The application of support vector machine in geotechnical engineering

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Abstract. With the improvement of data collection and storage ability, numerous data are accumulated in the field of geotechnical engineering, which provides the opportunity for the application of the machine learning techniques. An increasing number of researchers adopted machine learning technique to solve the problems which cannot be addressed by using traditional methods. The most advanced machine learning algorithm, Support Vector Machine (SVM), has been widely utilized in geotechnical engineering. The study aims to review the analytical method and application of SVM in geotechnical engineering. Firstly, the basic principles of SVM are introduced. Secondly, the application of the SVM algorithms is presented. The review suggests that SVM can be effectively used for classifying rock and soil mass, predicting the slopes stability accurately and deformation displacement. Meanwhile, physical strength parameters and the models used for earthquake mitigation that are produced by using SVM are the closest to real value.

1. Introduction
Geotechnical engineering is the basis for the various engineering project construction. Nowadays, a variety of engineering projects are widely carrying out in the world and the scale of construction objects is becoming larger and larger. The percentage of engineering accidents in major projects that are related to geo-technology is getting bigger and bigger. Since rock and soil’s mechanical properties have significant non-linearity and plasticity, most of traditional analysis research methods, such as finite element method, discrete element method and etc[1-3] to study the properties of rock and soil are based on linear relationship models. It is inevitable to simplify the relationships between them and discard many unimportant parameters when researchers use traditional means to establish models to predict the properties of rock and soil. Inaccurate physical parameters of rock and soil mass will unavoidably cause geotechnical prediction errors. Therefore, an effective method to analyse the mechanical properties of rock and soil is very absent.

Machine learning techniques are able to deal with non-linear and plastic issues of rock and soil effectively and avoid the weaknesses that may be caused by using traditional methods[4-5]. Kabiru
compared the Support Vector Machine (SVM) and Artificial Neural Network (ANN) on the prediction of the compressive strength of concrete[6]. In the study, he presented that the SVM with better performance in the aspect of the prediction of the compressive strength of concrete. Algorithms are the core of machine learning. SVM is the most popular machine learning algorithm applied in geotechnical engineering. The SVM is a new data mining approach based on statistical learning principles[7]. It can effective deal with regression and pattern recognition issues and it also can be applied in prediction and stability assessment aspects[8].

There are two objectives of this study. 1. The introduction of the basic principles of SVM. 2. The overview of the existing research findings about the application of SVM in geotechnical engineering.

2. Support Vector Machine Classification

2.1. The Principles of the Support Vector Machine Classification

The SVM is a binary classification model, which is able to establish a hyperplane to divide sample data to achieve structural risk minimization based on maximum margin principles. Due to the introduction of the kernel function the SVM is capable of solving no-linear partition[9]. The kernel function has the capacity to map the samples in low-dimension space to high-dimension space to address no-linear issues. In practical applications, many raw sample data space does not exist a hyperplane to divide the sample data in it correctly. For example, as the sample data in the two-dimension plane in Figure 1. It is impossible to find a line to separate the sample data correctly.

![Figure 1. Sample data in two-dimension plane](image1)

![Figure 2. Sample data in three dimensional space](image2)

However, the kernel function is able to map the sample data in the two-dimension plane to three dimension or higher dimension space, and finding a hyperplane in high dimension space divides the sample data. For instance, the sample data in the two-dimension plane are mapped to a three-dimension space in Figure 2.

![Figure 3. Support Vectors and Margin](image3)

It is obvious that a two-dimension surface in the three-dimension space can be found to divide the sample data by two sets. How to determine the optimum hyperplane is another problem that the SVM needs to solve. The SVM principle seeks the optimum hyperplane based on the Margin Maximization. The Margin Maximization Principle refers to looking for a hyperplane that has the largest distance with that sample points which have the smallest distance with it as the optical hyperplane. The sample points that are nearest to the optical hyperplane are called Support Vectors, and the distance between the support vectors and the optical hyperplane is known as Margin[10].

The support vectors for the optical hyperplane are Point 1 and Point 2, and the margin is V. Hence the issue of seeking the optical hyperplane transfer to the matter of calculating the minimum value of the Margin v that is a function of the coordinates of sample points as shown in equation (1).

\[ y_i(v \cdot x_i - b) \geq 1, \quad i = 1, 2, \ldots, n \]  

(1)
where, \(b\) is constant.

In order to make calculation convenient, finding the minimum value of \(W^2\) often is adopted to replace the computation of the least of \(W\). Hence the classification issue for the SVM is converted to solve the matter for the convex quadratic programming \(^{[11]}\) that the solution of it is unique, whereas the process of solving the issue of the convex quadratic programming is rather complex. In order to simplify the procedure of obtaining the optical solution of the convex quadratic programming matter, the Lagrange multiplier method is adopted to transform the primal issue to its dual problem, as shown from equation (2) to equation (4).

\[
L(v, b, a) = \frac{1}{2} \|v\|^2 + \sum_{i=1}^{n} a_i (1 - y_i (v^T x_i + b))
\]  

(2)

\[
\min_{a} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} a_i a_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^{m} a_i
\]  

(3)

\[
s.t. \sum_{i=1}^{m} a_i y_i = 0, 0 \leq a_i \leq l, i = 1, 2, ..., N
\]  

(4)

Where, \(a\) is constant. Hence through solving the dual problem, the optical hyperplane is obtained.

2.2. The application of the SVM classification in geotechnical engineering

The partition function of the SVM is applied widely to solve the problems of pattern recognition, matter classification and filter issues in geotechnical engineering \(^{[12]}\).

Soil and rock classification is a research hotspot in geotechnical engineering. Soil and rock classification can help engineers depend on the category of soil and rock to determine the corresponding construction materials and building methods to the safety of engineering. In terms of rock, Hong further introduced the Genetic Algorithm to improve the classification accuracy on rock. The results showed that the proposed model is able to deal with the non-linear relationship in dividing soil and the cluster precise is high \(^{[13]}\).

On the basis of above-mentioned, the SVM algorithm can validly group soil and rock based on the data about their properties. Slopes are mainly composed of soil and rock, and landslide is a topical research area in geotechnical engineering because landslides cause huge threats to the safety of the public and regularly lead to momentous property losses \(^{[14]}\). Hence, an increasing number of researchers use the SVM technique to analyse the landslide susceptibility. Yao used the Support Vector Machine techniques to establish a landslide susceptibility map based on the landslide records. One-class Support Vector Machine and two-class Support Vector Machine both can predict the landslide susceptibility effectively on account of small sample data, but the two-class Support Vector Machine is more sensitive to the number of samples and accuracy of it is higher than that of the one-class one \(^{[15]}\).
3. SVM Regression

3.1. The principles of SVM regression

Another important function of the SVM is to solve the regression problem. Regression problem refers to determining a regression model to describe the relationship of given sample data, as shown in equation (5).

\[ L = \{(x_1, y_1), (x_2, y_2), \ldots \} \]  

where, \( L \) is regression model, \( x_i (i=1,2,\ldots,n) \) is the x value of the sample data, \( y_i (i=1,2,\ldots,n) \) is the y value of the sample data.

To gain a regression model indicates the relationship between X and Y\(^{[16]}\). The principles and methods are adopted to solve the regression problem as that of the classification issue. The SVM can utilise few sample data to build a regression model based on the structural risk minimization principle\(^{[17]}\). The optical regression model means the difference value between \( f(x) \) and y is the least. The Support Vector Regression assumes that deviation value between \( f(x) \) and y that is less that \( s \) can be ignore when calculating the total difference value between \( f(x) \) and y, which manifests that only the deviation value that is larger than \( s \) is able to be reckoned in the total difference value\(^{[18]}\). As shown in Figure 4.

The deviations that are caused by the points in the area are omitted, and only the deflections that are result from the points that outside the region are included. Hence the problem of Support Vector Regression can be converted to the matter of searching minimum value, as shown in equation (6).

\[
\min_{\nu, b} \frac{1}{2} \| \nu \|^2 + s \sum_{i=1}^{n} (f(x_i) - y_i) \]  

where, \( s \) is constant.

This function is called s-incentive loss function\(^{[19]}\). Hence the Support Vector Regression issue is transformed to the matter of solving the convex quadratic programming. Regarding the linear regression problem, as that of the classification problem, the Lagrange Multiplier Method is adopted to convert the primal problem to its dual problem to simplify the calculation of it, as shown in equation (7).

\[
\max_{\alpha, \lambda} \sum_{i=1}^{n} y_i (\hat{\alpha}_i - \alpha_i) - \varepsilon (\hat{\alpha}_i + \alpha_i) - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\hat{\alpha}_j - \alpha_j) (\hat{\alpha}_j - \alpha_j)x_i^T x_j \]  

st. \[ \sum_{i=1}^{n} (\hat{\alpha}_i - \alpha_i) = 0, 0 \leq \alpha_i, \alpha_i \leq b \]

Then through solving the equation of the dual problem. The optical regression model is obtained, as shown in equation (8).

\[
f(x) = \sum_{i,j} (b_i - b_j^*) (x^* x_j) - b \]  

For the nonlinear regression problem, like that of the classification matter, mapping the nonlinear sample data from the low dimension space to the high dimension space by the kernel function converts the matter to the linear issue. Afterwards using the same procedures of solving the liner problem finds the optical regression model of it.

3.2 The application of the SVM regression in geotechnical engineering

The SVM regression is extensively used to solve the problems of nonlinear modelling and prediction as well as optical control in geotechnical engineering\(^{[20]}\).

The deformation behaviour of rock and soil under loading is a vital research site in geotechnical
engineering. As an example, Samui developed models that are based on Artificial Neural Networks and Support Vector Machine algorithms to predict the liquefaction susceptibility of soil under earthquake. The results manifest that the two models both can forecast the susceptibility of soil under earthquake effectively, but the performance of the Support Vector Machine is better than that of the ANN\textsuperscript{[21]}. In the aspect of rock, Yao proposed a multi-step-ahead model based on SVM to predict rock displacement, and the predicted results are validated by experiment outcomes. The research indicates that the SVM based model has higher forecast precise that on account of the ANN \textsuperscript{[22]}.

As shown in the above-analysis, the SVM is capable of forecasting the deformation of rock and soil accurately. Hence, many researchers combine the techniques of foretelling the displacement of rock and soil to build models to predict the landslide susceptibility. As an example, Marjanović compared the effectiveness of three machine learning methods: Support Vector Machine, Logistic Regression and DT on prediction the landslide susceptibility. The research manifested that the Support Vector Machine is the most effective mean to forecast the landslide susceptibility among the three methods, which can obtain the lowest wrong positives rate in the classification of steady ground \textsuperscript{[23]}.

4. Conclusion
The review listed the application of the SVM algorithm in geotechnical engineering. The application and principles of SVM algorithm in geotechnical engineering are introduced in detail. The vital findings are surmised as follows:

- SVM can be effectively used to classify soil, which is vital for geotechnical engineering.
- Rock cluster is significant to the construction of engineering, which is able to achieve by using SVM. The accuracy of classification through SVM can be shown.
- The deformation of subgrade rock has huge impact on the safety of engineering. SVM can be used to establish models to forecast the deformation of rock and soil validly, as well as correctly predict the properties of rock.
- The landslide map is able to be established based on SVM. In general, the SVM algorithm has the high accuracy in predicting the slope stability.

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