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APPLICATION OF LRN AND BPNN USING TEMPORAL BACKPROPAGATION LEARNING FOR PREDICTION OF DISPLACEMENT

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Abstract— Landslides are the most threatening geo-hazard. It is a kind of genetic type of slope and has same characteristics with slope. Chaotic time series of landslide displacement and its influential factors could reflect the history of landslide displacement of dynamic system. This study aims to investigate suitable model and predict future displacement values. Displacement could be predicted by considering and reconstructing the relationship among the triggering factors and LRN and BPNN could reflect relationship among variables. Temporal back propagation algorithm has been employed in traditional BPNN. Comparative analysis of the models with other existing techniques such as RBF shows that, RBF produces accurate results only during training but prediction error is not less than that of LRN and BPNN. Comparisons of all three models (RBF, LRN and BPNN) have been performed using MSE (Minimum Square Error) and regression values.

Keywords— LRN, BPNN, prediction of landslide displacement, temporal back propagation learning.

I. INTRODUCTION

Slope is a nonlinear dynamic system. There are various factors such as topography, groundwater, soil type, earthquake, rainwater are few parameters which trigger the landslide in a particular region. Landslides are the genetic type of slope and have same characteristics. Deformation of landslide can be predicted in short time by chaotic time series data recorded for any particular slope. Artificial neural network (ANN) model have an ability to recognize time series patterns and nonlinear characteristics, which gives better accuracy over the others methods, it become most popular methods in making prediction (Vaziri, 1997; Sharda, 1994; Jones, 2004; Toriman et al., 2009). Various network models have been adopted for predicting landslide, one such type of model based on RBF has been develop for prediction. In this research paper we have presented a layer recurrent network (LRN) and BPNN with temporal back propagation learning algorithm which is constructed using the time series data which is discussed in later section. The constructed networks have been compared with the RBF network.

II. RESEARCH METHODOLOGY

A. Backpropagation Neural Network (BPNN)

Backpropagation is the most widely used learning algorithm and is a popular technique because it is easy to implement. It requires data for conditioning the network before using it for predicting the output. Training a network by backpropagation involves three stages: the feed forward of the input training pattern, the backpropagation of the associated error, and the adjustment of the weights (Laurene, 1994).In BPNN network, there are four important considerations are comprised in network designs which are the network architecture determination, hidden neuron number determination, activation function optimization and training algorithm optimization. The network is trained using Levenberg-Marquardt algorithm. In the case of supervised learning, the network is presented with both the input data and the target data called the training set. Externally provided correct patterns are compared with the ANN output during training and feedback is used to adjust the weights until all training patterns are correctly categorized by the network.

B. Layer Recurrent Network (LRN)

LRN incorporate a static multilayer perceptron or parts thereof. They exhibit the nonlinear mapping capability of the multilayer perceptron. LRN can have one or more hidden layers, basically for the same reasons that static MPL are often more effective than those single hidden layer. Each computation layer of a recurrent network has a feedback around it as illustrated in Fig.1. Let the vector $x_1(n)$ denote the output of hidden layer, $x_{11}(n)$ denote the output of the second hidden layer, and so on. Let the vector $x_0(n)$ denote the output of the output layer. Then the dynamic behavior of the recurrent network, in general, in response to an input vector u(n) is described by the following system of equations:

$$x_1(n+1) = \varphi_1(x_1(n), u(n))$$
$$x_{11}(n+1) = \varphi_{11}(x_{11}(n), x_1(n+1))$$
$$.$$
$$.$$
$$x_0(n+1) = \varphi_0(x_0(n), x_K(n+1))$$

where $\varphi_1(\cdot,\cdot)$, $\varphi_{11}(\cdot,\cdot)$ denotes the activation functions characterizing the first hidden layer and second hidden layer, $\varphi_0(\cdot,\cdot)$ denote the activation function of output layer of LRN.

The recurrent network based on use of static multilayer perceptron and delay line memories, provides a method for implementing the nonlinear feedback system described by equations:

$$x(n+1) = \varphi(W_a x(n) + W_b u(n))$$
$$y(n) = Cx(n)$$

where W_a, W_b , C and y(n) represents the synaptic weights of hidden neurons in that are connected to feedback nodes in input layer, synaptic weights of hidden neurons connected to source nodes in input layer, synaptic weights of linear neurons in the output layer that are connected to hidden neurons and the output respectively. Activation functions used in the network can be logistic function or hyperbolic tangent function.

III. ENGINEERING EXAMPLE

1) Landslide Displacement Data

The monitoring data which has been used to construct the network model is recorded from August 2003 to July 2007. 47 group time series are obtained and time interval between each record is one month. It include seepage pressure, steel stress of central main reinforcement in the north of anti-slide pile, steel stress of central main reinforcement in the north of anti-slide pile and displacement. The monitored data is of Hong Shi-bao landslide obtained from Institute of Water Resources and Hydropower Research.

2) Establishing Forecasting Model

Landslide displacement is a direct reflection of the state of the landslide. External dynamical factor such as groundwater, seepage pressure contribute majorly in displacement. Whereas other factors such as anti-slide pile can be main resistant factor of landslide displacement. Landslide is evolved under the combined effects of these factors. The impact of groundwater to landslide is characterized by seepage pressure, while the working state of anti-slide pile is represented by steel stress in anti-slide pile.

3) Prediction Model

During training, the inputs to the feed forward network are just the real/true ones – not estimated ones, and the training process will be more accurate. Network models have been designed using MATLAB neural network toolbox. The network training function updates the weight and bias values according to Levenberg-Marquardt optimization (trainlm). In general, in function approximation problems, for networks that contain up to a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence. Training and testing data is divided using divider and function. 70% of training, 15% of validation and 15% of testing data is obtained from the total dataset of 47 group records.

3.1) BPNN Model with time delaynet

A three layer time lagged feed forward network have been designed using time delaynet function with delay at input layer only. Activation functions used in the network is logarithmic sigmoid function (logsig). This part presents the results of the experiment using BPNN. The number of neurons in the hidden layer is determined by trial and error method. The trials initialize at error with 2 nodes first. Then, the process is repeated until 15 nodes. A comparison of the MSE value for all number of nodes was carried out. The lowest MSE value will be selected as optimum number of nodes in hidden layer. Based on Table 1, the lowest MSE value is 0.005 with 4 nodes in hidden layer. This result is also supported by the R value which is the highest (0.998) at 4 nodes. The R value measures correlation between Outputs and Targets. An R value close to 1 means a close relationship while vice versa indicates a random relationship. Hence, 4 nodes are selected as optimum number of nodes in hidden layer.

TABLE I. - BPNN NETWORK

Nodes	MSE	R	Nodes	MSE	R
2	0.049	0.988	9	0.0017	0.999
3	0.041	0.997	10	0.034	0.997
4	0.005	0.998	11	0.033	0.997
5	0.023	0.998	12	0.036	0.998
6	0.010	0.993	13	0.020	0.998
7	0.009	0.994	14	0.031	0.996
8	0.019	0.993	15	0.046	0.997

3.2) Layer Recurrent Network

LRN is a dynamic network, in this there is a feedback loop, with a single delay, around each layer of the network. The Fig2 illustrates a two layer LRN.

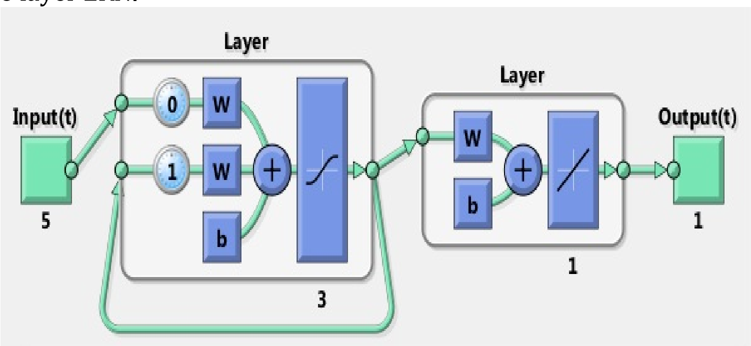

Fig2 Two layer LRN Network with feedback

The LRN network in toolbox have been designed using newlrn function, goal to be achieved set to value 0.001.Training function trainlm have been used. The number of neurons in hidden layer is determined by trial and error method. Feedback loop set to tapped delay value of 1. Table2 shows that minimum error is achieved at 3 hidden nodes.

TABLE II- LRN NETWORK

No. of Nodes	MSE	R	No. of Nodes	MSE	R
2	0.2382	0.9850	9	0.0698	0.9957
3	0.0041	0.9997	10	0.0119	0.9950
4	0.0380	0.9874	11	0.0462	0.9970
5	0.0175	0.9989	12	0.0540	0.9965
6	0.0203	0.9936	13	0.0301	0.9981
7	0.1149	0.9607	14	0.0270	0.9982
8	0.0836	0.9989	15	0.0126	0.9998

3.3) RBF Neural Network

Radial basis function based neural network is also constructed for comparison of prediction results and for determination of efficacy of the network present in this paper. A RBF network is designed using newrb function which designs a RBF network starting with 0 neurons in hidden layer and at each step it increase the number of neuron by one, thereby decreasing the error value in each step. The number of hidden neurons can reach up to N, where N is the number of data points in training set.Table3 represents the MSE values achieved against number of nodes in hidden neuron. It shows that minimum error achieved is 0.006 with 27 hidden neurons and regression value of 0.996.

TABLE III - RBF NETWORK

No. of Nodes	MSE	No. of Nodes	MSE
2	4.9123	15	0.1422
3	2.8120	16	0.1232
4	1.5778	17	0.1123
5	1.5231	18	0.0921
6	0.7031	19	0.0810
7	0.6681	20	0.0646
8	0.6624	21	0.0478
9	0.5398	22	0.0375
10	0.4085	23	0.0345
11	0.2980	24	0.0337
12	0.2242	25	0.0307
13	0.2200	26	0.0285
14	0.1660	27	0.0060

3.4) Model Selection

All the three networks which have been developed are compared on minimum square error and regression values. The model having the lowest MSE can be used for prediction. Table3 shows the MSE and R values for respective networks.

TABLE IV - CALCULATION RESULTS

Network	MSE	R
LRN	0.0041	0.9997
BPNN	0.0050	0.9988
RBF	0.0060	0.9996

The above table shows small fraction of variation in MSE values. But the way different networks converge the error gradient differs. RBF model employs curve fitting in high-dimension space. Spread factor of RBF effect the prediction results. Too large a spread means a lot of neurons are required to fit a fast-changing function. Too small a spread means many neurons are required to fit a smooth function, and the network might not generalize well. RBF with N hidden neurons, where N is number of training examples, will produce zero error with design vectors, but error in testing vectors is not acceptable as compared to other networks. Feed forward networks such as BPNN with time delays to perform temporal processing can be used for prediction. A supervised learning algorithm in which the actual response of each neuron in output layer is compared with a desired (target) response at each time instant. Error $e_j(n)$ at each output node is calculated by:

$$e_j(n) = d_j(n) - y_j(n)$$

where index j refers to a neuron in output layer, $d_j(n)$ is desired value and $y_j(n)$ is actual output of node. The goal is to minimize a cost function defined as the value of $\mathcal{E}(n)$ computed over all time:

$$\mathcal{E}_{total} = \Sigma\, \mathcal{E}(n)$$

The weight update equation for the temporal backpropagation is as follows:

$$W_{ij}(n+1) = W_{ij}(n) + \acute{\eta}\, \delta_j(n)\, x_i(n)$$

where $\acute{\eta}$ is the learning rate. The local gradient $\delta_j(n)$ is thus formed is not by simply taking a weighted sum but by backward filtering through each primary synapse. In temporal back propagation the symmetry between the forward propagation of states and the backward propagation of error terms is preserved. Table3 shows that recurrent networks can achieve lower error for prediction of landslide displacement. LRN does not suffer from under fitting or over fitting. The training sample of displacement data provided to the LRN is representative of the non-stationary behaviour of the environment.

IV. CONCLUSIONS

The prediction of landslide displacement was related to several influencing factors and there were interactions in factors. Various Neural networks establish nonlinear relationship among those factors. Different architectures of recurrent networks can be used for temporal processing. The approaches which we have presented in this paper have shown that minimum error is achieved through LRN for displacement prediction. The LRN model can be considered as an alternative model for forecasting purposes of landslide displacement.

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REFERENCES

1. Vaziri, M., (1997). Predicting Caspian Sea surface water level by ANN and ARIMA models. J. Waterway, Port, Coastal Ocean Eng., 123: 158-162.
2. Laurene, F. (1994). Fundamentals of Neural Networks: Architectures, Algorithm, and Applications. United States: Florida Institute of Technology.
3. Yao Zeng, Echuan Yan, Chunfeng Li, Ying Li, (2008). Application of Multivariable Time Series Based on RBF Neural Network in Prediction of Landslide Displacement, 9th International Conference for Young Computer Scientists, IEEE Computer Society, DOI 10.1109/ICYCS.2008.163.
4. Howard Demuth, Mark Beale. (2013). Neural Network Toolbox for use with MATLAB, User's Guide Version 4, The Math Works, Inc.
5. Simon Haykin, Neural Networks A Comprehensive Foundation, Second Edition (2004). Pearson Education.
6. LIU Yong-jian, ZHANG Bo-you. “Application of Chaotic Time-series in Slope Displacement Forecasting”, Journal of Liaoning Technical University, 2007, 26(1), pp. 74～76