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A new interactive model for improving the learning performance of back propagation neural network

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Abstract

The Back Propagation Neural Network (BPNN) has been used widely in construction management, but in fact, the BPNN is limited by a non-optimum weight adjustment manner and negatively influenced the convergence results. For this reason, this paper proposes the Individual Inference Adjusting Learning Rate technique (IIALR) to enhance the learning performance of the BPNN. The mechanism of the weight adjustment in the IIALR is an individual learning rate for each weight. Furthermore, this paper also establishes the Batch-Online Weight Updating Frequency mode (BOWUF) for the IIALR model, so as to adjust the connected weight of the BPNN properly and effectively. Finally, three cases are used to verify that the IIALR model can be more effective than other modifications of the BPNN. The IIALR model is conducive for assisting with the decision making process of construction management.
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1. Introduction

The Back Propagation Neural Network (BPNN) is one of the best-known neural networks using a supervised learning. The BPNN has often been employed to predict, classify, and optimize in the practice of construction management, such as cost estimating (Gunaydin [1]), risk analysis (Attalla [2]), and contractor rating (Wang [3]), etc. However, since the weight connections of the BPNN are not optimum, the non-optimum weight connections generate a low percentage of the correct output for those problems (Erdogan [4]).

For solving this, two approaches have been developed for promoting the learning performance of the BPNN. One approach focuses on the network architecture and the other aims at the learning environment. Both approaches guide the BPNN to the optimal solutions, and this paper focuses on the posterior approach.

In the first approach, attention has been paid to adaptive selection of the network architecture of the BPNN. Generally, the number of nodes in the input and output layers are determined by the dimensionality of the problem. Thus, although smaller networks can prove to be very beneficial in terms of generalization, their training may require a lot of efforts (Bebis [5]). Small networks get trapped to local minima easily, so new hidden nodes are added to change the shape of the weight space and to escape the local minima.

Some algorithms attempt to improve the generalization capabilities of a network by modifying the architecture as training proceeds. Among these algorithms, the Genetic algorithm (denoted as GA in this paper) and the Fuzzy logic are two popular ones.

The GA, inspired by the biological mechanisms of reproduction, operates iteratively on a population of architectures. Each chromosome represents a candidate solution to the problem that the algorithm tries to solve. Through the evolution process of population, the GA can create the optimization solution. Based on the mechanism, Leung [6] and Tsai [7] both had adopted the GA to find the optimum architecture of the BPNN.

Leung [6] proposed the tuning of the structure and parameters of a neural network using an improved GA. In

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Leung's research, the number of hidden nodes is chosen manually by the increase from small number until the learning performance in terms of fitness is good enough.

For the capability to explore globally of the GA, Tsai [7] combined the traditional GA with the Taguchi method. The new algorithm is named hybrid Taguchi-genetic algorithm (HTGA). Using the HTGA, users can solve the problem of tuning both network structure and parameters for a feedforward neural network.

The other popular algorithm for adjusting network architecture of the BPNN is the Fuzzy logic. For its strong reasoning ability, the fuzzy logic is usually used to be a substitute of transferring unit of the BPNN, or to be a part of adjusting mechanism of architecture of the BPNN. The reinforcement structure/parameter learning algorithm is called the Fuzzy Neural Network model (denoted as the FNN in this paper), which can promote learning performance of the BPNN.

Lin [8] proposed the FNN model that used the fuzzy membership functions to be the transferring functions of the hidden nodes of the BPNN. Moreover, the learning algorithm adopts the fuzzy similarity measure to learn the optimal network architecture of the FNN. The fuzzy similarity measure can get a proper node number of hidden layer (amount of the fuzzy rules).

Huang [9] adopted the rough set theory to construct a modified FNN. The modified FNN is a knowledge-based network that uses the fuzzy threshold to shit the unnecessary fuzzy rules out. The number of the reduced rules is used as the number of hidden layers' nodes.

Jang [10] proposed the Temporal Back Propagation model that uses both circle and square nodes in an adaptive network. A square node (adaptive node) has modifiable parameters while a circle node (fixed node) has none. The parameter set of an adaptive network is the union of parameter sets of each adaptive node.

The second approach is related to the learning environment, which includes the issues of learning rates and updating frequency. This paper focuses on the learning environment to promote the learning performance of the BPNN.

The learning rate, denoted as η, is an important controlling variable for the weight adjustment in the BPNN. The value of η is usually set to be a constant and obtained through trial and error. The constant learning rate means that one learning rate is employed for all weights in the whole learning process. However, Ye [11] proposed that the constant learning rate of the BPNN fails to optimize the search for the best weight combination. Such a search methodology has been classified as a "blind-search".

Jacobs [12] first indicated that the learning rate of each iteration should be different in the weight adjustment process, and the scale of dimensions in the weight space cannot fit for all weights. Hamey [13] furthermore proved that the surface of weight space is rough, and has many peaks and valleys within, because the scales of dimensions in weight space are different. It may generate producing a local minimum in the weight searching of the BPNN.

In addition, the manner of the weight updating frequency is another important factor that influences the learning performance of the BPNN. The Batch mode and the Online mode are the most commonly used for the weight updating frequency. Heskes [14] indicated that the flat and fixed adjustment types of weight searching make the search results fall into a local minimum of error, when the BPNN adopts the Batch mode and the learning rate is closed to zero. This local minimal value causes a false convergence and a premature termination of the learning process.

On the other hand, Wilson [15] proposed that when the Online mode is used, the large learning rate may help the search leap local minimum of weight space, but the noise of the training data results in an unsteady influence on the local gradient of the weight adjustment and the learning rate. This leads to "over-shooting" in the search for the best weight combination and produces a minimum output error.

In order to overcome the above problems in the approach of learning environment, this paper proposes an interactive model for improving the learning performance of the BPNN. A new adjusting learning rate technique and a new weight updating frequency manner are developed. This new model is able to adjust the connected weight of the BPNN properly and effectively.

The individual learning rates can fit the different scales of dimensions of error space of the BPNN, and the mechanism of network structure adjustment tries to fit the error space of the BPNN, too. Therefore, the new adjusting learning rate technique can avoid the trapping local minima in the best weight combination searching process.

Furthermore, the new individual weight updating frequency mode is developed for the variable learning rate. It combines the advantages of the Batch weight updating frequency mode and the Online weight updating frequency mode, so as to adjust the learning rate timely.

2. Basic concept of modeling

With these characteristics now well defined, a course of action in dealing with them must be determined. Many algorithms were derived to adjust the learning rate and find the error function using different methods of weight searching. The Delta-bar-delta method is previously introduced by Jacobs [14] to solve these issues. In this method, the increase or decrease of the learning rate depends on the positive or negative values of the weight gradient, respectively, which is derived from the error function of previous learning iterations.

Additionally, Yamada [16] proposed the STELA method to improve the learning rate, in which an interval learning state is defined as the saturated state of the nodes in the hidden layer. In the interval learning state, the gradient of the weight adjustments is decreased until the termination of the interval learning. Then the gradient of weight adjustments for the following iterations will be recovered to the original value.

Through the two above-mentioned algorithms, it can be proved that the learning rate and weight adjustment can be decided by the state of weight change. Unfortunately, the learning rates of these two algorithms only show the adjustment direction that the learning rates have calculated, and the exact

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