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Technical Note

Pullout capacity of small ground anchors: a relevance vector machine approach

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Abstract. This paper examines the potential of relevance vector machine (RVM) in prediction of pullout capacity of small ground anchors. RVM is based on a Bayesian formulation of a linear model with an appropriate prior that results in a sparse representation. The results are compared with a widely used artificial neural network (ANN) model. Overall, the RVM showed good performance and is proven to be better than ANN model. It also estimates the prediction variance. The plausibility of RVM technique is shown by its superior performance in forecasting pullout capacity of small ground anchors providing exogenous knowledge.

Keywords: relevance vector machine; small ground anchor; pullout capacity; artificial neural network.

1. Introduction

This paper examines the potential of Relevance Vector Machine (RVM) to predict pullout capacity of small ground anchors. The primary function of ground anchors is to provide a concentrated force to the ground. Ground anchors are used extensively in mining and civil engineering applications to stabilize rock slopes and underground openings and to resist uplift and overturning forces in foundations and retaining structures. Geotechnical engineers use different methods for determination of uplift capacity of ground anchor. The details of small ground anchors are given by Shahin and Jaksa (2006). The published information about the pullout capacity of small ground anchors are very limited. RVM provides an empirical Bayes treatment of function approximation by kernel basis expansion. It can be seen as a probabilistic version of support vector machine (SVM). It is exactly equivalent to a Gaussian process (GP), where the RVM hyperparameters are parameters of the GP covariance function. However, the covariance function of the RVM seen as a GP is degenerate: its rank is at most equal to the number of relevance vectors of the RVM. The paper has the following aims:

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- To investigate the feasibility of RVM model for predicting pullout capacity of small ground anchors.
- To estimate the prediction variance.
- To compare the performance of RVM model with ANN model proposed by Shahin and Jaksa (2006).

2. Methodology

The present study uses the RVM model to predict the pullout capacity (Q) of small ground anchors. The details of RVM methodology has been given by Tipping (2001). This study uses the database collected by Shahin and Jaksa (2006). The database contains the information about the equivalent anchor diameter (D_{eq}), embedment depth (L), average cone resistance (q_c) along the embedment depth, average sleeve friction (f_s) along the embedment depth, installation technique and Q. In RVM modeling, the data has been divided into two sub-sets; a training dataset, to construct the model, and a testing dataset to estimate the model performance. In this study, 83 out of the possible 119 cases of small ground anchor are considered for training dataset and the remaining 36 data is considered as testing dataset. The data has been scaled between 0 and 1 before being presented to the model. In the case of RVM training, three types of kernel functions – namely, Gaussian kernel, polynomial kernel, and spline kernel – have been used. In training process, kernel specific parameters have been chosen by trial-and-error approach. The programs are constructed using MATLAB.

3. Results and discussion

In this study, the performance of RVM model for different kernels is measured by the coefficient of correlation (R). Table 1 summarizes the best simulation performance of RVM. From Table 1, it is clear that overfitting ratio (Das and Basudhar 2007) for all kernels is close to one. So, RVM has the ability to avoid overfitting. RVM model uses approximately 15 to 17% (Gaussian kernel=16.86%, polynomial kernel=15.66% and spline kernel=16.86%) of training data as relevance vectors. This relevance vector is only used for final prediction. So, there is real advantage gained in terms of sparsity. Sparseness is desirable in RVM as well as SVM for several reasons, namely (Figueiredo 2003):

- Sparseness leads to a structural simplification of the estimated function.
- Obtaining a sparse estimate corresponds to performing feature/variable selection.

Table 1 General performance of RVM model for different kernel

Kernel	Training Performance (R)	Testing Performance (R)	Number of Relevance Vector	RMSE	MAE	Overfitting ratio
Gaussian, width (σ)=0.5	0.945	0.944	14	0.2562	0.1931	1.001
Polynomial, degree=3	0.936	0.932	13	0.2811	0.2221	1.004
spline	0.937	0.935	14	0.2757	0.2166	1.001

• The generalization ability improves with the degree of sparseness.

Sparseness means that a significant number of the weights are zero (or effectively zero), which has the consequence of producing compact, computationally efficient models, which in addition are simple and therefore produce smooth functions. The advantage of RVM lies in its ability to provide uncertainty. Fig. 1 represents the bar chart of variance of testing dataset for Gaussian, polynomial and spline kernel respectively. The obtained prediction variance allows one to assign a confidence interval about the model prediction.

A comparative study has been done between developed RVM model and ANN model (Shahin and Jaksa 2006). The values of root-mean-square-error (RMSE) and mean-absolute-error (MAE) of RVM have been given in Table 1. The value of RMSE and MAE for ANN model is 0.3971 and 0.3079 respectively. So, it is clear that developed RVM model outperforms ANN model in terms of RMSE and MAE. RVM uses mainly one kernel parameter. In ANN, there are a larger number of controlling parameters, including the number of hidden layers, number of hidden nodes, learning rate, momentum term, number of training epochs, transfer functions, and weight initialization methods. Obtaining an optimal combination of these parameters is a difficult task as well. The determination of pullout capacity of small ground anchor is a complex problem in geotechnical engineering. For most mathematical models that attempt to solve this problem, the lack of physical understanding is usually supplemented by either simplifying the problem or incorporating several assumptions into the models. In contrast, as shown in this study, RVM uses the data alone to determine the parameters of the model. In this case, there is no need to simplify the problem or to incorporate any assumptions (Tipping 2001). Moreover, RVM can always be updated to obtain better results by presenting new training examples as new data become available. For RVM, maximization of the type-II likelihood removes much of the noise in the data. It also provides control over model complexity in a way that alleviates the problems of overfitting and underfitting. Developed RVM model has the following advantages:

• In RVM, there are no ‘nuisance’ parameters to validate, in that the type-II maximum likelihood procedure automatically sets the ‘regularisation’ parameters.

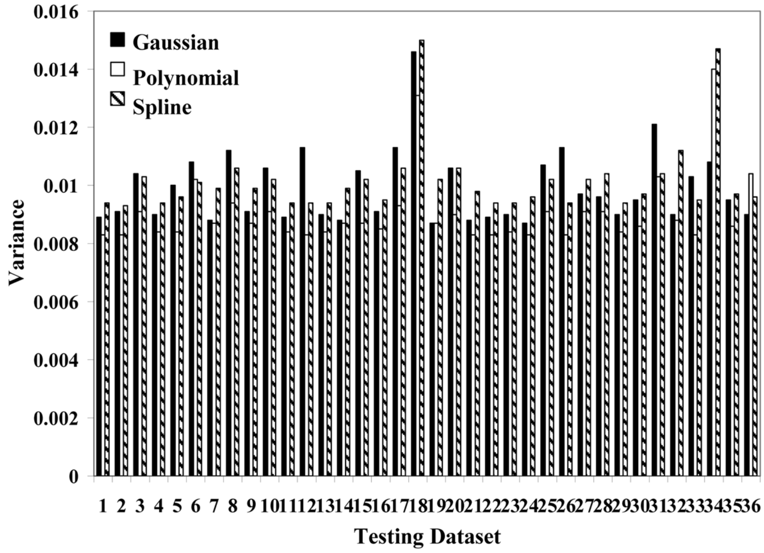

Fig. 1 Variance of testing dataset using different kernels

- It includes the automatic estimation of parameters.
- It uses arbitrary basis functions which are not necessary 'Mercer' kernels.

4. Conclusions

The study presented in this paper shows the potential of a newly emerging learning machine, Relevance Vector Machine, in predicting the pullout capacity of small ground anchor over ANN. The developed RVM model can be used as an accurate and quick tool for estimating output variables without a need to perform any manual work such as using tables or charts. It achieves very good generalization performance and yields sparse models. The comparison between RVM and ANN indicates that RVM is better model than ANN. It has the added advantage of probabilistic interpretation that yields prediction uncertainty. Summarizing, it can be concluded that RVM is a robust model for predicting pullout capacity of small ground anchors.

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Notations

D	: Dataset
ω	: Parameter vector
α	: Hyperparameter vector
R	: One dimensional vector