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Generation and Evaluation of CPT Data Using Kriging Interpolation Technique

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Abstract

The cone penetration test (CPT) has been the de facto field exploration method in geotechnical engineering for decades. Variations of CPT can measure parameters for seismic, environmental, and hydrological applications. Analyzing response often requires properties in areas that have little or no data. Therefore, given the limited CPT data, it is critical to understand how to accurately estimate the soil properties at unsampled locations. In this paper, we generated soil shear wave velocity profiles using the kriging interpolation technique and assessed their performance using site response analysis. Four kriging interpolation-based shear wave velocity profiles and four additional CPT-based shear wave velocity profiles defined site conditions for response analysis. We performed a series of 1-D equivalent linear site response analyses using STRATA software. The site response analysis results are presented as amplification factors (AF), peak ground acceleration (PGA) profiles, surface spectral acceleration, and surface acceleration time histories. Compared to CPT-based profiles, the results of kriging interpolation-based profiles were evaluated and discussed. The results confirmed the reliability of the kriging interpolation technique in predicting soil parameters at unsampled locations.

Keywords

kriging interpolation, semi-variogram, CPT, shear wave velocity profile, site response

1 Introduction

The cone penetration test (CPT) has been the de facto standard for field exploration in geotechnical engineering [1–6]. Variations of CPT can measure parameters for seismic, environmental, and hydrological applications. CPT has been used widely because of its precision, accuracy, and the fact that it continually generates cone tip resistance (q_c) and sleeve friction (f_s) data [3]. Based on methods developed by previous researchers, CPT results enable the identification and estimation of physical and mechanical properties of a wide variety of soils. For example, CPT-derived soil parameters include soil behavior type index I_c [1], unit weight [7], and shear wave velocity (V_s) [3], [8–11] thereby enabling engineers to perform site-specific seismic response analysis.

CPT is often carried out with a broad sample spacing, resulting in insufficient soil data. Due to the spatial variability of soil, identifying its properties at non-sampled locations can be challenging. Comparing the CPT data to neighboring soundings may reveal major differences. Therefore, it is essential to understand how to reasonably predict the soil parameters of a large area, given the limited CPT data. To achieve this objective, existing data must be interpolated while considering the spatial correlation of the key soil parameters.

Over the past few decades, researchers have developed several techniques frequently used in geotechnical engineering to forecast the spatial variability of soil parameters, including geostatistics [12] and random field theory [13]. Geostatistics uses a special modelling technique called geostatistical kriging for this spatial interpolation [14]. There is a larger link between samples that are close together inside a soil layer than between samples that are further apart [15]. Autocorrelation exists between measured values of CPT and hence between soil parameters.

This study aims to geostatistically characterize soil properties through kriging interpolation to generate soil profiles that serve as input to site response analysis. Thus, this research has two goals: (1) to provide reasonable forecasts of soil parameters in non-sampled areas using previously collected CPT data. Kriging interpolation will

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produce estimates and uncertainty for the CPT data (i.e., q_c and f_s) at each interpolation point. (2) To evaluate the performance of a kriging-based soil profile compared to a CPT-based soil profile in assessing seismic site response. This comparison proves that the kriging interpolation method can reliably and effectively forecast the soil parameters required for site response analysis.

2 Data

The CPT data utilized for this study originated from ISSMSG TC304 Student Contest Committee [15]. Blue square dots in Fig. 1(a) represent a total of 232 CPT sample locations on a 50 × 50 meter field. The average drilling depth was 5 m below the ground surface, and the q_c and f_s measurement interval was 5 mm. The red points in Fig. 1(a) represent locations where kriging interpolation takes place. Only four (CPT-6, CPT-7, CPT-E6, and CPT-E7) of the 232 CPT data sets contributed to the site response analysis. These CPT points are located in the SRR region shown in Fig. 1(a) and Fig. 1(b). In addition, to evaluate the performance of kriging interpolation, four additional CPT data sets (K-D6, K-D7, CPT-E6, and CPT-E7) were generated using kriging interpolation in the same region were considered.

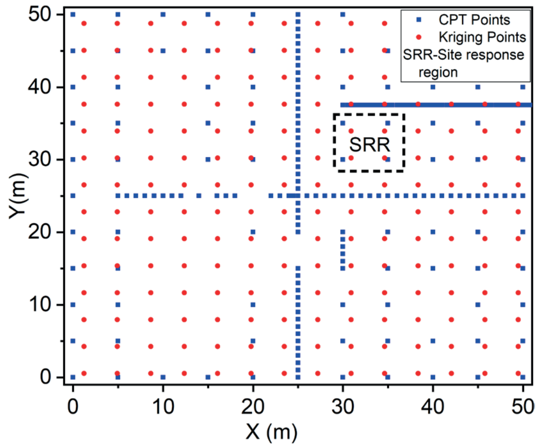
Table 1 displays the statistical analysis results performed on CPTs and kriging data sets. A quick comparison reveals that the mean value of qc is around 30 times greater than the mean value of fs for both CPT and Kriging data sets. The mean and median values of the two variables are relatively close. The kurtosis values for the CPT data sets are approximately 0.8, while kriging data sets have kurtosis values greater than 3, indicating a departure from the normal distribution. Compared to CPT-measured data, the statistical summary of kriging output and that of CPT show a good approximation of kriging interpolation.

3 Kriging interpolation

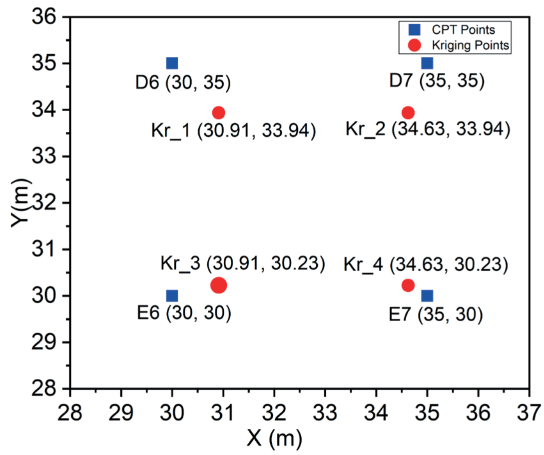
The core component of the kriging interpolation technique is the semi-variance $\gamma(d)$. The semi-variance is the average of the squared difference between all pairs of regionalized variables $Z(y)$ with the same lag distance d between them [2].

$$\gamma(d) = \frac{1}{2N(d)} \sum_{i=1}^{N(d)} \left[Z(x_i) - Z(x_i + d) \right]^2 , \quad (1)$$

where $N(d)$ represents the number of observation pairs spaced by lag distance d. The open-source programming language R performed the kriging interpolation. Programming code is presented in Appendix A.



(a)



(b)

Fig. 1 The CPT and kriging interpolation locations and CPT (a) and kriging interpolation points with (x, y) coordinates considered for site response analysis (SRR) (b)

Table 1 Sample statistical summary of CPT and Kriging data at a depth of 500 mm

	Kriging_q_c	CPT_q_c	Kriging_f_s	CPT_f_s
Mean	3	3.74	0.11	0.13
Standard Error	0.1	0.21	0	0.01
Median	2.56	2.28	0.1	0.11
Standard Deviation	1.49	3.23	0.05	0.1
Kurtosis	6.92	0.8	4.42	0.79
Skewness	2.5	1.31	1.47	1.06
Minimum	1.25	0.29	0.01	0
Maximum	10.53	15	0.36	0.46
Count	210	232	210	232

Semi-variogram refers to a scatter plot of the semi-variance *vs* the distance d. In order to obtain more accurate results from a kriging interpolation, a parametric variogram model must first approximate the experimental points. Different models, including exponential, Gaussian, and spherical, are used for fitting the variogram based on the scatter plot of semi-variance (see Fig. 2). The sill, nugget, and range are the primary parameters of a variogram model, and they are adjusted iteratively to provide a better fit to the experimental points [16, 17]. The sill is the variance at which the empirical variogram appears to level off, and the range is the distance beyond which the auto-correlation disappears. The nugget is an additional essential element of the model that represents the variability of the data at a small scale. The best-fit parameters for the semi-variograms appear in Table 2. Following the development of the semi-variogram, Ordinary Kriging estimations follow as [2]:

$$Z^*\left(x_o\right)=\sum_{i=1}^{N}\lambda_i Z(x_i)\,, \tag{2}$$

where $Z^*(x_o)$ is the kriging interpolation estimator, λ_i is an unbiased weight for measured regionalized variables at each sampling point, $Z(x_i)$ is measured regionalized variable at thes ith sampling point, N is the number of measured values and x_o is the prediction point. In this research, we performed kriging interpolation at every 0.5 m along the soil depth.

4 Site response

CPT data can estimate a variety of soil parameters, including shear wave velocity [3], soil behavior type index I_c [1], unit weight and others. In order to evaluate the performance of the kriging interpolation technique in geotechnical earthquake engineering, we created shear wave velocity profiles (Fig. 3(a)) based on interpolation results. We performed 1-D equivalent linear site response analysis using

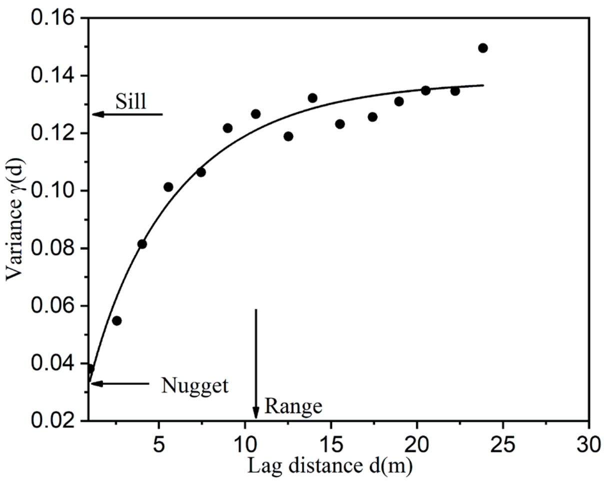


Fig. 2 An example of an exponentially fitted variogram with parameters

Table 2 Variogram parameters for qc and fs at different depth

Depth (mm)	Variables (MPa)	Sill	Nugget	Range
500	q_c	14.5	3.7	9
	f_s	0.0145	0.004	9
1000	q_c	9	3	9.5
	f_s	0.0155	0.005	14
1500	q_c	3.2	0.4	11
	f_s	0.0098	0.0015	15
2000	q_c	1.7	0.1	10
	f_s	0.0078	0.0015	20
2500	q_c	1.2	0.15	20
	f_s	0.008	0.0015	20
3000	q_c	0.58	0.08	17
	f_s	0.005	0.001	9
3500	q_c	0.26	0.05	19
	f_s	0.0042	0.001	9
4000	q_c	0.22	0.03	19
	f_s	0.004	0.0008	10
4500	q_c	0.13	0.04	15
	f_s	0.0038	0.0008	10
5000	q_c	0.1266	0.038	10.6
	f_s	0.0038	0.0005	9.5

STRATA [18]. In the current study, we developed two sets of V_s profiles, as shown in Fig. 3(a). One set comes from CPT data (V_s_CPT), and the other from kriging interpolation data (V_s_K). Within each set, there are four different V_s profiles. Similarly, the soil behaviour type indexes (I_c-K) and (I_c-CPT) used kriging interpolation and CPT data to identify soil types, as shown in Fig. 3(b).

The shear wave velocity of the soil layer can be estimated as follow:

$$V_S=\sqrt{\left(\frac{q_t-\sigma_v}{p_a}\times 10^{0.55 I_{SBT}+1.68}\right)}\,, \tag{3}$$

where I_{SBT} is soil behavior type index and is commonly estimated using the following equation [19]:

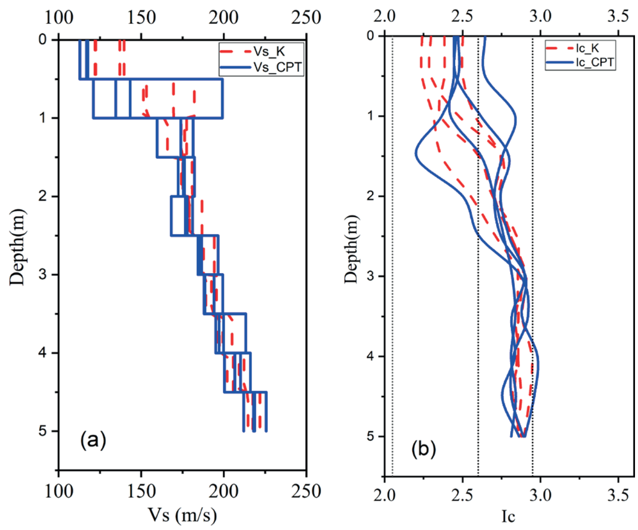
$$I_{SBT}=\sqrt{\left(3.47-\log(q_t/p_a)^2+(\log R_f+1.22)^2\right)}\,, \tag{4}$$

where q_t = corrected cone resistance (or CPT cone resistance q_c), R_f = friction ratio $R_f = (f_s/q_t) \times 100\%$, f_s = CPT sleeve friction

CPT parameters estimate the unit weight of the soil by using the following expression [7]:

$$\gamma/\gamma_w = 0.27\log R_f + 0.36\log(q_t/p_a)+1.236\,, \tag{5}$$

where γ_w is unit weight of water, p_a is atmospheric pressure.



(a) (b)

Fig. 3 Shear wave velocity profile (a) and Soil behaviour type index profile (b)

Fig. 3(a) shows the estimated V_s profiles derived from CPT and kriging interpolation data. Shear wave velocities vary between 112–140 m/s at a depth of 0.5 m and 212–226 m/s at 5 m depth. Fig. 3(b) demonstrates the variation of I_c with depth. As shown in the figure, the vast majority of soils extending to depth of 1.5 meters have I_c values between 2.05 and 2.6. I_c values for soils between 1.5 and 5 meters depth range from 2.6–2.95. According to Table 3, the soil types are clay and silt mixtures.

In this study, we assumed a depth of 5 m to bedrock. Additional assumptions included the bedrock shear wave velocity was 750 m/s, the unit weight was 24 kg/m^3, and the damping ratio was 2%. The material non-linearity, which includes the modulus reduction and damping curves, was taken from the work of [20] and provided within Strata software.

The last part of a site response analysis involves choosing the input rock motion based on some parameters. The PGA value, the distance from the source to the site,

Table 3 Soil behavioral type (SBT) classes

SBT zone	I_c	SBT Classification
2	ISBT > 3.6	Clay - organic soil
3	2.95 < ISBT < 3.6	Clays: clay to silty clay
4	2.6 < ISBT < 2.95	Silt mixtures: clayey silt & silty clay
5	2.05 < ISBT < 2.6	Sand mixtures: silty sand to sandy silt

the size of the controlling earthquake, and the type of site all have a role in determining the input rock motion [21]. In this study, we selected seven groups of input motions from the rock motions recorded in the past using the Rexel computer program [22] for the site response analysis. Rexel uses scaling techniques (increasing or decreasing acceleration amplitude) to meet specific search criteria. The user has options to set a suitable degree of variation in Rexel software such that the software will search out those records that meet the criteria. To find suitable sets of earthquake recordings, we selected Eurocode 8 type I (High and moderate seismicity zones, expected earthquake magnitude, $M > 5.5$) as a criterion. In addition, we set the expected earthquake magnitude (M) between 5.5 and 7 and the distance radius (R) between 0 and 30 km as search criteria. Based on these search criteria, seven input motions shown in Table 4 served as input bedrock motions to compute surface response.

The output results provided data for comparison of a kriging-based soil profile to a CPT-based soil profile specifically, surface spectral acceleration (Sa), Peak Ground Acceleration, Amplification Factor (AF), and surface acceleration-time histories. Figs. 4–7 represent these parameters to provide comparison. Fig. 4 depicts the median PGA profile up to 5 m depth for each soil profile. Median PGA values at 5 m are 0.19 g, whereas those at the surface range from 0.33 to 0.35 g. For every soil profile, there is a depth-dependent change in PGA value. The PGA values obtained from

Table 4 seven input rock motion returned by REXEL

Earthquake Name	Date	Mw	Fault Mechanism	Epicentral distance [km]	PGA_X (m/s^2)	PGA_Y (m/s^2)	Scale Factor	EC8 Site class
Campano Lucano	11/23/1980	6.9	normal	25	0.5878	0.5876	3.33	A
Izmit (aftershock)	9/13/1999	5.8	oblique	15	0.7138	3.112	2.75	A
Lazio Abruzzo	5/7/1984	5.9	normal	22	0.628	0.6706	3.12	A
South Iceland (aftershock)	6/21/2000	6.4	strike-slip	15	1.2481	1.1322	1.73	A
South Iceland	6/17/2000	6.5	strike-slip	13	1.2916	1.5325	1.28	A
South Iceland (aftershock)	6/21/2000	6.4	strike-slip	14	1.7476	1.1423	1.72	A
Golbasi	5/5/1986	6	oblique	29	0.3831	0.538	3.65	A

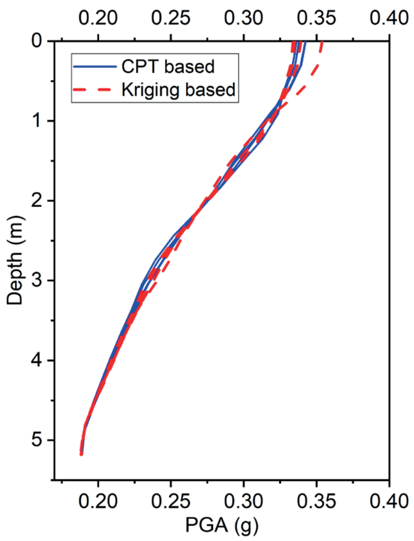


Fig. 4 PGA for CPT-based and Kriging-based site profile

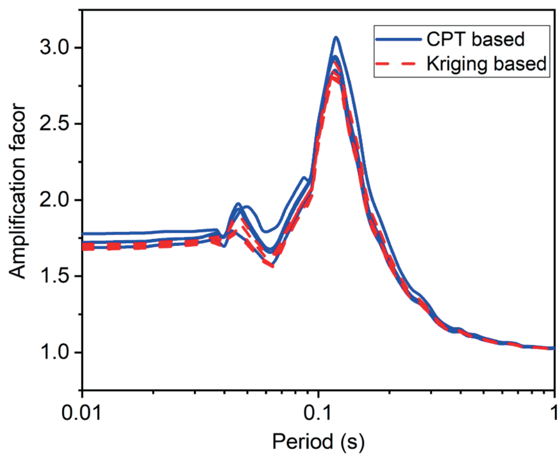


Fig. 5 Amplification factor for CPT-based and kriging-based site profile

kriging-based soil profiles are quite close to the PGA values obtained from CPT-based soil profiles. The amplification factors provide the same observed outcomes (Fig. 5). We can observe that the maximum median amplification factors for each profile are about 2.9.

Fig. 6 depicts the median spectral acceleration at each period for each site profile. At each period, the kriging-based site profile generates similar spectral acceleration to the CPT-based profiles. Fig. 7 shows that surface acceleration time histories achieved similar results.

5 Conclusions

Since CPT examines only a small volume of soil with a considerable gap between two stations, the data received from the test is typically insufficient. Lack of exploration and soil variability present further challenges to confidently

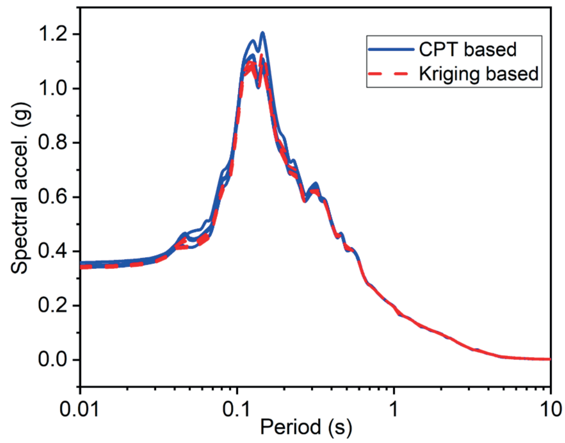


Fig. 6 Spectral acceleration for CPT-based and kriging-based site profile

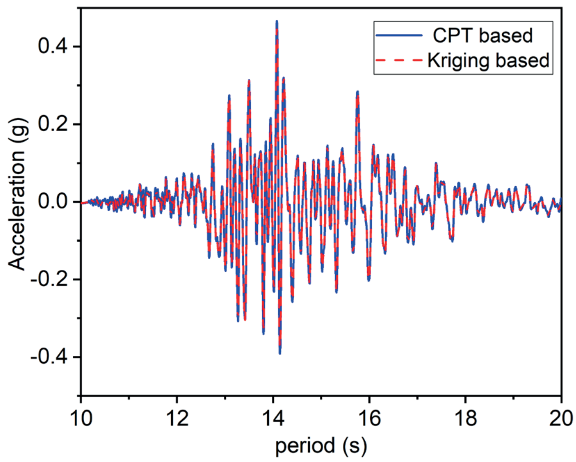


Fig. 7 Surface acceleration time-history for CPT-based and kriging-based site profile

evaluating soil properties. In this study, we attempted to use the kriging interpolation method to reasonably estimate CPT data at un-sampled locations. Seismic site response analysis provided a useful way to assess the efficacy of the kriging interpolation method. In order to carry out site response analysis, two distinct sets of soil profiles (i.e., CPT-based soil profiles and kriging interpolation-based soil profiles) were created utilizing CPT and Kriging interpolation results from data sets. Parameters for the analysis include the PGA, AF, spectral acceleration, and acceleration time histories. Kriging interpolation-based site response results were compared to CP-based site response results to evaluate the performance of the kriging interpolation technique. The outcomes demonstrated the validity of the kriging interpolation approach in predicting the soil parameters necessary for site response analysis.

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Appendix A

Kriging interpolation program code using *R* [23]

```
AY<-read.csv("D:/R/Ayele (R)/Krig CPT data/CPT_5000.csv")#Import CPT data to R

library(gstat)#Load packages

library(sp)

f_spdf=sp::SpatialPointsDataFrame(coords=cbind(AY$x,AY$y),data=AY,proj4string=sp::CRS(projargs=
"+init=epsg:32631"))

#Creat special point data frames

var=gstat::variogram(object=QC~1,location=f_spdf)#performs the variogram

plot(var,col="red",pch=15,lw=3)#Plot variogram

#nugget ~0.038, sill ~0.126, range, ~10.6

write.csv(data.frame(var),"qc VarData sets.csv",row.names=FALSE)#export variogram data set as csv file

fit_var=gstat::fit.variogram(object=var,model=gstat::vgm(psill=0.126,nugget=0.038,range=10.6,
model="Exp"))

plot(var,model=fit_var,col="red",pch=15,lw=4)#fit variogram

samp=sp::spsample(x=f_spdf,n=200,type="regular")#generate 200 regularly spaced kriging locations

krig=gstat::krige(formula=QC~1,location=f_spdf,newdata=samp,model=fit_var)#perform kriging on cone tip
resistance data

write.csv(data.frame(krig),"qc_Predicted values.csv", row.names=FALSE)#export qc predicted values as
csv file for further analysis

#END
```