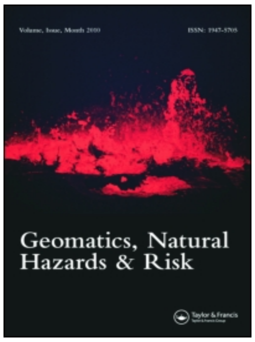

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Determination of stability of epimetamorphic rock slope using Minimax Probability Machine

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The article employs Minimax Probability Machine (MPM) for the prediction of the stability status of epimetamorphic rock slope. The MPM gives a worst-case bound on the probability of misclassification of future data points. Bulk density (d), height (H), inclination (β), cohesion (c) and internal friction angle (ϕ) have been used as input of the MPM. This study uses the MPM as a classification technique. Two models {Linear Minimax Probability Machine (LMPM) and Kernelized Minimax Probability Machine (KMPM)} have been developed. The generalization capability of the developed models has been checked by a case study. The experimental results demonstrate that MPM-based approaches are promising tools for the prediction of the stability status of epimetamorphic rock slope.

1. Introduction

The prediction of natural hazards is a challenging task due to uncertainty. Researchers use Artificial Neural Network (ANN) for prediction of different natural hazards (Lee & Liu 2000; Huang et al. 2003; Lui et al. 2006; Mishra et al. 2007; Pradhan & Lee 2007; Lee 2008; Adeli & Panakkat 2009). Although ANN gives reasonable performance, it has various limitations such as black box approach, arriving at local minima, low generalization capability, overfitting, etc. (Park & Rilett 1999; Kecman 2001). Researchers successfully adopted Adaptive Neuro Fuzzy Inference System (ANFIS) for modelling different natural hazards (Konstantanaras et al. 2004; Bacanli et al. 2009; Sezer et al. 2011). However, ANFIS does not give any probabilistic output. Support Vector Machine (SVM) has been successfully adopted to model different natural hazards (Goh & Goh 2007; Samui 2012). The SVM suffers the following limitations:

- SVM has high computational complexity due to quadratic programming (Vapnik 1998).
- It has three tuning parameters {capacity factor(C), error insensitive zone (ε) and kernel parameter (Samui 2008)}. The determination of the design value of these tuning parameters is a difficult task.

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This article examines the capability of Minimax Probability Machine (MPM) for the determination of the stability of epimetamorphic rock slope. The failure of epimetamorphic rock slope is quite common due to the presence of thicker weathered layer and extremely broken rock mass (Chen et al. 2011). Researchers use different techniques for slope stability analysis (Fellenius 1936; Bishop 1955; Bishop & Morgenstern 1960; Morgenstern & Price 1965; Michalowski 1994, 1995, 2002; Sah et al. 1994; Griffiths & Lane 1999; Yang et al. 2004; Kumar & Samui 2006; Gao 2009). Fellenius (1936) used the method of slices for assessing the stability of slopes. It was seen that this method generally provides a conservative estimate of the factor of safety. Bishop (1955) used the method of slices in obtaining the stability of slopes. The results obtained from this method compare very closely with the more rigorous approaches such as the finite element method. Morgenstern and Price (1965) attempted to satisfy all the equations of statical equilibrium in obtaining the solution of the stability problem using the method of slices. They assumed a different distribution of inter-slice forces so as to obtain the solution. It should be mentioned that the previously available methods of slices, namely, Fellenius (1936) and Bishop (1955) do not satisfy all the conditions of statical equilibrium. Using the upper bound limit analysis, Michalowski (1995) presented a stability analysis of slopes based on a translational mechanism failure mechanism. Michalowski (2002) also used the upper bound theorem of limit analysis in order to obtain the stability numbers for homogeneous slopes in the presence of pore water

Table 1. Summary of the available methods for slope stability.

Reference	Brief methodology
Fellenius (1936)	Fellenius assumed that the resultant of inter-slice forces acts in a direction parallel to the base of each slice.
Taylor (1948)	Taylor (1948) used the friction circle method to obtain the stability numbers (N_s) for homogeneous soil slopes.
Bishop (1955)	Bishop (1955) used the method of slices in obtaining stability of slopes.
Janbu (1957)	This method also used the method of slices to solve the problem. Janbu solved the problem by assuming the point of application of the inter-slices forces.
Morgenstern and Price (1965)	Morgenstern and Price (1965) attempted to satisfy all the equations of statical equilibrium in obtaining the solution of the stability problem using the method of slices.
Chen (1975)	Chen (1975) used the upper bound theorem of the limit analysis to obtain the critical heights for homogenous soil slopes.
Michalowski (1994)	Michalowski (1994) also used the upper bound theorem of limit analysis in order to obtain the stability numbers for homogenous soil slopes.
Michalowski (1995)	Using the upper bound limit analysis, Michalowski (1995) presented a stability analysis of slopes based on a translational mechanism failure mechanism.
Michalowski (2002)	Michalowski (2002) also used the upper bound theorem of limit analysis in order to obtain the stability numbers for homogeneous slopes in the presence of pore water pressures as well as pseudo-static horizontal earthquake body forces.

Table 2. Statistical parameters of the data-set.

Input variable	Mean	Standard deviation	Skewness	Kurtosis
d (kN/m^3)	23.88	2.60	−0.19	1.33
H (m)	46.45	16.09	0.50	3.82
β (°)	32.67	7.60	0.17	3.90
C (kPa)	33.69	8.77	−1.35	4.70
ϕ (°)	29.94	5.85	−0.26	1.74

pressures as well as pseudo-static horizontal earthquake body forces. The available methods have their own limitations. Table 1 shows the summary of the available methods for the determination of slope stability. This study uses the database collected by Chen et al. (2011). The data-set contains information about bulk density (d), height (H), inclination (β), cohesion (c) and internal friction angle (ϕ) and the status of slope (the status of slope means whether the slope was stable or had failed). Table 2 shows the statistical parameters of the data-set. MPM is a discriminant classifier and it is derived from probabilistic framework (Lanckriet et al. 2002a, 2002b). It has been successfully used for solving different problems (Hoi & Lyu 2004; Zhou et al. 2011; Zhou et al. 2013). The developed MPM has been applied for a case study.

Details of MPM

This section will give a small description about the MPM model. More details are given by Lanckriet et al. (2002a, b). The MPM assumes positive definite covariance matrices for each of the two classes. Assume two random vectors x and y represent two classes of data points. The mean and covariance of x is $\bar{x}$ and $\sum_x x$, respectively. The mean and covariance of y is $\bar{y}$ and $\sum_y y$, respectively, where $x, y, \bar{x}, \bar{y} \in R^n$ and $\sum_x x, \sum_y y \in R^{n\times n}$.

In this study, $x = [d, H, c, \beta, \phi]$ and $y = [d, H, c, \beta, \phi]$.

The MPM uses the following optimal hyperplane that separates the data into two classes

$$a^T z = b \qquad (a, z \in R^n, a \neq 0, b \in R). \tag{1}$$

Lanckriet et al. (2002a) give the following mathematical formulation:

$$\max_{\alpha, b, a \neq 0} \alpha.$$

Subjected to

$$\begin{aligned} \inf P_r\{a^T x \geq b\} \geq \alpha \\ \inf P_r\{a^T y \leq b\} \geq \alpha. \end{aligned} \tag{2}$$

The above optimization problem is solved by the Lagrangian Multiplier. After applying the Lagrangian Multiplier, the optimization problem takes the following form:

$$\max_{\kappa,a} \kappa.$$

Subjected to

$$\begin{aligned} -b + a^T x &\geq \kappa\sqrt{a^T \sum\nolimits_x a} \\ b - a^T y &\geq \kappa\sqrt{a^T \sum\nolimits_y a}. \end{aligned} \tag{3}$$

The above optimization problem turns into (after eliminating κ) the following expression

$$\min_a \sqrt{a^T \sum\nolimits_y a} + \lambda\sqrt{a^T \sum\nolimits_x a}.$$

Subjected to

$$a^T(\bar{x} - \bar{y}) = 1. \tag{4}$$

The above MPM method has been adopted to predict the stability of epimetamorphic rock slope. To develop the MPM, 41 data-sets (see table 3) have been used as training data-sets. The remaining 12 data-sets (see table 4) have been used as testing data-sets. Testing data-set has been used to verify the developed MPM. The training and testing data-sets are the same as used by Chen et al. 2011. The data-sets are normalized between 0 and 1. Radial basis function has been used as kernel function. A value of -1 is assigned to the failed rock slope while a value of $+1$ is assigned to the stable rock slope so as to make this a two-class classification problem. The MPM program has been developed by using MATLAB.

Results and discussion

Linear MPM (LMPM) and Kernelized MPM (KMPM) have been tried to get the best performance. The performance of training data-set is expressed in percentage and is determined as the ratio of the number of data predicted accurately by MPM to the total number of data in the training set. The performance of testing data-set is expressed in percentage and is determined as the ratio of the number of data predicted accurately by MPM to the total number of data in the testing set. For training data-set, the developed LMPM correctly classified 39 data-sets. So, the training performance is 95.12%. The developed LMPM gives 91.67% testing performance. The performance of training and testing has been shown in table 3 and 4, respectively. Table 5 shows the value of α. The value of α is greater than the training as well as testing performance. So, the validity of α has been checked for the LMPM model. For KMPM, the design value of width (σ) of radial basis function has been determined by the trial and error approach. Figure 1 shows the effect of σ on the training performance (%). It is clear from figure 1 that the developed KMPM gives the best performance at $\sigma = 0.1$. The developed KMPM gives training performance = 100%

Table 3. Performance of training data-set.

d (kN/m^3)	H (m)	β (°)	C (kPa)	ϕ (°)	Actual class	Predicted class by LMPM	Predicted class by KMPM
20	10	10	8	20	−1	−1	−1
27.3	30	30	37.3	31	1	1	1
20.6	35	25	26.31	22	−1	−1	−1
21.6	50	40	6.5	19	−1	−1	−1
22.4	35	28	28.9	24	−1	−1	−1
23.2	33	30	31.2	23	−1	1	−1
26.8	26	30	37.5	32	1	1	1
27.4	42	25	38.1	31	1	1	1
21.8	50	50	32.7	27	−1	−1	−1
21.8	60	35	27.6	25	−1	−1	−1
26.5	21	30	35.4	32	1	1	1
26.5	39	35	36.1	31	1	1	1
27	69	30	35.8	32	1	1	1
27	22	25	38.4	33	1	1	1
21.4	52	50	28.8	20	−1	−1	−1
26	55	38	42.4	37	1	1	1
26	30	25	39.4	36	1	1	1
25.6	26	25	38.8	36	1	1	1
20	53	45	30.3	25	−1	−1	−1
25.8	50	30	34.7	33	1	1	1
21.8	99	35	28.8	26	−1	−1	−1
21.8	60	30	31.2	25	−1	−1	−1
24	51	30	41.5	36	1	1	1
24	50	35	40.8	35	1	1	1
20.6	70	35	27.8	27	−1	−1	−1
20.6	55	35	32.4	26	−1	−1	−1
25.8	40	27	38.2	33	1	1	1
25.8	45	25	39.4	33	1	1	1
21.1	31	40	33.5	28	−1	−1	−1
21.1	75	30	34.2	26	−1	−1	−1
26.6	52	25	42.4	37	1	1	1
26.6	42	35	44.1	38	1	1	1
26.6	60	35	40.7	35	1	1	1
25.8	40	30	41.2	35	1	−1	1
25.8	33	30	43.3	37	1	1	1
21.7	60	45	32	27	−1	−1	−1
20.6	65	40	28.5	27	−1	−1	−1
21.5	70	40	29.8	26	−1	−1	−1
26.5	36	34	42.9	38	1	1	1
20.8	45	30	15.6	20	−1	−1	−1
20.8	40	30	14.8	21	−1	−1	−1

and testing performance = 100%. Tables 2 and 3 show the performance of KMPM model. For KMPM, the value of α is given by table 4. The value of α is equal to the performance of KMPM. Therefore, the developed KMPM validates the value of α. The developed LMPM and KMPM have been applied on the Wangjiazhai slope in Kaili–Sansui highway. The details of the slope are as follows (Chen et al. 2011): $d = 19.8$ kN/m^3, $H = 98$ m, $\beta = 26°$, $c = 8.6$ kPa and $\phi = 17.8°$. The actual

Table 4. Performance of testing data-set.

d (kN/m^3)	H (m)	β (°)	C (kPa)	ϕ (°)	Actual class	Predicted class by LMPM	Predicted class by KMPM
19.6	58	40	29.6	23	−1	−1	−1
25.4	35	20	33	33	1	1	1
22.4	50	50	29.3	26	−1	−1	−1
26.2	30	35	41.5	36	1	1	1
26.2	36	23	42.3	36	1	−1	1
25.6	32	30	39.8	36	1	1	1
25.6	60	35	36.8	34	1	1	1
26.2	37	30	42.8	37	1	1	1
26.2	68	35	43.8	38	1	1	1
20.6	42	30	32.4	26	−1	−1	−1
26.5	54	42	41.8	36	1	1	1
20.8	53	30	15.4	21	−1	−1	−1

Table 5. Performance of the LMPM and KMPM.

Models	Training performance (%)	Testing performance (%)	α
LMPM	95.12	91.67	96%
KMPM	100	100	100%

condition of the Wangjiazhai slope is failure. The status of the Wangjiazhai slope has been checked by the developed LMPM and KMPM. The output of LMPM and KMPM is −1. So, the output from LMPM and KMPM was matched with the actual condition.

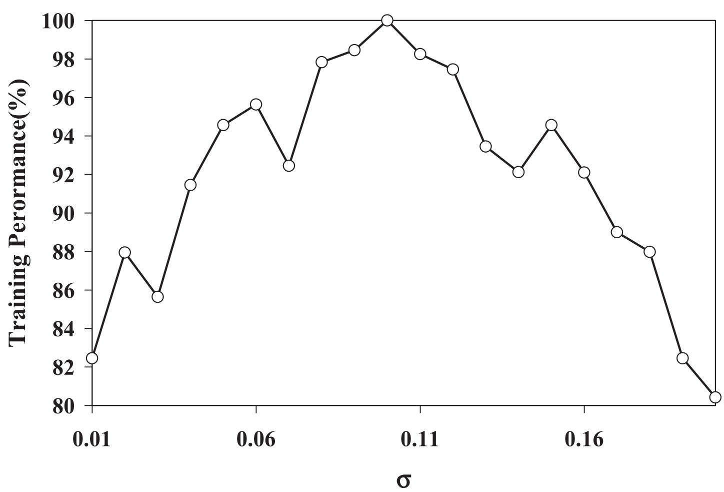

Figure 1. The effect of σ on training performance (%).

Conclusion

This article has proposed models based on the MPM for the prediction of the stability of epimetamorphic rock slope. Fifty-three data-sets have been utilized to construct the MPM models. Two models (LMPM and KMPM) have been developed. The prediction of MPM matches well the actual result. The main advantage of the developed MPM model is that it provides low bound on classification accuracy. The performance of the KMPM is better than the LMPM model. The developed models (LMPM and KMPM) give accurate prediction for a case study. So, it shows good generalization capability. The developed MPM can be used to model different problems in natural hazard.

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