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Application of Displacement Prediction Method Based on Displacement Increment and CS-BP Neural Network in Mine Landslide

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Abstract—The research on landslide displacement prediction can help the early warning and prevention of landslide disasters in mining areas. In view of the problem that BP neural network is prone to local convergence and considering that the network trained based on time-series cumulative displacement may produce large errors in prediction, this paper proposes a method combining displacement increment and CS-BP (Cuckoo Search-Back Propagation) neural network to predict landslide displacement. Compared with the conventional landslide displacement prediction methods, this method uses displacement increment instead of the commonly used cumulative displacement as the network input data, selects the CS algorithm with fewer parameters and easy to implement to optimize the BP network to construct the prediction model, and predicts the corresponding amount of displacement change at the next moment by the historical landslide displacement increment. Combined with the measured data of three feature points of a mine in Xinjiang, China, obtained by the micro-deformation monitoring radar, the displacement prediction accuracy of the proposed model on the three measured data sets is compared with the prediction accuracy of the BP, GA-BP (Genetic Algorithm, GA), and FA-BP (Firefly Algorithm, FA) network prediction models based on cumulative displacement and incremental displacement, respectively. The experimental results show that this method achieves superior performance with an average root mean square error of 0.3261 and an average mean absolute error of 0.2785 across the three feature points, outperforming the other models, and holds promising applications in disaster prevention and control work.

1. INTRODUCTION

Landslide is one of the major geological hazards in China, and it is of great practical significance to carry out the prevention and control of landslide hazards. Out of the national consideration for safety production, landslide monitoring in mining areas has been constantly receiving attention and focus from all sides in recent years. The terrain of mining areas is steep and dangerous, which is inconvenient for field observation. The use of traditional monitoring means (GPS, level measurement, etc.) cannot achieve real-time and continuous monitoring of large areas. With its advantages of all-day, all-weather, high accuracy, and no need to contact the monitoring area, micro-deformation monitoring radar has become a potential technology in the field of landslide monitoring [1]. The antenna system is an indispensable and crucial component of the entire radar system, and the choice of radar antenna directly affects the accuracy of micro-deformation monitoring radar in range and angle measurements. Relevant scholars have proposed many excellent antennas, such as super-wide impedance bandwidth

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planar antenna for microwave and millimeter-wave applications [2], novel compact printed leaky-wave antenna with beam steering capability [3], and hexa-band planar antenna with asymmetric fork-shaped radiators [4]. Advanced antenna systems contribute to the radar's ability to acquire more precise deformation data. However, it is worth discussing and researching how to use the measured data obtained by micro-deformation monitoring radar to predict the deformation displacement of landslide potential areas, and then assist in the early warning and prevention of landslides in mining areas.

In recent years, with the rapid development of modern computer technology and data storage technology, machine learning technology has been revived again and is widely used in various fields. Regarding the research on landslide displacement prediction, machine learning methods have become the choice of more and more researchers [5–7]. BP neural network is one of the classical machine learning algorithms, which has been widely used in landslide displacement prediction. For example, Zhang and Men used BP neural network to establish a landslide deformation prediction model for short-term landslide prediction [8]; Yue et al. also used BP neural network to predict landslide displacement data [9]. However, BP neural network has a series of problems, such as being easy to fall into local convergence and sensitive to the initial weights of the network. Therefore, the introduction of intelligent optimization algorithms to improve the network based on the original BP neural network has become a new technical route for landslide displacement prediction research. For example, Cheng et al. proposed the CPSO-BP model for landslide prediction [10], while utilizing the global search capability of the CPSO algorithm to some extent to avoid BP getting trapped in local optima. This model has limited adaptability and requires manual adjustment of certain CPSO algorithm parameters to fit different landslide displacement prediction scenarios; Qiao and Wang proposed a landslide displacement prediction method based on GSA-BP model [11], and GSA algorithm also possesses some global search capability, but its performance highly depends on parameter settings, including gravitational constant and iteration count, and parameter configuration significantly impacts algorithm performance, necessitating continuous parameter tuning and optimization; Qu et al. combined the improved Harris Eagle optimization algorithm with BP neural network to achieve high accuracy prediction of landslide displacement [12], and this model exhibits good generalization ability and effectively enhances landslide displacement prediction accuracy; however, it has a relatively slow convergence rate, resulting in substantial computational overhead as problem complexity increases. Cuckoo Search (CS) algorithm is a new bionic intelligent optimization algorithm proposed by Yang and Deb in 2009 based on the hatching parasitic behavior of cuckoo [13], which requires fewer parameters, has strong search capability and good generality, and has been successfully used in a variety of scenarios, such as structural optimization [14], photovoltaic systems [15], support vector machine [16], neural network training [17], and multi-objective optimization [18].

Based on the above background, this paper proposes a method combining CS algorithm and BP neural network to achieve landslide displacement prediction in mining areas. In addition, the cumulative landslide displacement is usually a monotonically increasing sequence, and the network obtained by using the previous cumulative displacement data as training data will produce a prediction range beyond the training data range when predicting the subsequent data, which will affect the prediction accuracy. The landslide displacement increment is a non-monotonically increasing sequence, and using it as training data can effectively avoid this situation. Therefore, in this paper, we use BP, GA-BP, FA-BP, and CS-BP neural networks to predict landslide displacement based on cumulative displacement and incremental displacement, respectively, and evaluate the prediction accuracy by using root mean square error and mean absolute error. Finally, the feasibility of the method proposed in the prediction of landslide displacement in mining areas is compared and analyzed.

2. LANDSLIDE DISPLACEMENT PREDICTION MODEL CONSTRUCTION

2.1. BP Neural Network

BP neural network is a typical multi-layer feed-forward network. The network consists of input layer, output layer, and hidden layer. The input layer receives external input signals; the output layer outputs the results of the network; and the middle hidden layer is responsible for processing the signals of the input layer. The learning process of BP neural network is accomplished by forward transmission of signals and backward propagation of errors [19]. First, the training data is input to the network to get the output result of the network. Then, the error term is calculated by comparing the error between the output result and the actual result. Next, the error term is propagated layer by layer from the output layer to the input layer, and the weights of each neuron are adjusted according to the error size in order to make the output result of the network gradually close to the actual result. This process is repeated until the output of the network meets the predetermined accuracy requirements, or the proposed learning times are reached.

The signal forward transmission process is calculated as:

$$y_l = f\left(\sum_{n=1}^{N} w_{nl}x_n + b_l\right) \tag{1}$$

where x_n is the input of the network, $n = 1, 2, \dots N$; N represents the number of neurons in the input layer of the network; w_{nl} represents the connection weight between node n and node l; b_l represents the threshold of node l, $l = 1, 2, \dots, L$; L represents the number of neurons in the hidden layer of the network; y_l represents the output of the network; f represents the activation function used by the network.

The expression for the error calculation is:

$$\Delta E = \frac{1}{2}\sum_{t=1}^{T}(Y_t - \hat{y}_t)^2 \tag{2}$$

where $t = 1, 2, \dots, T$; T represents the number of neurons in the output layer of the network; ΔE represents the computational error; Y_t is the predicted output value of the network; and y'' is the true value.

2.2. Cuckoo Search Optimization Algorithm

The cuckoo search algorithm is inspired by the cuckoo's egg-laying strategy. The cuckoo uses a special parasitic host nesting method to breed, in which it places incubated eggs into the nest of a parasitic host and allows the host to incubate the cuckoo eggs [20]. When the parasitic host finds an unfamiliar egg in the nest, it abandons the nest and re-nests to reproduce. Yang and Deb proposed the CS algorithm based on the observation of the above phenomenon. The CS algorithm follows the following three basic assumptions [13].

1) Each cuckoo lays one egg at a time and randomly selects a host nest for storage.
2) In the process of random nest selection, the best nest will be kept to the next generation.
3) The number of parasitic host nests available is fixed, and the probability of exotic cuckoo eggs being found by the host is P_a.

Based on the above three assumptions, it can be considered that the host nest is used to refer to the solution of the problem to be solved; the process of cuckoo searching for the host nest to lay eggs is the process of searching for a solution in n-dimensional space; and the quality of the host nest symbolizes the quality of the solution.

In the CS algorithm, the nest location is updated according to the Lévy flight, and the update expression is as follows:

$$x_i(t+1) = x_i(t) + \alpha \otimes Levy(\beta) \tag{3}$$

where $x_i(t)$ and $x_i(t+1)$ represent the location of the ith nest at the tth and $t+1$th iterations, respectively; $\otimes$ represents the point-to-point multiplication; $Levy(\beta)$ represents the random flight path, which obeys the Lévy probability distribution; α represents the step size information, which is used to control the cuckoo's search range, and α is calculated by the following expression:

$$\alpha = \alpha_0(x_i(t) - x_{best}) \tag{4}$$

where α_0 is a constant, and x_{best} represents the optimal location in the current iteration.

During the update iteration, when the partial nest location is updated according to the discovery probability, the update is achieved by means of a random preference wandering, and the expression for generating the new location is as follows:

$$x_i(t+1)=x_i(t)+r \otimes Heaviside(P_a-\varepsilon) \otimes (x_k(t)-x_j(t)) \tag{5}$$

where r and ε are random numbers that follow the normal distribution in the interval $[0, 1]$; $Heaviside(\mu)$ is the step function; P_a represents the probability that the host finds an exotic cuckoo egg; and $x_k(t)$ and $x_j(t)$ represent two random positions at the tth iteration.

2.3. Displacement Prediction Method Based on Displacement Increment and CS-BP Neural Network

2.3.1. Feasibility of Predicting Landslide Displacement by Displacement Increment

The factors affecting landslides in mining areas are numerous and complex, and it is very difficult to construct a definite physical model to describe its change process. One of the advantages of using neural networks for landslide displacement prediction is that it is not necessary to investigate the intrinsic causes of change, but to analyze the results of change to achieve prediction of its time series. The change of landslide displacement increment sequence is usually consistent with the change process of landslide. When the landslide is in the accelerated change phase, the displacement increment will show an increasing trend, and when the landslide is in the smooth change phase, the displacement increment will also show a smooth change trend. Therefore, it is theoretically feasible to use the landslide displacement increment to predict the landslide displacement in the mining area aiming to improve the prediction accuracy.

2.3.2. CS-BP Neural Network Prediction Method

The CS algorithm can achieve global optimization search. Before training the BP neural network, the CS algorithm is first used to find the optimal parameters of the BP neural network, and then the optimal initial weights and thresholds are given to the network to improve the performance of the network through the optimal parameter settings. This method of combining CS algorithm with BP neural network can effectively avoid the problem that a single BP neural network tends to fall into local convergence, so that the network has better prediction ability.

The process of predicting landslide displacement by CS-BP neural network based on displacement increment is shown in Fig. 1, which can be summarized as follows:

1) Obtain time series data of landslide displacement increment and deduce the average deformation velocity corresponding to each sampling moment based on the displacement data. Preprocess the acquired data using data mining techniques to provide foundational data support for training landslide displacement prediction model.
2) Determine the network structure parameters of BP neural network. The number of input layer neurons is determined by the number of input data in a group, while the number of output layer neurons is determined by the number of output values. The number of hidden layer neurons needs to be determined through multiple iterations to find the optimal value, along with the selection of activation function and learning rate.
3) The optimal parameter solution is searched using the CS algorithm and used as the initial weights and thresholds of the BP neural network. The search steps are entered as follows:
   a. Initialize the number of nests n, the probability of discovery P_a, and set the maximum number of iterations or the accuracy requirements for terminating iterations.
   b. In the specified search range, n initial locations of bird nests are randomly generated $X_0 = (x_1^{(0)}, x_2^{(0)}, \ldots, x_n^{(0)})^T$, and each nest location corresponds to a set of weights and thresholds. The fitness function value is used as the evaluation index of the nest location, while the reciprocal of the training error of the BP network is used to represent the fitness function value. The fitness value of the nest is calculated to find the contemporary best nest location $x_d^{(0)}$ and record it.
   - Retain the best nest position from the previous generation $x_d^{(0)}$. Update the nest location by Lévy flight $X_t = (x_1^{(t)}, x_2^{(t)}, \ldots, x_n^{(t)})^T$, and the fitness value of the updated nest is calculated and compared with the fitness value of the previous generation position. If it is better, the position is updated; otherwise, the previous generation nest position is retained.

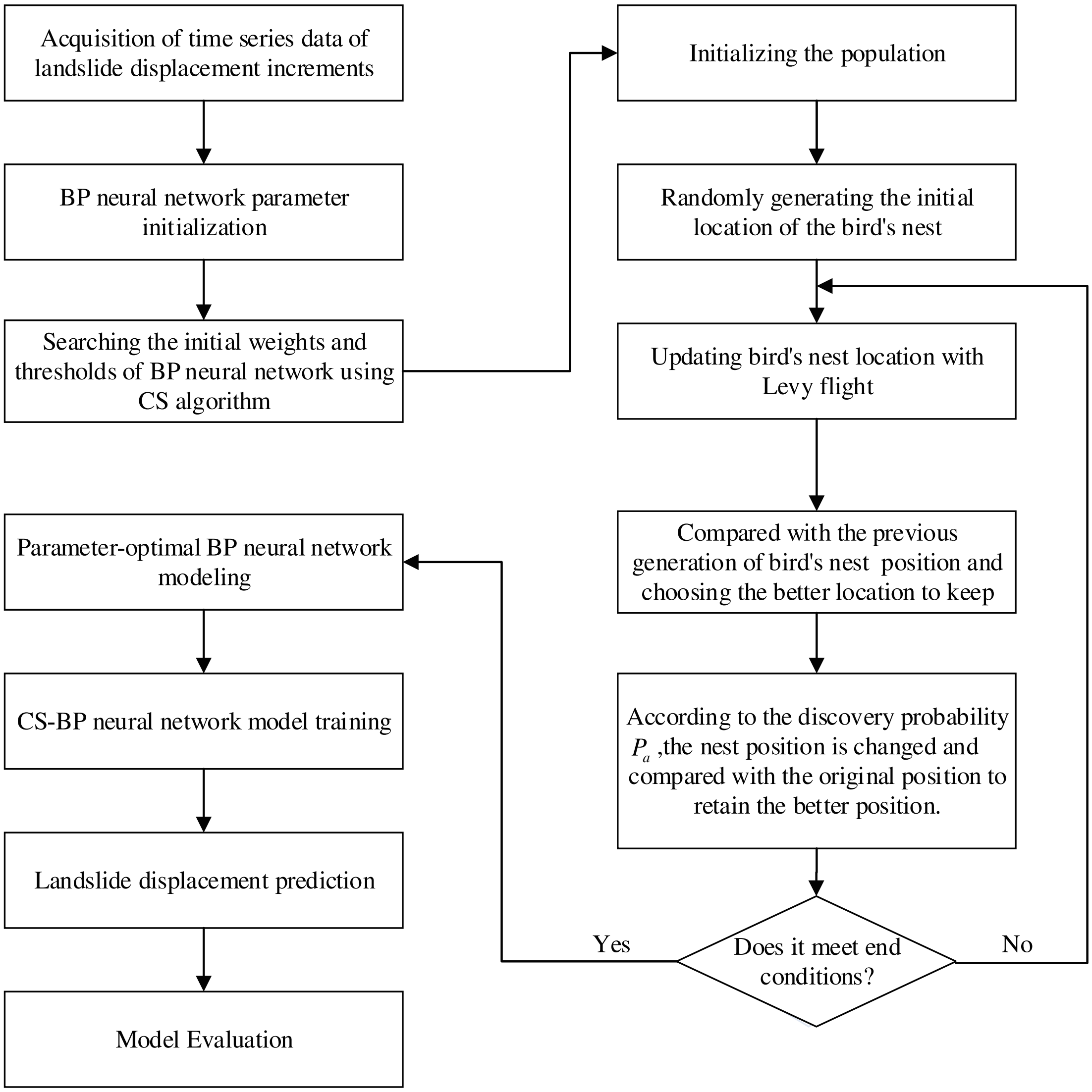

Figure 1. Technical route of landslide displacement prediction model based on displacement increment and CS-BP neural network.

c. Generate a random number r to compare with P_a to update the nest position again. If $r > P_a$, then the nest position is updated with random preference wandering; otherwise, the original position remains unchanged. After updating the position, the new fitness value is calculated and compared with the value of the original position, and if it is better the updated nest is kept; otherwise, the original nest position is used. At this point, the updated nest position is $X_{t+1} = (x_1^{(t+1)}, x_2^{(t+1)}, \ldots, x_n^{(t+1)})^T$.

d. Loop iterates until the iteration termination condition is reached (reaching the maximum number of iterations or achieving the accuracy requirements for terminating iterations), and the optimal nest location $x_d^{(t+1)}$ is used as the optimal weights and thresholds of the BP network.

4) Construct a BP neural network prediction model with optimal parameters. Use historical displacement increment and deformation velocity as inputs, with the corresponding displacement increment at the next time as the output. The model is trained; displacement prediction is performed; and the prediction accuracy of the model is also evaluated.

3. APPLICATION OF ACTUAL MEASUREMENT DATA AND ERROR ANALYSIS

3.1. Study Area Overview

In this paper, a mine in Xinjiang, China, is selected as the landslide study area. The mine is an open pit mine located in the middle and low slope of the Altai Mountains, with an altitude of 1000–1300 m. The terrain is high in the north and low in the east, with a relative height difference of 50–300 m. Due to the mining of the open pit mine, the original topography has been destroyed, and an obvious bedrock slope has been formed. Fig. 2 shows the panoramic view of the open pit mine obtained by using radar.

The experimental data used in this paper are the measured data obtained by linear scanning micro-deformation monitoring radar. Based on the analysis of the deformation map of the mine area to determine the landslide hazard area, three feature points are selected in the landslide hazard area for landslide displacement prediction study. Fig. 3 shows the locations of landslide potential area Area1 and feature points a1, a2, and a3. The source of the data set is the displacement deformation data obtained from April 19, 2021 to April 21, 2021 for the three feature points, and the data sampling frequency is 20 min. Landslide displacement time series of 127 groups for each feature point are finally obtained after collation.

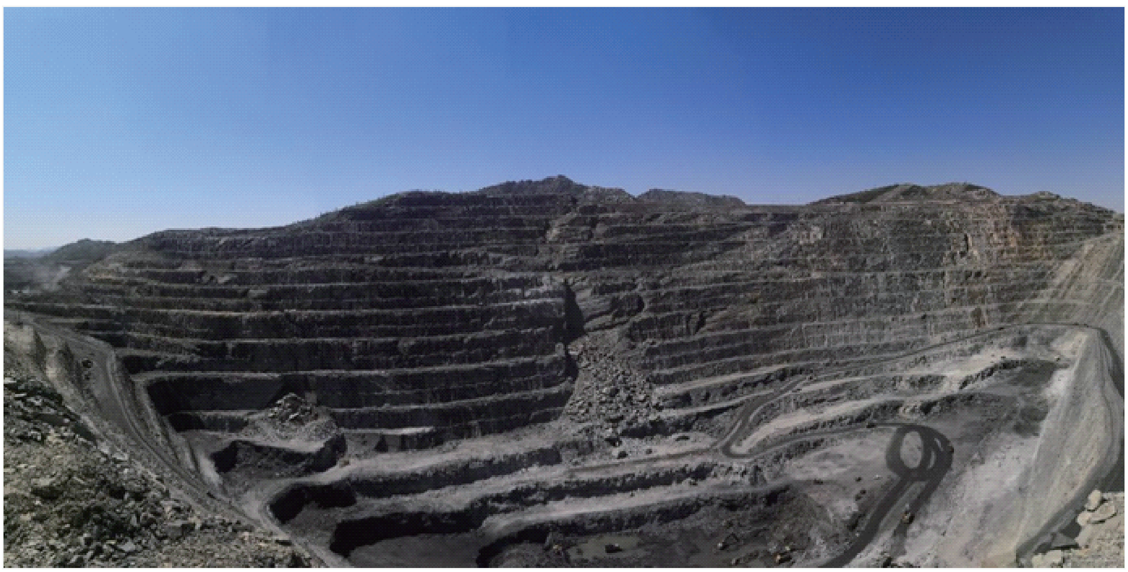

Figure 2. Panoramic view of open pit mine.

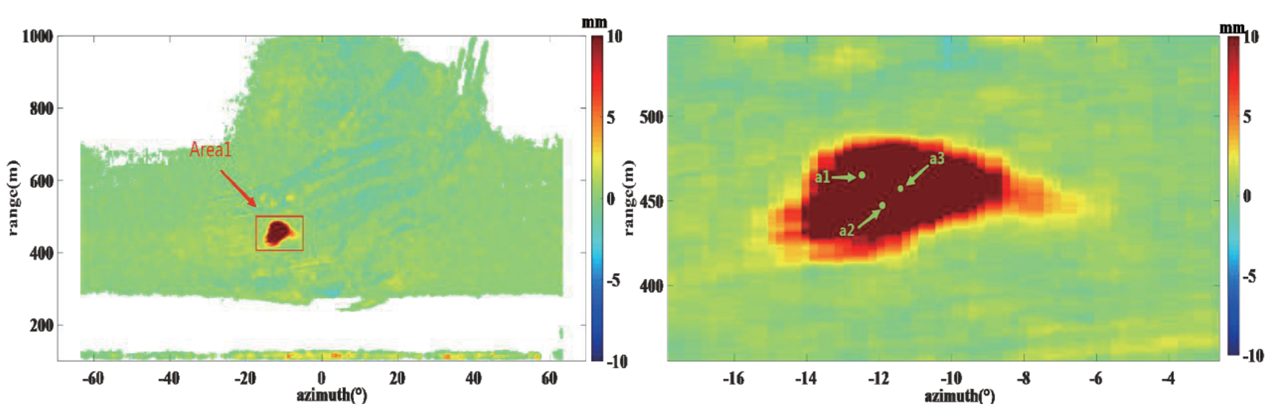

Figure 3. Distribution map of landslide potential hazard area and feature points selection.

3.2. Model Prediction and Comparison

In this paper, a 3-layer CS-BP neural network model is used, and the input information is the displacement corresponding to the first 4 sampling moments (cumulative displacement/displacement increment) and the deformation velocity corresponding to the 4th sampling moment, and the output is the displacement corresponding to the next sampling moment. The last 10 sets of data corresponding to each of the 3 feature points are used as the test set and the rest as the training set. The number of iterations is set to 100, and the number of nests is 10 when building the network. Meanwhile, in order to clearly demonstrate the superiority of the combination of displacement increment and CS-BP network in predicting landslide displacement, this paper also constructs BP, GA-BP, FA-BP, and CS-BP networks based on cumulative displacement and BP, GA-BP, and FA-BP networks based on displacement increment for displacement prediction, and compares and analyzes the prediction results of different models.

Firstly, the cumulative displacement is used as the input of the network, and the prediction results of the test samples with 3 feature points using BP, GA-BP, FA-BP, and CS-BP networks respectively are shown in Fig. 4.

From Fig. 4, it can be observed that for the three feature points a1, a2, and a3, the CS-BP model provides displacement predictions for the test samples that are overall closer to the actual values.

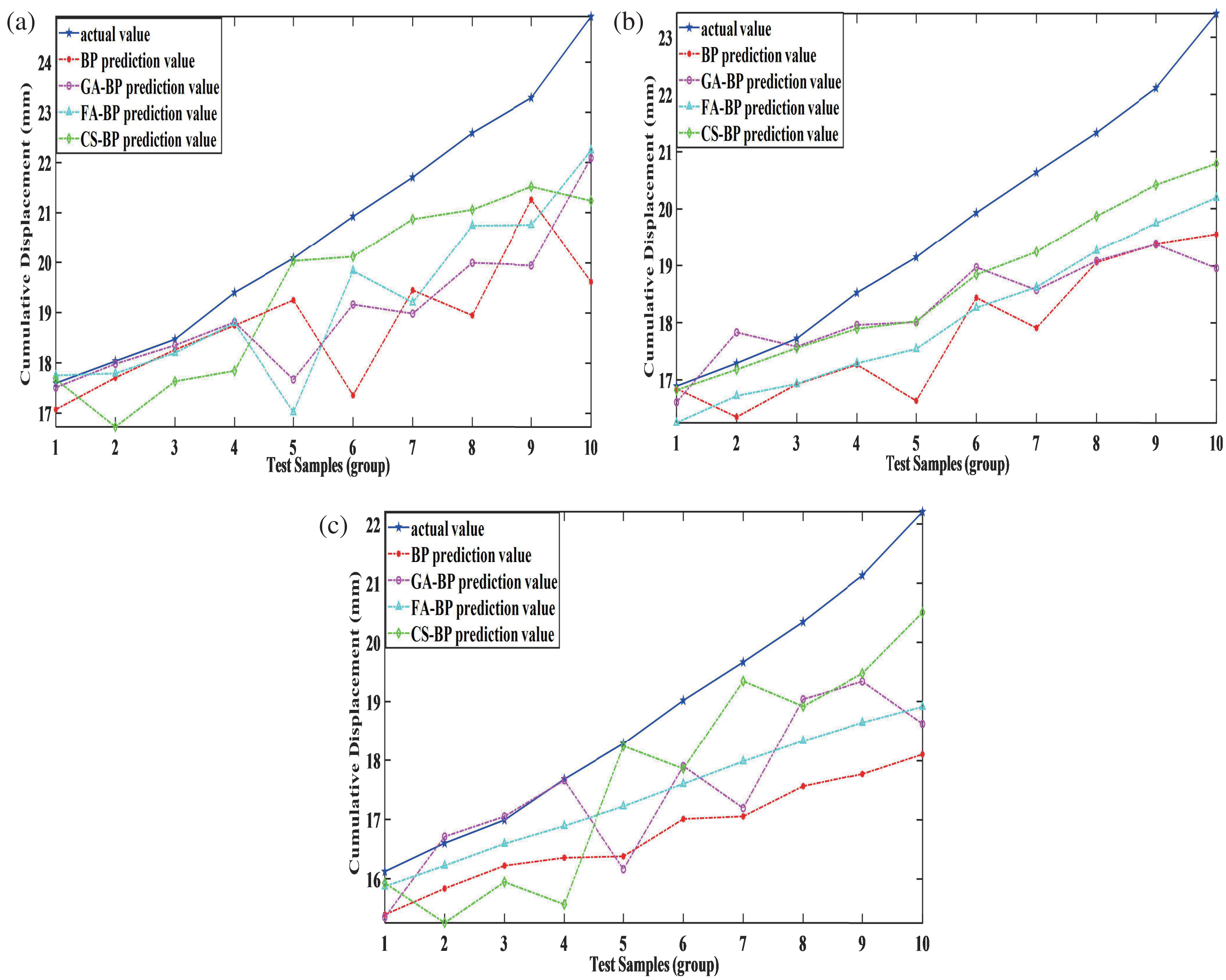

Figure 4. Comparison of displacement prediction by different models based on cumulative displacement. (a) Feature point a1. (b) Feature point a2. (c) Feature point a3.

The prediction accuracy of CS-BP is superior to that of the standalone BP network, and the overall predictive capability of CS-BP is slightly higher than that of the GA-BP and FA-BP models. Based on the analysis of simulation results, it can be considered that the predictive model obtained by optimizing the BP network using the CS algorithm exhibits relatively good predictive performance.

Considering that the displacement increment can better reflect the change process of landslide than the cumulative displacement, it is used as the input data of the network to train the network. At this time, the network prediction results are as follows.

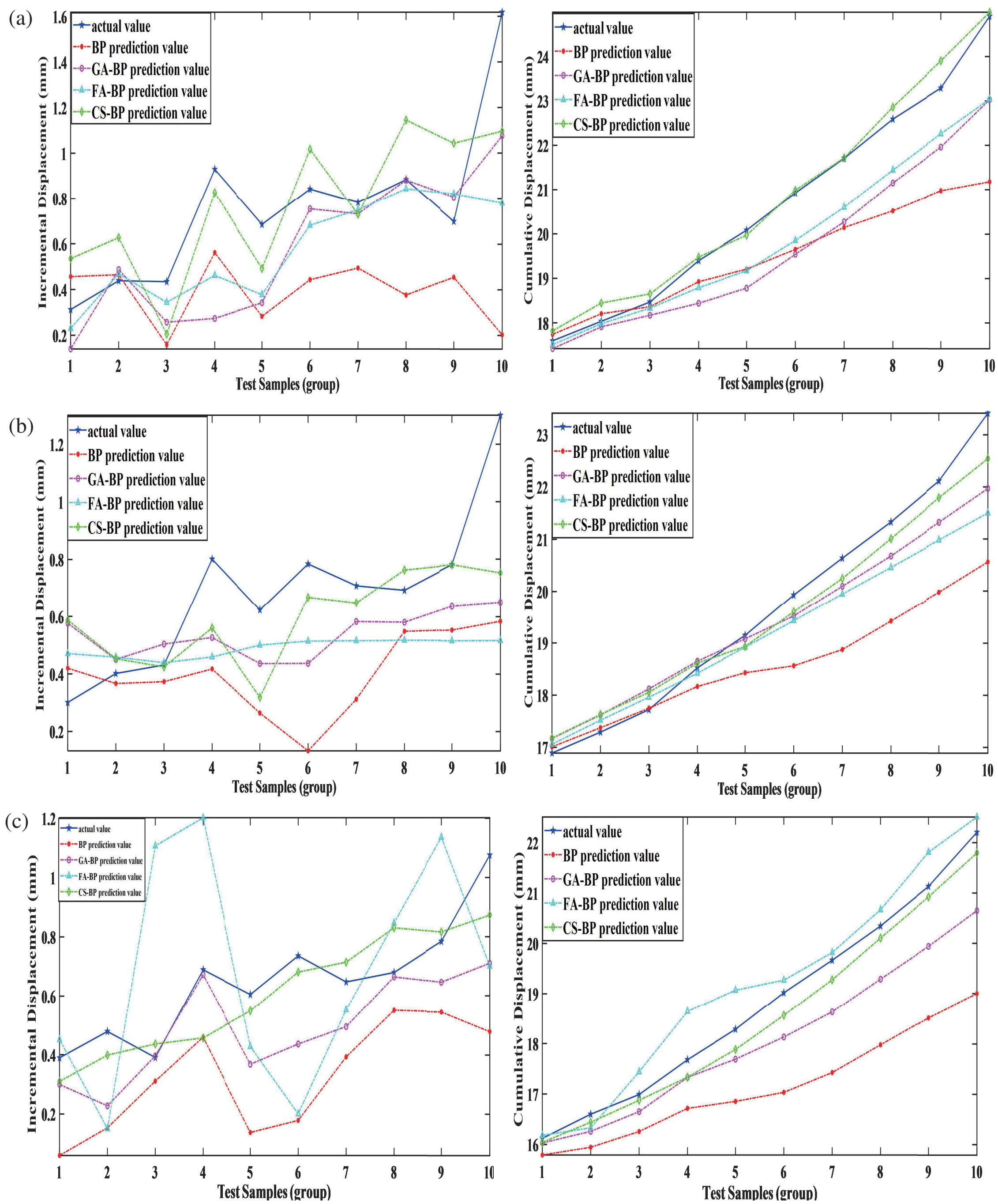

Figure 5. Comparison of displacement prediction by different models based on displacement increment. (a) Feature point a1. (b) Feature point a2. (c) Feature point a3.

In Figs. 5(a), (b), and (c), the left panels show the prediction results of displacement increment corresponding to each of the three feature points, and then the predicted displacement increment is converted into cumulative displacement prediction as shown in the right panels. The results shown in Fig. 5 once again verify the predictive superiority of the CS-BP network model. More importantly, comparing Fig. 5 with Fig. 4, it is obvious that the use of displacement increment as the input to the network makes the network prediction more accurate when the landslide displacement prediction is based on the same network.

To further quantify the comparative analysis, based on the above prediction results, Table 1 shows the corresponding root mean square error (RMSE) and mean absolute error (MAE) when different models are used for prediction. From Table 1, it can be observed that under the same input data conditions, the prediction accuracy of the CS-BP network is higher than that of the single BP network, GA-BP network, and FA-BP network. Specifically, for feature point a1, when using cumulative displacement as input, the RMSE of the CS-BP model on the test set is 1.59 mm, which represents an improvement in prediction accuracy of 37.67%, 23.07%, and 14.87% compared to the BP model, GA-BP model, and FA-BP model, respectively. Similarly, for feature point a2, also based on cumulative displacement as input, the CS-BP model achieves an RMSE of 1.29 mm on the test set, corresponding to improvements of 40.11%, 34.95%, and 28.28% in prediction accuracy compared to the BP model, GA-BP model, and FA-BP model, respectively. For feature point a3, using cumulative displacement as input, the CS-BP model also achieves an RMSE of 1.29 mm on the test set, representing improvements in prediction accuracy of 44.59%, 26.11%, and 24.30% compared to the BP model, GA-BP model, and FA-BP model, respectively. Furthermore, when using displacement increment as input, the CS-BP model exhibits varying degrees of improvement in displacement prediction accuracy for all three feature points compared to the other three models. Specifically, using RMSE as the evaluation criterion, the CS-BP model achieves prediction accuracy improvements of 84.04%, 77.24%, and 72.28% for a1 compared to the BP model, GA-BP model, and FA-BP model, respectively. For a2, the CS-BP model's prediction accuracy improves by 73.16%, 36.81%, and 51.20% compared to the BP model, GA-BP model, and FA-BP model, respectively. Finally, for a3, the CS-BP model's prediction accuracy improves by 83.64%, 64.41%, and 38.82% compared to the aforementioned three models, respectively.

Table 1. Comparison of prediction accuracy of landslide cumulative displacement in mining area.

Monitoring feature points	Evaluation Indicators	Based on cumulative displacement				Based on displacement increment			
		BP	GA-BP	FA-BP	CS-BP	BP	GA-BP	FA-BP	CS-BP
a1	Root mean square error/mm	2.5452	2.0621	1.8635	1.5864	1.6943	1.1880	0.9756	0.2704
	Average absolute error/mm	2.2345	1.6496	1.5083	1.2452	1.2728	1.0330	0.8043	0.2051
a2	Root mean square error/mm	2.1617	1.9903	1.8051	1.2946	1.4843	0.6305	0.8164	0.3984
	Average absolute error/mm	1.8656	1.5134	1.6183	1.0371	1.1344	0.5032	0.6091	0.3495
a3	Root mean square error/mm	2.3203	1.7401	1.6984	1.2857	1.8913	0.8696	0.5059	0.3095
	Average absolute error/mm	2.0366	1.3367	1.3991	1.1007	1.6533	0.7448	0.4230	0.2808

Also, it can be seen from Table 1 that when the displacement increment is used as the input to the prediction network, the cumulative displacement prediction resulting from the conversion of the displacement increment prediction is closer to the true value than the prediction result produced by using the cumulative displacement as the input directly. For example, in the case that use both CS-BP model for prediction and root mean square error as the evaluation criterion, for feature point a1, the prediction accuracy of the network based on incremental displacement is 82.96% higher than that of the network based on cumulative displacement; for feature point a2, the prediction accuracy of the network based on incremental displacement is 69.23% higher than that of the network based on cumulative displacement; for feature point a3, also according to the same comparison, the prediction accuracy of the former network is improved by 75.93% compared with the latter.

The combined results of the above analysis show that the CS-BP prediction model based on displacement increment proposed in this paper shows better prediction ability in the displacement prediction of all three feature points, and it also shows that the model has better feasibility for landslide displacement prediction in mining areas.

4. CONCLUSION

In this paper, we propose a landslide displacement prediction method combining displacement increment and CS-BP neural network to address the limitations in predicting landslide displacement in mining areas based on cumulative displacement using a single BP neural network, and compare and verify the reliability and feasibility of the proposed method using a mine in northwest China as an example.

(1) In order to avoid the problem that the prediction range of the network obtained by using the previous cumulative displacement as the training data will exceed the training range when predicting the subsequent data, which will affect the prediction accuracy, the displacement increment is used as the training data, which can effectively avoid the above situation.

(2) The introduction of CS algorithm to optimize the BP neural network solves the problem that a single BP neural network tends to fall into local convergence, so that the network has higher prediction accuracy in displacement prediction.

Therefore, the prediction method proposed in this paper has some practical value in the prediction of landslide displacement in mining areas. However, there are many factors affecting the landslide instability, and how to combine the parameters of many factors and more advanced prediction algorithms to establish a comprehensive prediction model will be the next research direction.

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