DATA MINING TECHNIQUES FOR SLOPE STABILITY ESTIMATION WITH PROBABILISTIC NEURAL NETWORKS

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Abstract: Probabilistic neural networks are applied to facilitate slope stability estimation by making use of data mining techniques and an intelligent system. Data mining can draw attention to meaningful structures in the archives of such slope stability data. The soil mechanical characteristics and the slope shapes with significant influences on slope stability are used to train and test the neural networks. Validation is performed to show the efficiency of probabilistic neural networks for estimation of slope stability. The simulation results show that probabilistic neural network models generate higher predicting precision than the conventional linear regression, limit equilibrium method and maximum likelihood estimation.

Key words: neural network; data mining; slope stability; state estimation

1. INTRODUCTION

The stability of slopes has been received wide attention to its practical importance in the design of excavations, embankments, earth and rockfill dams, and tailing dams. Generally, limit equilibrium techniques are commonly used to assess the stability of the sloped, as complex geological subsoil profiles, seepage, and external loads can be easily dealt with.[1] A difficulty with all the equilibrium methods is that they are based on the assumption that the failing soil mass can be divided into slices[2]. This in turn necessitates further assumption relating to side force directions between

slices, with consequent implications for equilibrium. The economic and social values of slope stability analysis are very high. As a result, the problem has attracted many researchers in the area of computational intelligence recently.

Data mining, also known as “knowledge discovery in databases”, is the process of discovering interesting patterns in databases that are useful in decision making[3]. Data mining is a discipline of growing interest and importance, and an application area that can provide significant competitive advantage to an organization by exploiting the potential of large data warehouses. The central focus of the data mining enterprise is to gain insight into large collections of data. Often, achieving this goal involves applying machine learning methods to inductively construct models of the data at hand[4]. A number of algorithms have been developed in domains, such as machine learning, statistics, and visualization, to identify patterns in data[5]. Of these, statistical modeling approaches are the oldest. The data set must conform to rigid distribution criteria to employ statistical modeling methods. Pattern discovery algorithms based on machine learning techniques, however, impose fewer restrictions and produce patterns that are easy to understand.

Recently, intelligent systems specifically ANNs, have been applied as a novel approach for modeling of complex, highly nonlinear dynamic systems. The main advantage of ANNs is in cases where intrinsic nonlinearities in the dynamics prevent the development of exactly solvable models. All of these criteria are present in the sense that the dynamics are inherently nonlinear, and prediction is one of the main goals. An ANN is a computational method inspired by studies of the brain and nervous systems in biological organisms. An ANN is constructed of a highly interconnected network of many basic computing processors named as neurons. Two of the characteristics of ANNs are their capability of self-organization and autonomous learning. ANNs are well suited to problems involving matching input pattern to a set of output patterns where deep reasoning is not required. The ANN approaches have been applied to many problem domains in the civil engineering field with the main objective of assisting project engineers in decision making[6]. The objective of the paper is to propose an intelligent procedure for estimation of slope stability with probabilistic neural networks.

This paper is organized as follows: Section 2 describes the basic features of ANN, the principles of data mining with ANN, and the training process of probabilistic neural networks. In section 3, the applications of probabilistic neural networks to slope stability forecasting are executed and some comparisons with different methods for estimating slope stability are shown.

2. DATA MINING TECHNIQUES WITH PROBABILISTIC NEURAL NETWORKS

Data mining refers to the application of machine learning methods, as well as other automatic knowledge acquisition methods, to the generation of potentially useful knowledge from the organization and analysis of raw data. In overview, the implementation steps of data mining for slope stability analysis are: 1) objective determination. The slope stability estimation is divided into two categories, which is stable or failed state. 2) data preparation. Prior to a pattern recognition analysis, making a principal components plot gives a good idea of how difficult the classification will be and consideration of the loadings of principal components usually gives a preliminary idea of the importance of variables. 3) data transformation; data mining; and analysis of results. Making use of intelligent algorithms, for examples, genetic algorithm, neural networks, and other machine learning techniques; the classification and forecast problem for slope stability can be estimated. .

Several machine learning techniques have been proposed to acquire knowledge in soil and rock engineering. Some of them are symbolic learning, case-based learning, and ANN. The factors that influence the applicability of machine learning techniques include comprehensibility of knowledge, the complexity of representing input data and knowledge, the ability to handle missing values or noisy data, and so on. The comprehensibility of knowledge of the relation between slope stability and input parameters i.e., rock mechanical characteristics and the slope shape is opaque. Therefore, ANN is an appropriate machine learning technique in this case.

Figure 1. Architecture of three-layer probabilistic neural networks

Probabilistic neural networks(PNNs) are a kind of radical basis networks suitable for classification and will be used for modeling the data sets. The Architecture of three-layer probabilistic neural networks is shown in Fig.1. It has the three layers, including an input layer, which has as many elements as there are separable parameters needed to describe the objects to be classified. It has a hidden layer, also called a pattern layer, which organizes element represents each input vector. And finally, the network contains an output layer, called the summation layer, which has as many processing elements as there are classes to be recognized. Each element in this layer combines via processing elements within the pattern layer which relate to the same class and prepares that category for output.

PNNs are known for their ability to be trained quickly on sparse data sets by separating data into a specified number of output categories. PNNs are three-layer networks wherein the training patterns are presented to the input layer and the output layer has one neuron for each possible category. The number of neurons in the hidden layer must be equal to the number of training patterns. PNN determines which category that one pattern belongs to. It measures how far a given sample pattern is from patterns of the training set in the R-dimensional space, where R is the number of inputs in the problem. These layers of neurons in the input, hidden and output layers constitute a number of sensory units. The information passes from the input layer through the hidden layer to the output layer, that is, the signal processing from neurons of a layer to the neurons of the succeeding layer.

Figure 2. Basic description of slope stability analysis

As shown as Fig.2, the main factors of impact on slope stability are listed as follows: the unit weight of the soil γ ; cohesion of soil c ; internal friction angle φ ; slope angle α ; slope height H ; pore pressure ratio γ_u . The main role of the input layer is to map all the external signals into the hidden layers. Thus, it requires a scaling function for each input neuron to normalize the range of external signals into a specific range that the neural network can process. The neurons in the hidden layer enable mapping of the non-linearity

relations between the input and output values and thus give PNN models a better performance over others. The final output classifications are determined by values of the output layer generated by the PNN model. The network produces activation in the output layer, corresponding to the probability density function estimated for each category. The highest output represents the most probable category. The number of neurons in the input layer is the number of inputs to the problem, and the number of neurons in the output layer corresponds to the number of categories. As the purpose of a PNN network is to separate outputs into different categories, two or more output neurons are normally required, with output values normalized to fall within 0 and 1.

The output of the pattern layer is expressed as follows:

$$\varphi_j(x) = \exp\left(-\frac{(x - c_j)^2}{2\sigma_j^2}\right) \quad (1)$$

Where x is the input vector of for an input pattern; c_j is the center of j -th basis function; σ_j denotes a smooth parameter and is the deviation of radial basis function; φ is the radial basis function. Probabilistic neural networks can be used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a competitive transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes.

The expression for the net input of a radial basis neuron is different from that of neurons in back propagation. The net input to the radial basis transfer function is the vector distance between its center vector c and the input vector x . The radial basis function has a maximum of 1 when its input is 0. As the distance between c and x decreases, the output increases. Thus, a radial basis neuron acts as a detector that produces 1 whenever the input x is identical to its center vector c . The output of the probabilistic neural network, $y(x)$, which is a model based on linear regression, is expressed as follows

$$y_i(x) = \sum_{j=1}^m w_{ij} \varphi_j(x, c) \quad i = 1, 2, \dots, p \quad (2)$$

Where p is the number of neurons in the output layer; w_{ij} is the weight linking the i -th neuron in the output layer to the j -th neuron in the hidden

layer. The outputs of the summary layer are binary values. If y_i is larger than input of other neurons, y_i is set to 1, otherwise it is set to zero.

The learning process of probabilistic neural network is divided into two stages. The first stage is non-supervised learning, which Euclidian distance, d_j , is formulated as

$$d_j(t) = \|x - c_j(t-1)\| \quad j = 1, 2, \dots, m \quad (3)$$

Where t is the number of iteration. The center is adjusted as follows

$$c_j(t) = \begin{cases} c_j(t-1) + \xi[x(t-1) - c_j(t-1)] & j = \min d_j(t-1) \\ c_j(t-1) & \text{others} \end{cases} \quad (4)$$

The second stage is the supervised learning, in which the W is adjusted by using LMS method. In matrix notation, Eq(2) becomes

$$Y = W\Phi \quad (5)$$

Where Y is the real output matrix, W and Φ are the weight matrix and radial basis matrix, respectively. The weight matrix can be computed by using pseudo inversion method

$$W = \Phi^+ D \quad (6)$$

Where Φ^+ is the pseudo inversion of matrix Φ , and D is the expected output response matrix. The pseudo inversion can be expressed as

$$\Phi^+ = (\Phi^T \Phi)^{-1} \Phi^T \quad (7)$$

3. ESTIMATION OF SLOPE STABILITY WITH PROBABILISTIC NEURAL NETWORK

As shown as Figure 1, the factors influencing slope stability includes the unit weight of the soil γ , cohesion c , internal friction angle φ , slope angle α , slope height H and pore pressure ration γ_u . As a result, there were six neurons in the input layer of ANN, 46 neurons in the hidden layer and 2 neurons in the output layer. Designing network architecture requires more than selecting a certain number of neurons, followed by training only. Especially phenomena such as over-fitting and under-fitting should be recognized and avoided in order to create a reliable network. And 46 input-output samples were gotten from reference[7].

Preprocessing is numerically operating on the data in order to increase the useful information for pattern recognition.

$$\hat{x}_k = \frac{2(x_k - x_{k\min})}{(x_{k\max} - x_{k\min})} - 1 \tag{8}$$

Where $\hat{x}_k$ is the normalized network input, $x_{k\min}$ and $x_{k\max}$ are respectively minimum and maximum of the k-th property of soil parameters in all training pairs.

Table 1. Basic mechanical parameters of soil slopes

Case No.	$\gamma/\text{kN}\cdot\text{m}^{-3}$	c/kN	$\phi/^\circ$	$\alpha/^\circ$	H/m	γ_u
E1	18.50	25.00	0.00	30.0	6.00	-
E2	12.00	0.00	30.00	35.0	4.00	-
E3	18.84	0.00	20.00	20.0	7.62	0.45
E4	14.00	11.97	26.00	30.0	88.0	0.45
E5	22.40	10.00	35.00	45.0	10.0	0.40

The basic mechanical parameters of soil slopes are listed in Table1. After training ANN with the practical engineering samples, the prediction of slope stability for the other 5 cases of the slope failure or stable are done with well trained ANN. Table 2 gives the comparison between the estimated and practical states of slope safety with different search methods. The practical application of proposed intelligent forecast procedure for slope stability shows that a well trained artificial neural network reveals an extremely fast convergence, a better generalization and a high degree of accuracy.

Table 2. Comparison between the estimated and practical states of slope safety with different methods

No.	Limit equilibrium method	Maximum likelihood estimation	Neural network	Practical states of slopes
E1	stable	stable	failed	failed
E2	stable	stable	stable	stable
E3	stable	failed	failed	failed
E4	failed	failed	failed	failed
E5	failed	failed	failed	failed

4. CONCLUSION

Probabilistic neural networks (PNN) can be used for classification problems. Their design is straightforward and does not depend on training. A PNN is guaranteed to converge to a Bayesian classifier providing it is given enough training data. These networks generalize well. Neural networks have a more suitable inductive bias than other commonly used data mining methods. This paper describes the application of a data mining technique, probabilistic neural networks, to tackle a commonly faced problem in a slope stability project: estimation of slope stability based on the soil mechanical properties and geotechnical slope shapes. The study demonstrates the ability of data mining to deliver new project insights in areas where traditional techniques had not been so successful.

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