Data fusion technique for predicting shear strength and stress history from piezocone penetration tests

Technique de fusion de données pour prédire la résistance de cisaillement et l'histoire de contraintes à partir des résultats de pénétration piezocone

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ABSTRACT
Existing methods used to infer soil properties from piezocone penetration test (PCPT) data are not always reliable due to the complexity of cone penetration. This study examines the feasibility of training an artificial neural network (ANN)-based data fusion model to estimate soil properties, including overconsolidation ratio (OCR), coefficient of lateral earth pressure at rest (K_o), and undrained shear strength (s_u), directly from multiple piezocone penetrometer sensor measurements. Additional features were created by mathematically combining the PCPT measurements in a manner consistent with the work of previous researchers in an attempt to improve the performance of the trained data fusion model. Overall, the values of OCR, K_o, and s_u predicted by the data fusion models were found to compare very well with the reference values and to be generally more reliable than the results of the current interpretation methods.

RÉSUMÉ
Les méthodes courantes, qui sont utilisées pour déduire les propriétés des sols à partir de données du piezocone penetration test (PCPT), ne sont pas toujours fiables à cause de la complexité du pénétromètre. Cette étude examine la possibilité d'entraîner un modèle de fusion de données basé en artificial neural network (ANN) pour estimer les propriétés des sols, inclus overconsolidation ratio (OCR), coefficient of lateral earth pressure at rest (K_o), undrained shear strength (s_u), directement des mesures détectées par le pénétromètre. Des caractéristiques additionnelles ont été développées en combinant mathématiquement les mesures du PCPT d'une manière consistante avec les travaux de chercheurs pour améliorer la performance du modèle de fusion de données. Dans l'ensemble, les valeurs OCR, K_o, et s_u, prédites par les modèles, comparent bien avec les valeurs de référence et sont plus fiables que les résultats interprétés par les méthodes courantes.

Keywords : data fusion, neural networks, piezocone penetration test, soil properties

1 INTRODUCTION

Data fusion techniques combine data from multiple sensors or sources in order to achieve inferences that may not be feasible from data obtained using just a single sensor (Hall and Llinas 1997). This is because a combination of additional independent and/or redundant data tends to have a synergistic effect, resulting in improved inferences. For example, having two eyes (visual sensors) allows for stereoscopic vision (i.e., depth perception) in humans. The brain, which fuses data (sight, sound, smell, taste, touch) from multiple sensors (eyes, ears, nose, tongue, skin) and uses its memory, experience, and a priori knowledge to make inferences about the external world, is an excellent example of a data fusion system (Gros 1997). Data fusion is currently being used in numerous applications, including military defense, robotics, medical diagnosis, non-destructive evaluation of equipment, and weather forecasting. In this study, it is proposed that the process of data fusion be used to estimate soil properties, including overconsolidation ratio (OCR), coefficient of lateral earth pressure at rest (K_o), and undrained shear strength (s_u), directly from in situ test measurements and additional created features, and that data fusion algorithms, through training, may be able to overcome some of the limitations of the current piezocone penetration test (PCPT) interpretation methods.

2 DATA FUSION FOR INTERPRETING PCPT DATA

The most popular area of data fusion is feature-level identity fusion, which is the fusion of parametric data to determine the identity and/or attributes of an observed object. In the feature-level fusion approach, "feature extraction" is performed on the raw data (i.e., sensor measurements) to yield a feature vector from each sensor. The feature vectors consist of characteristics, or features, of the data that will aid in the identification of the object. The feature vectors from all sensors are then concatenated together into a single joint feature vector from which an identity declaration is made (Hall and Llinas 1997). Because feature-based pattern recognition techniques, such as artificial neural networks (ANNs), are often used for identity fusion, the success of these methods depends on the selection of good, representative features (Hall and Llinas 2001). Figure 1 depicts the feature-level identity approach for extracting features (q_t, u_2) from raw piezocone sensor data and using an ANN to perform a nonlinear transformation between the input feature vector and the output declaration of identity (i.e., soil attributes of OCR, K_o, and s_u).

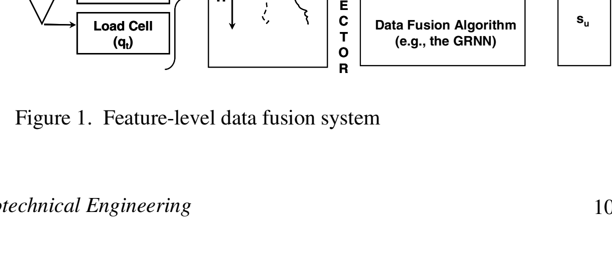

Figure 1. Feature-level data fusion system

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3 PREDICTION OF OCR, K_O, AND S_U FROM PCPT DATA USING DATA FUSION

3.1 *Overview of Methodology*

In order to predict values of OCR, K_o, and s_u from PCPT data, a database consisting of values of corrected cone tip resistance (q_t), pore pressure measured just behind the cone base (u_2), vertical total stress (σ_v), and hydrostatic pore pressure (u_o), together with reference values of OCR, s_u, and K_o obtained from one-dimensional consolidation test results, triaxial compression and field vane shear test results, and empirical correlations, were used to train and test an ANN-based data fusion model (Griffin 2007). Data fusion model predictions were compared with the reference values, as well as with the estimates obtained using existing interpretation methods, to determine if the reliability of inferred soil properties can be improved by using data fusion techniques.

3.2 *Database*

The database used herein, obtained from Sandven (1990) and Chen (1994), contained PCPT measurements (q_t and u_2) and corresponding OCR, s_u, and K_o data obtained from 19 intact clay sites located in seven countries, including Norway, Canada, Sweden, the United States, Scotland, Singapore, and Taiwan. Sleeve friction (f_s) measurements were not available from all of these sites; therefore, f_s was not used. The reference values of OCR were determined from one-dimensional consolidation tests, while the reference values of s_u were estimated from isotropically consolidated undrained triaxial compression (CIUC) tests, anisotropically consolidated undrained triaxial compression (CAUC) tests, and in situ field vane shear tests. Since K_o was not measured in the laboratory or in situ, the reference values included for each case in the database were calculated using empirical correlations for normally consolidated and overconsolidated soils (e.g., Jaky 1944; Mayne and Kuhawy 1982). In total, the database contained 153 cases, ranging from soft, normally consolidated cohesive deposits to stiff, overconsolidated clays. OCR values in the database fell between 1.0 and 11.4; values of s_u ranged from 8 to 286 kPa for the laboratory tests (99 cases) and from 12 to 94 kPa for the field tests (54 cases); and computed K_o values ranged from 0.45 to 1.51.

3.3 *Feature Creation*

In an attempt to improve the performance of the data fusion model, additional features were created by mathematically combining the original set of features in a manner consistent with the work of previous researchers. Domain knowledge (i.e., that of a geotechnical expert) was employed to construct seven new features, or input variables, from the PCPT and in situ stress data for use in training the data fusion models. These new features included vertical effective stress ($\sigma_v' = \sigma_v - u_o$), excess pore pressure at the u_2 location ($\Delta u_2 = u_2 - u_o$), net cone resistance ($q_n = q_t - \sigma_v$), normalized net cone resistance [$Q_t = (q_t - \sigma_v)/\sigma_v'$], effective cone resistance ($q_e = q_t - u_2$), pore pressure ratio [$B_q = \Delta u_2/(q_t - \sigma_v)$], and normalized excess pore pressure ($NEPP = \Delta u_2/\sigma_v'$). Many of these relationships, or features, have been proposed for interpretation of PCPT measurements since the piezocone was first introduced in the early 1970s. In particular, q_n has been related to both preconsolidation pressure (Tavenas and Leroueil 1987) and s_u (Robertson and Campanella 1983), while q_e has been correlated to s_u (Senneset et al. 1982; Campanella et al. 1982; Chen and Mayne 1994). Wroth (1988) reasoned that Q_t could be effectively used to evaluate OCR in natural clays, while Kulhawy and Mayne (1990) proposed a correlation between Q_t and K_o. Azzouz et al. (1983) and Mayne (1986) proposed relationships between NEPP and OCR; and Senneset et al. (1982), Wroth (1984), and Robertson et al. (1986) offered correlations for OCR using B_q. Finally, a number of relationships have been proposed between Δu_2 and s_u (Vesic 1972; Massarsch and Broms 1981).

3.4 *Training and Testing Data Fusion Models*

Two feature-level data fusion models were developed using the general regression neural network (GRNN), a feature-level data fusion technique developed by Specht (1991) and presented in Kurup and Griffin (2006). Split-sample, or holdout, validation, in which a representative portion of the cases is reserved for testing, was used to estimate generalization error in the data fusion models. The testing set was comprised of 51 cases, representing approximately one-third of the available data, while the training set was comprised of the remaining 102 cases. In accordance with standard testing procedures, the testing cases were chosen randomly from each piezocone site and were not used in any way during training.

The PCPT data and in situ stresses (inputs), together with the corresponding values of OCR, K_o, and s_u (targets), were used to develop two GRNN-based data fusion models (Models 1 and 2). The smaller feature vector for Model 1 consisted of five input variables, including σ_v, u_o, q_t, u_2, and s_u type. The larger feature vector for Model 2 consisted of 12 input variables, including σ_v, σ'_v, q_t, u_2, Δu_2, q_n, q_e, Q_t, B_q, NEPP, and s_u type. The "s_u test type" input was used in order to predict values of both $s_{u(TC)}$ and $s_{u(FV)}$, with an "s_u type" of 1 denoting a triaxial compression (TC) test and an "s_u type" of 2 denoted a field vane shear (FV) test. The architecture of the GRNN is depicted in Figure 1, in which a feature vector is input on the left side of the neural network, the trained GRNN performs a nonlinear transformation (feature-level fusion) between the input and target variables, and an identity declaration is output on the right side of the neural network.

Prior to training the data fusion models, all input and output data were scaled, or normalized, so that they fell within the range of 0 to 1. Training then consisted of repeatedly presenting 85% of the training data to the network and subsequently testing it with the remaining 15% (termed "tuning data") to find the optimal value of the smoothing parameter, σ, which essentially determines how closely the function implemented by the GRNN fits the training data (smaller σ for large training sets or "clean" data, larger σ for small training sets or "noisy" data). Because this process can result in different optimum σ values for each target parameter (OCR, K_o, and s_u), a σ which gave favorable results for all three targets was chosen. This training procedure was repeated twice more, each time with a different 15% of the training data being used for tuning. After the optimum σ was found for each data fusion model (0.05 for Model 1 and 0.10 for Model 2), the models were tested with a testing set consisting of previously unseen data obtained from the same clay sites used in training.

3.5 *Data Fusion Model Results*

After testing, the GRNN data fusion model predictions were compared to the reference OCR, K_o, and s_u values to determine the models' success. For Model 1, which simultaneously predicted these target soil parameters from a smaller feature vector, the predicted values are plotted against the corresponding reference values and the normalized predicted values are plotted for each testing case in Figure 2. For Model 2, which simultaneously predicted the target soil parameters from a larger feature vector, both the predicted values and the normalized predicted values are plotted in Figure 3. Note that perfect predictions fall on the 1 to 1 (45°) correlation line and have normalized values of unity. Included on all numeric plots are the correlation coefficient (CC), mean absolute error (MAE), and relative absolute error (RAE) of the numeric predictions, which provide a measure of error for the predicted values. Included on all normalized plots are the mean and standard deviation (SD) of the normalized predictions, which give an indication of the central tendency and variability of the normalized values, respectively.

The larger feature vector used for Model 2, which included the additional constructed features, resulted in better predictions of OCR, K_o, and s_u than the smaller feature vector used for Model 1. The computed performance measures for the predictions of Model 2 all showed improvement over the performance measures for the predictions of Model 1, including a higher CC, lower MAE, and lower RAE for the predicted values and a better mean (closer to 1) and lower SD for the normalized predicted values.

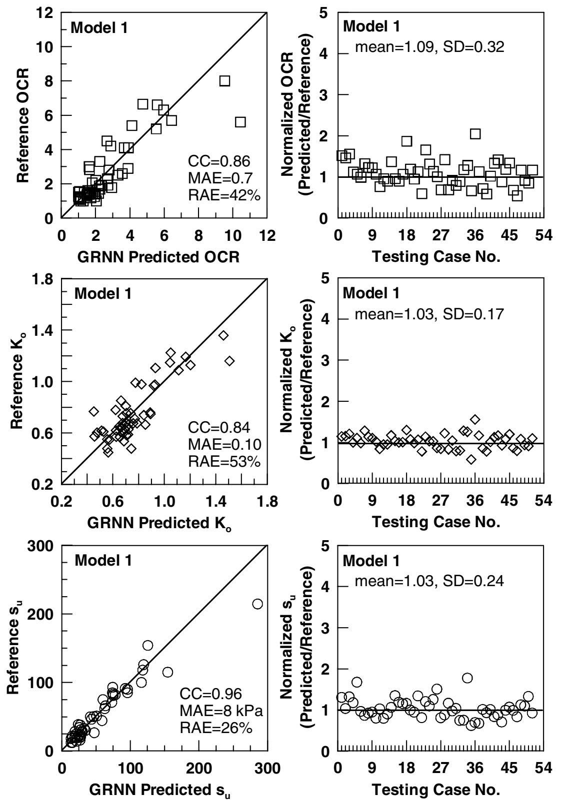

Figure 2. Data fusion Model 1 results

3.6 *Interpretation Method Results*

For comparative purposes, values of OCR, K_o, and s_u were each estimated using an existing interpretation method. The values of OCR were estimated using the normalized effective cone resistance correlation proposed by Chen and Mayne (1994); values of K_o were estimated using the normalized net cone resistance correlation proposed by Kulhawy and Mayne (1990); and values of s_u were estimated using the net cone resistance empirical correlation ($s_u = q_n/N_{kt}$). In using the net cone resistance relationship to predict s_u, site-specific correlations for the empirical cone factor, N_{kt}, were not developed for each piezocone site; instead, values of N_{kt} were varied until single values which worked well were found for each s_u test type ($s_{u(TC)}$ and $s_{u(FV)}$) in the training set. For this database, the value of cone factor N_{kt} was chosen as 11 for $s_{u(TC)}$ and 17 for $s_{u(FV)}$. The interpretation method results are plotted in Figure 4. The CC, MAE, and RAE of the numeric predictions are included on the numeric plots, and the mean and SD of the normalized predictions are included on the normalized plots.

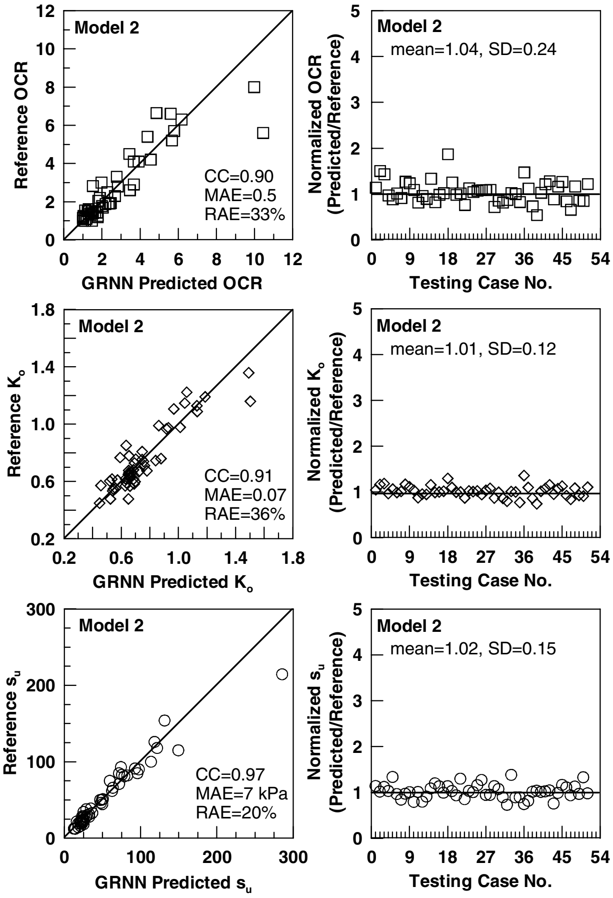

Figure 3. Data fusion Model 2 results

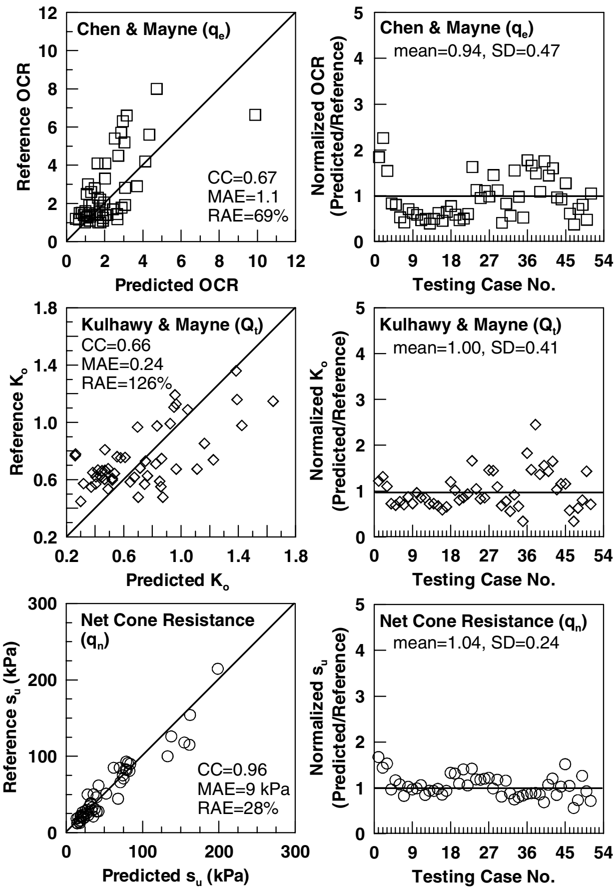

Figure 4. Interpretation method results

4 DISCUSSION OF RESULTS

The GRNN feature-level data fusion technique performed well in predicting OCR, K_o, and s_u from the PCPT data and related features. The use of additional features improved the "accuracy" of the OCR, K_o, and s_u predictions of the GRNN-based data fusion model. Greater accuracy is defined herein as those values exhibiting an overall decrease in MAE and RAE and an increase in CC, and whose normalized values typically exhibit a better mean (closer to 1) and a decrease in SD. The use of the smaller feature vector for Model 1 resulted in OCR predictions having a MAE of 0.7, RAE of 42%, and CC of 0.86; K_o predictions having a MAE of 0.10, RAE of 53%, and CC of 0.84; and s_u predictions having a MAE of 8 kPa, RAE of 26%, and CC of 0.96 (Figure 2). The use of the large feature vector for Model 2 resulted in OCR predictions having a MAE of 0.5, RAE of 33%, and CC of 0.90; K_o predictions having a MAE of 0.07, RAE of 36%, and CC of 0.91; and s_u predictions having a MAE of 7 kPa, RAE of 20%, and CC of 0.97 (Figure 3).

Overall, the data fusion models performed better than the PCPT interpretation methods in predicting OCR, K_o, and s_u. Compared to both data fusion models, Chen and Mayne's (1994) correlation for estimating OCR and Kulhawy and Mayne's (1990) correlation for estimating K_o resulted in predictions having higher values of MAE and RAE and a lower CC for the numeric predictions and a higher value of SD for the normalized predictions (Figure 4). In estimating values of s_u, data fusion Model 1 resulted in predictions having values of MAE, RAE, CC, and SD comparable to the predictions using the net cone resistance (q_n) empirical correlation, as the interpretation method resulted in s_u values having an MAE of 9 kPa, an RAE of 28%, and a CC of 0.96 for the numeric predictions and an SD of 0.24 for the normalized predictions (Figure 4). Data fusion Model 2 yielded better s_u predictions than the interpretation method.

The GRNN performs well as a feature-level data fusion technique. Because the GRNN has the ability to deal with noisy training data caused by errors or anomalies in the laboratory and field test methods, it is very effective in modeling nonlinear multivariate problems. As such, the ANN-based data fusion models generally outperform the existing PCPT interpretation methods. Because the interpretation methods used herein do not account for such factors as soil fabric, sensitivity, mineralogy, aging, and geologic origin, it is hoped that the data fusion models may be able to "learn" some of these complex nonlinear relationships among sample data through training.

5 CONCLUSIONS

This study has demonstrated the effectiveness of data fusion in inferring soil properties from PCPT measurements, and the use of additional created features was shown to improve soil property predictions. The values of OCR, K_o, and s_u predicted by the data fusion models were found to compare very well with the reference values and to be generally more reliable than the results of the current interpretation methods. Thus, data fusion may represent an improvement over the methods currently being employed to interpret piezocone penetrometer sensor data. In addition, data fusion techniques may be capable of combining the features constructed from PCPT measurements into one predictive model, essentially combining years of previous PCPT research.

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