Landslide Early Warning Model Based on the Coupling of Limit Learning Machine and Entropy Method

Ning Zhang, Qing Li *, Chuangjiang Li and Yongbo He

National and Local Joint Engineering Laboratories for Disaster Monitoring Technologies and Instruments, Hangzhou, Zhejiang, 310018, China.

*Corresponding author Qing Li: lq13306532957@163.com

Abstract. Monitoring and early warning are the means and methods to reduce landslide hazards. Traditional landslide monitoring methods are single, and the accuracy of statistical prediction model and deterministic prediction model are low. Aiming at this situation, a landslide warning model is proposed to comprehensively monitor the landslide impact factor and combine the Extreme Learning Machine with the Entropy method. The experimental results show that the results obtained by this method are consistent with the actual situation, and the predicted values are basically consistent with the measured values; the accuracy is 97.21%, which is higher than BP neural network; provide a feasible method for landslide warning model.

1. Introduction
The current landslide prediction methods include creep damage theory, limit equilibrium method, GM (1,1) gray model, BP neural network model, decision tree mode, et al. But these methods have the following problems: The limit equilibrium method need to know the shape of the landslide body, the calculation time, and it will bring great inconvenience[1]. Decision tree model prediction accuracy is not high enough, longer prediction time[2]. Data mutation will affect the accuracy of the theoretical model of cusp catastrophe, and the final comprehensive evaluation value is generally higher[3]. BP neural network is easy to fall into local optimum and over-fitting phenomenon[4].

Extreme Learning Machine has the characteristics of fast calculation speed, not easy to fall into local optimum, and good generalization performance[5]. It requires minimal manual intervention and have good generalization performance. They are widely used in classification, regression and feature learning problems[6]. Considering the factors that affect the landslide, this paper monitors the comprehensive factors affecting landslides, builds a landslide warning model coupled with ELM and entropy method, and discusses its accuracy.

2. Design of integrated measurement system and construction of monitoring system
Integrated measurement system including sensor acquisition system and host computer display system.

2.1. Geotechnical disaster simulation simulation field construction
Due to the many influencing factors affecting slope landslides, several high impact factors on landslides are considered, including rainfall, soil moisture content, soil sliding stress, soil displacement in all layers of the ground, and the angle of slope. The geotechnical catastrophe simulation test field consists of a large-scale simulation equipment consisting of a rain system, an experimental tank and a...
hydraulic lifting system, as shown in ‘figure 1’.

2.2. Integrated measurement system design
The measurement system consists of two parts: the monitoring sensor and the host computer display system. The underground displacement sensor is composed of 10 nodes, as shown in ‘figure 2’. When a landslide occurs, the sensor collects the displacement and angle change of each node. The nodes of underground displacement sensor collected values through RS485. The remaining sensors are collected by the STM32 microprocessor as shown in ‘figure 3’. The sensor's output signal is sent to the receiving module, then converted to digital and transmitted to the host computer.

2.3. Host computer display system
Each layer of the sensor for the subsurface displacement deformation sensor measures the AD values in the horizontal and vertical directions, and the mutual inductance voltage values of the various layers of the sensor characterize the offset angle and displacement of each layer. The data collected by other sensors is to read the data to the host computer through the serial port, each parameter displays the change curve of each parameter through the web page, so that the parameter change can be monitored remotely in real time.

3. Entropy method and ELM coupling model

3.1. Entropy method for evaluating comprehensive measurement weights
The entropy method is a comprehensive evaluation method that can determine the weight of evaluation indicators from multiple levels and multiple objectives. It can objectively reflect the degree of influence of each factor used for evaluation on the evaluation target[7]. The evaluation indexes of different evaluation objects are calculated to compare the importance levels between the objects[8]. The method is as follows:

(1) Followed by the calculation of the proportion of the i-th program under the j-th indicator.

\[
P_{i,j} = \frac{X_{i,j}}{\sum_{i=1}^{n} X_{i,j}} \quad (j = 1, 2, \ldots, m)
\]  

(2) Calculate the entropy of the j-th indicator.

\[
e_j = -k \sum_{i=1}^{m} P_{i,j} \log (P_{i,j})
\]
(3) Final calculation of comprehensive score,

\[ S_i = \sum_{j=1}^{n} W_j \ast X_{i,j}, \quad i = 1, 2, \ldots, n, \quad w_j \text{ is the weight.} \quad (3) \]

4. Extreme learning machine model (ELM)
The Extreme Learning Machine is a new fast learning algorithm for three-layer networks with random initialization weights and offsets proposed by Huang Guangbin.

4.1. Extreme learning machine concept and principle
The Extreme Learning Machine is based on the interpolation theorem and the limit theorem. It is pointed out that the single hidden layer feedforward neural network has its learning ability related to the network structure when its hidden layer mapping function is infinitely different, and has nothing to do with the input weight and threshold. Therefore, an appropriate network structure can be selected to achieve error-free fitting of continuous functions. The method of implementing the Limit Learning Machine is to randomly give the input weight of the neuron weight and the offset value of the hidden layer neuron, it not need to adjust the weight in the training, but directly calculate it by the least squares method. Thereby avoiding the disadvantages brought by the gradient descent method and improving the speed of generalization performance.

4.2. Algorithm flow
Suppose X is a sample for a given Q and Y is the output, among them.

Forward transmission,

\[ X = \begin{bmatrix} t_1, t_2, \ldots, t_Q \end{bmatrix} \]

\[ T_j = \sum_{i=1}^{J} \beta_{jm} g \left( w_i x_i + b_i \right) \quad (4) \]

And w is the weight between the hidden layer and the input layer, \( \beta \) is the connection weight between the hidden layer and the output layer, and b is the threshold of the hidden layer neurons, g(x) is the activation function of the hidden layer neurons. The above formula can be written as:

\[ H \beta = T' \quad (5) \]

In the formula, \( \lambda \) is an adjustable parameter and can be obtained by the ridge regression algorithm, thus calculating:

\[ \beta = H^+T \quad (6) \]

4.3. Activation function, data normalization and training
Extreme Learning Machines are suitable for almost all nonlinear activation functions. The typical functions are Sigmiod, Sine and Hardlim.

From the perspective of the whole process of landslide monitoring, the amount of landslide data is extremely poor. Therefore, the data used for training often differs greatly. In order to prevent the huge data from causing interference to the smaller data, when training the network model, the data is first normalized, and each training data is made to the model. Positive contribution. The normalization formula is as follows:

\[ y = (x - \text{min}) / (\text{max} - \text{min}) \quad (7) \]

5. Experiment analysis
In this paper, the experimental data is obtained through the integrated measurement system, and a three-layer extreme learning machine network model is built. The rainfall, soil moisture content, displacement and sliding stress collected by the sensor are taken as input samples, the comprehensive scores of parameters were calculated by the entropy method. The risk factor for the landslide is used as
the output of the model. The Sigmoid type function is selected as the excitation function of the model.

5.1. Comprehensive monitoring of experimental data
The values collected by the integrated monitoring system were processed to obtain 63 sets of experimental data, and the comprehensive score was obtained by the entropy method. The risk factor of the landslide is shown in ‘figure 4’. The curve in the figure is consistent with the time-series displacement of the landslide deformation in the test.

![Figure 4. Landslide hazard coefficient.](image)

The 63 sets of data obtained from the experiment and the comprehensive scoring coefficient calculated by the entropy method are divided into training samples and test samples. The training samples are approximately 50 sets, as shown in table 1. Because of too much training sample data, only some data is given in the table.

| Angle/°  | Moisture (shallow)/% | Moisture (deep)/% | Soil stress/kPa | Rainfall/mm | Displacement/mm | Risk factor |
|----------|----------------------|-------------------|----------------|-------------|----------------|-------------|
| 25       | 23.9                 | 34.6              | 14.18          | 37.14       | 64.79          | 0.1313      |
| 40       | 24.95                | 30.06             | 14.69          | 75.02       | 369.64         | 0.5522      |
| 20       | 24.65                | 12.6              | 14.3           | 13.58       | 0.34           | 0.0205      |
| 40       | 23.65                | 31.9              | 30.14          | 68.15       | 235.29         | 0.3804      |
| 30       | 25.05                | 33.45             | 14.3           | 53.7        | 148.68         | 0.2557      |

In the same way, 13 sets of data samples of the extreme learning machine were obtained to detect the effect of the model.

5.2. Comparison between model and BP neural network algorithm
The activation functions of Sigmoid, Sine and Hardlim were selected to train the model. The accuracy of the Sigmoid function obtained in the experiment is higher than the other two functions. So choose the Sigmoid function as the activation function. After the model established in this paper is trained, it compares with the results of BP neural network model, the results of this paper and BP neural network are compared as follows table 2.

| times of training | BP    | This article |
|-------------------|-------|--------------|
| 1                 | 0.72  | 0.99         |
| 2                 | 0.83  | 0.96         |
| 3                 | 0.95  | 0.96         |
| 4                 | 0.91  | 0.97         |
| 5                 | 0.75  | 0.99         |

The model of this paper built by the experiment is superior to the BP neural network model in accuracy. The results obtained from the model built in this paper are shown in ‘figure 5’. And the model error constructed in this paper is shown in ‘figure 6’.
6. Conclusion

(1) This paper analyzes from multiple factors affecting landslides and builds an integrated measurement system. It solves the limitation of “The measured area is not deformed, and the deformation is not measured”, in the presence of a single factor when the geotechnical catastrophe occurs.

(2) Introducing the entropy method to calculate the landslide hazard coefficient under the comprehensive measurement parameters, and combining the Limit Learning Machine with the early warning model to improve the model accuracy and achieve prediction. The simulation calculation time and generalization performance are greatly reduced. Experiments show that the early warning model proposed in this paper is suitable for the geotechnical disaster warning with high nonlinear variation, and this model has obvious advantages compared with the traditional BP neural network model.

Acknowledgments

Finally, the paper will be funded by the National Key Research and Development Program (2017YFC0804604), the Zhejiang Provincial Key Research and Development Program (2018C03040) and the National Quality Supervision, Inspection and Quarantine Bureau Science and Technology Program (2017QK053).

References

[1] Zheng, Y., Zhao, S.Y., Deng C.J., et al. (2006) The Development and application of Finite Element Limit Analysis in geotechnical engineering. J. China Engineering Science, 26(8): 39-61.

[2] Mao, Y.M., P, Y., Chen, Z.G. (2014) Application of uncertainty decision tree classification algorithm in landslide hazard prediction. J. Journal of Computer Applications, 31(12): 3646-3650.

[3] Shao, D.G., Yao, C.L., (2009) Improved catastrophe theory based evaluation method and its application to drought disaster risk evaluation. J. Journal of Hydraulic Engineering, 40(07): 858-869.

[4] Zhao, J.B., Liu, Y.X., Liu, N. (2019) Spatial Prediction Method of Regional Landslide Based on Distributed BP Neural Network Algorithm under Massive Monitoring Data. J. Rock and Soil Mechanics, (07): 1-8.

[5] Huang, G.B., Zhu, Q.Y., Siew, C.K. (2006) Extreme Learning Machine: theory and applications. J. Neurocomputing, 70 (1): 489-501.

[6] Tang, X.F., Chen, L. (2018) Extreme Learning Machine for imbalance data learning. J. Application Research of Computers, 35(10): 2990-3002.

[7] Wang, H., Guo, C.Y. (2017) Effect analysis of linear dimensionless methods on the index weights by entropy method. J. China Population, Resources and Environment, 27(S2): 95-98.

[8] Zhang, C., Wang, Q., Chen, J.P., et al. (2011) Evaluation of debris flow risk in Jinsha River based on combination weighting process. J. Rock and Soil Mechanics, 32 (3) : 831-836.