determined by SBT chart using the pair of $F_R$ and $Q_t$ interpolation results. Finally, boundaries of soil layers and zones are delineated using an edge detection method. The proposed method was illustrated using both a simulated example and real CPT data from New Zealand.

The results have shown that the proposed method performs reasonably well. Both the spatial variability of CPT data and layer boundary fluctuation are characterized properly. An
accuracy ratio is used to quantify the accuracy and reliability of the proposed method. The high mean value of accuracy ratio suggests that the proposed method accurately classifies subsurface soils and properly identifies soil zonation from limited CPT soundings. In addition, the low standard deviation and COV of accuracy ratio implies that the proposed method is robust and reliable. Moreover, the proposed method provides convergent results. As the number of CPT soundings increases, the SBT zonation obtained from the proposed method converges to the case where every point in the cross-section is measured.

Acknowledgements

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**List of symbols**

- $a$: cone area ratio
- $A_{t}^{2D}$: submatrix of $B_{t}^{2D}$ with the same dimension as $Y$, and $A_{t}^{2D}=\Psi_{x_{1}} B_{t}^{2D} \Psi_{x_{2}}$
- $B_{t}^{2D}$: the $t$-th 2D basis function with dimension $N_{x_{1}} \times N_{x_{2}}$
- $D$: a diagonal matrix with dimension $N_{x_{1}} \times N_{x_{2}}$
- $E()$: expectation operator
- $f_{s}$: sleeve friction
\( \mathbf{F} \) real-valued 2D signal matrix (e.g., CPT data within a 2D vertical cross-section) with dimension \( N_{x_1} \times N_{x_2} \)

\( \hat{\mathbf{F}} \) approximated 2D signal matrix

\( \mathbf{F}_R \) normalized friction ratio

\( \mathbf{J} \) matrix with dimension \( N_{x_1} \times N_{x_2} \)

\( J_{ls} \) the \((t, s)\) element of \( \mathbf{J} \) matrix, and \( J_{ls} = tr[\mathbf{A}_t^{2D}(\mathbf{A}_t^{2D})^T] \)

\( M \) number of CPT soundings

\( M_{x_i} \) rows number of matrix \( \mathbf{Y} \)

\( M_{x_j} \) columns number of matrix \( \mathbf{Y} \)

\( N_{x_i} \) rows number of matrix \( \mathbf{F} \)

\( N_{x_j} \) columns number of matrix \( \mathbf{F} \)

\( q_t \) corrected cone tip resistance

\( Q_t \) normalized cone resistance

\( t \) index of 2D basis function \( \mathbf{B}_t^{2D} \)

\( tr(\cdot) \) trace operator of matrix

\( u \) pore pressure

\( \mathbf{V}_{u \tau} \) a vector with length \( N_{x_1} \times N_{x_2} \)

\( x_{i_1} \) the \( i \)-th row of \( \mathbf{F} \)

\( x_{m_1} \) the \( m \)-th row of \( \mathbf{F} \)

\( x_{h_1} \) the \( j \)-th column of \( \mathbf{F} \)

\( x_{h_n} \) the \( n \)-th column of \( \mathbf{F} \)

\( \mathbf{Y} \) measurement data matrix

\( \alpha_t \) the \( t \)-th non-negative parameters

\( \Delta x_v \) the vertical distance between points \((x_{i_v}, x_{h_v})\) and \((x_{i_v'}, x_{h_v'})\)

\( \Delta x_h \) the horizontal distance between points \((x_{i_h}, x_{h_h})\) and \((x_{i_h'}, x_{h_h'})\)

\( \omega_t^{2D} \) weight coefficient of \( \mathbf{B}_t^{2D} \)

\( \hat{\omega}_t^{2D} \) estimated weight coefficient of \( \mathbf{B}_t^{2D} \)

\( \Psi_{x_i} \) problem-specific measurement matrix with dimension \( M_{x_i} \times N_{x_1} \)

\( \Psi_{x_j} \) problem-specific measurement matrix with dimension \( N_{x_2} \times M_{x_2} \)
\( \mu_{\hat{\omega}_2^{2D}} \) best estimate of the \( \hat{\omega}_2^{2D} \) vector

\( \mu_{\hat{\omega}_t^{2D}} \) the \( t \)-th element in \( \mu_{\hat{\omega}_2^{2D}} \)

\( \mu_{\hat{\Phi}} \) best estimate of \( \hat{\Phi} \)

\( \mu \) the mean used in random field simulation

\( \sigma \) the standard deviation used in random field simulation

\( \sigma_v \) vertical total stress

\( \sigma'_v \) vertical effective stress

\( \lambda_h \) the horizontal correlation length used in random field simulation

\( \lambda_v \) the vertical correlation length used in random field simulation
**Figure Captions**

Fig 1. Challenge in subsurface soil zonation and stratification

Fig. 2 Simulated $F_R$ and $Q_t$ for a 2D vertical cross-section with spatially varying soil layer boundaries

Fig. 3 Profiles of simulated CPT soundings at M1-M5

Fig. 4 Soil behavior type classification chart (after Robertson 1990)

Fig. 5 Example of soil layer delineation in soil behavior type (SBT) map: (a) SBT map with two soil layers and boundary (red bold line) between soil layers; (b) SBT gradient map and boundary delineation by edge detection

Fig. 6. A flowchart of the proposed method

Fig. 7. A simulated 2D cross-section with different soil zones

Fig. 8 Interpolation results of $F_R$ and $Q_t$ from 5 CPT soundings using 2D BCS

Fig. 9 Comparisons between the original CPT profiles and interpolated profiles at four unsampled locations U1-U4

Fig. 10 Subsurface soil zonation results: (a) SBT map obtained from the proposed method with five CPT soundings; (b) Soil zonation from SBT gradient map

Fig. 11 Comparison between original SBT profiles and those obtained from the proposed method with 5 CPT soundings

Fig. 12 Effect of the number of CPT soundings on obtained SBT map

Fig. 13 Effect of the number of CPT soundings on interpolated SBT profile

Fig. 14. Plan view showing locations of 10 CPT soundings and the cross-section to be interpolated at a site in Christchurch

Fig. 15 Profiles of normalized cone resistance $Q_t$ and normalized friction ratio $F_R$ for the 10 CPT soundings at Christchurch site

Fig. 16. Soil classification and zonation results within the 2D cross-section: (a) SBT map; (b) SBT gradient map and soil layer/zone delineation at Christchurch site

Fig. 17. Comparison between the CPT results, the SBT classification results and borehole logging at Christchurch site
### Tables and Figures

#### Table 1 Parameters used in random field simulation of CPT data in each layer

<table>
<thead>
<tr>
<th>Layer</th>
<th>Mean, $\mu$ of $\ln F_R$</th>
<th>Standard deviation, $\sigma$ of $\ln F_R$</th>
<th>Mean, $\mu$ of $\ln Q_t$</th>
<th>Standard deviation, $\sigma$ of $\ln Q_t$</th>
<th>Horizontal correlation length $\lambda_h$ of $\ln F_R$</th>
<th>Vertical correlation length $\lambda_v$ of $\ln Q_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layer 1</td>
<td>1.7</td>
<td>2.6</td>
<td>0.15</td>
<td>0.15</td>
<td>15m</td>
<td>4m</td>
</tr>
<tr>
<td>Layer 2</td>
<td>0.9</td>
<td>3</td>
<td>0.15</td>
<td>0.15</td>
<td>30m</td>
<td>4m</td>
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<tr>
<td>Layer 3</td>
<td>0.3</td>
<td>3.6</td>
<td>0.15</td>
<td>0.15</td>
<td>25m</td>
<td>4m</td>
</tr>
<tr>
<td>Layer 4</td>
<td>-0.3</td>
<td>4.4</td>
<td>0.15</td>
<td>0.15</td>
<td>20m</td>
<td>4m</td>
</tr>
</tbody>
</table>

#### Table 2 Effect of number of CPT soundings on the accuracy of the results obtained from the proposed method

<table>
<thead>
<tr>
<th>Layer</th>
<th>Number of correctly obtained points</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 CPT soundings</td>
</tr>
<tr>
<td>Layer 1</td>
<td>6696 (97.5%)</td>
</tr>
<tr>
<td>Layer 2</td>
<td>3599 (76.9%)</td>
</tr>
<tr>
<td>Layer 3</td>
<td>12441 (94.0%)</td>
</tr>
<tr>
<td>Layer 4</td>
<td>10032 (94.8%)</td>
</tr>
<tr>
<td>Total</td>
<td>32768 (93.1%)</td>
</tr>
</tbody>
</table>

Note: the number in ( ) is accuracy = number of the correctly obtained points/number of points in column 2

#### Table 3 Statistics of accuracy of the results obtained from the proposed method with five CPT soundings from 100 sets of random realizations

<table>
<thead>
<tr>
<th>Layer</th>
<th>Mean of the accuracy (%)</th>
<th>Standard deviation of the accuracy (%)</th>
<th>Coefficient of variation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layer 1</td>
<td>96.7</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Layer 2</td>
<td>81.2</td>
<td>4.8</td>
<td>5.9</td>
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<td>Layer 3</td>
<td>92.6</td>
<td>1.6</td>
<td>1.7</td>
</tr>
<tr>
<td>Layer 4</td>
<td>95.1</td>
<td>1.6</td>
<td>1.7</td>
</tr>
<tr>
<td>Total</td>
<td>93.0</td>
<td>0.8</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Fig. 1. Challenge in subsurface soil zonation and stratification

Fig. 2 Simulated $F_R$ and $Q_t$ for a 2D vertical cross-section with spatially varying soil layer boundaries

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Soil behavior type classification

<table>
<thead>
<tr>
<th>Area</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Sensitive, fine-grained</td>
</tr>
<tr>
<td>2</td>
<td>Organic soils (peats)</td>
</tr>
<tr>
<td>3</td>
<td>Clays (clay to silty clay)</td>
</tr>
<tr>
<td>4</td>
<td>Silt mixtures (clayey silt to silty clay)</td>
</tr>
<tr>
<td>5</td>
<td>Sand mixtures (silty sand to sandy silt)</td>
</tr>
<tr>
<td>6</td>
<td>Sands (clean sand to silty sand)</td>
</tr>
<tr>
<td>7</td>
<td>Gravelly sand to sand</td>
</tr>
<tr>
<td>8</td>
<td>Very stiff sand to clayey sand</td>
</tr>
<tr>
<td>9</td>
<td>Very stiff, fine-grained</td>
</tr>
</tbody>
</table>

Fig. 3 Profiles of simulated CPT soundings at M1-M5

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