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Bacterial Foraging Optimization Algorithm for Evolving Artificial Neural Networks

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ABSTRACT
Artificial Neural Network (ANN) is a powerful artificial tool suitable for solving combinatorial problems such as prediction and classification. The performance of ANN is highly dependent upon its architecture and connection weights. To have a high efficiency in ANN, selection of an appropriate architecture and learning algorithm is very important. ANN learning is a complex task and efficient learning algorithm has a significant role to enhance its performance. The process of weight training is a complex continuous optimization problem. This paper deals with the application of swarm intelligence based algorithm, Bacterial Foraging Optimization (BFO) for training feed-forward and cascade-forward ANNs. BFO algorithm which is based on the foraging strategy of bacteria is adopted to train the connection weights and to evolve the ANN learning and accuracy. The experiments performed on dataset taken from promise repository verify the potential of BFO algorithm and showed that classification accuracy of BFO-ANN is more than the traditional ANN.

General Terms
Artificial Neural Networks, Bacterial Foraging Optimization Algorithm

1. INTRODUCTION
The structure and methodology of an ANN is based on the functioning of human brain. ANN has the ability to identify patterns in data. Artificial Neural Networks has been well recognized for its approximation capability provided the input-output data are available.

An ANN is also highly accurate in classification and prediction of output because of its massively parallel processing, fault tolerance, self organization and adaptive capability which enables it to solve many complex problems.

The advantage of ANN lies in the fact that they do not require any complex mathematical formulations or quantitative correlation between inputs and outputs. However, training a neural network, regardless of the training method chosen, is not an easy task, as the performance of an ANN is dependent on the factors such as ANN architecture and connection weight values.

One of the most popular training algorithms in the domain of neural networks is the back-propagation technique, which is gradient descent method to adjust weight values so as to minimize the error between the desired output and actual outputs for particular inputs to the network. However, Back Propagation has drawback of converging into local minima.

To deal with this convergence problem, many researchers have proposed many powerful optimization algorithms. In this study, the adaption of neural network connection weights using Bacterial Foraging Optimization Algorithm (BFOA) is proposed as a mechanism to improve the performance of Artificial Neural Network in classification of a Dataset. BFOA is a new global search technique based on swarm intelligence which mimic the food searching and reproduction strategy of bacteria.

2. ANN AND ANN TRAINING
Artificial neural networks consist of interconnected simple processing elements known as artificial neurons with internal adjustable parameters known as connection weights. Artificial neurons weight, sum and threshold incoming signals to produce an output. Information is stored within the strength of the interconnections or weights and the thresholds/biases. These networks can learn an arbitrary vector mapping from the space of input to the space of output by modification of the weight values.

The process of optimizing the connection weights is known as training or learning. The optimal connection weights are difficult to set. It is a continuous optimization problem. The goal of the neural network training procedure is to find the optimal set of connection weights that will cause the output from the artificial neural network to match the actual target values. The network learns a function by adapting the strength of its connection weights in response to the training examples presented to it in accordance with a predefined learning law. ANNs are trained by applying an optimizing algorithm, which attempts to reduce the error in the network output by adjusting the matrix of network weights. The primary objective of ANN training is to find a set of connection weights that minimizes the error function.

During learning, the network is presented pairs of input/output data and the error (difference between predicted output and actual output) is computed. An attempt is made to search for a global minimum on the performance function surface over the space of the network parameters or weight values. Once trained, the ANN can then be used to predict outputs from unseen inputs.

3. BFOA IN ANN LEARNING
BFOA is employed to optimize the connection weights and learning of ANN. The training process of artificial neural network involves providing input/output pairs. The main goal of training ANN is to obtain a set of connection weights that gives minimum error. Initially, feed forward and cascade forward artificial neural network is trained using scaled conjugate back propagation algorithm. Accuracy is calculated and extracts the connection weight values of the network. These connection weights are then optimized by employing

BFOA. The number of bacterium is equal to the number of values to be optimised i.e. equals to number to connection weights. The optimizing variables are weight matrix (w_1, w_2, ..., w_n).

The parameters to be optimized represent coordinates of the bacteria in solution search space. After each chemotactic step, the bacteria move to new position (new coordinate values) and at each new position cost function is calculated and then, depending upon this cost function , next movement of the bacteria is decided by decreasing direction of cost function. This leads bacteria to a position (set of optimization values) with highest fitness. BFOA calculates cost function after each iterative step of the program as the program executes and progressively leads to optimal solution with better fitness (less cost function). Mean Squared Error is taken as the cost function in this study.

Advantages of BFOA over back-propagation

- Less dependence on the initial weight values since multiple starting points are used in the search process.
- Population based search is less prone to premature convergence on local minima than back propagation.
- Derivatives of activation function and error function is not used, thus the activation function and the error function need not to be differentiable.

4. RESULTS

4.1 Performance Comparison

The comparison of normal neural networks and BFOA trained ANNs is shown in following tables.

Table 1 Performance Comparison of Feed Forward SCG Backpropagation ANN and BFOA-ANN

	Evaluation					
	SCG-Feed Forward ANN			BFOA-Feed Forward ANN		
	Accuracy	Mean Absolute Error	Root Mean Square Error	Accuracy	Mean Absolute Error	Root Mean Square Error
1st Iteration	76.5854	0.2341	0.4839	79.0244	0.2098	0.4580
2nd Iteration	76.0976	0.2439	0.4939	80.0000	0.2000	0.4472
3rd Iteration	78.0488	0.2195	0.4685	80.4878	0.1951	0.4417
4th Iteration	77.0732	0.2293	0.4788	79.5122	0.2049	0.4526
Mean Value	76.95125	0.2317	0.481275	79.5061	0.20245	0.449875

Table 1 shows the results after applying data sets on SCG Backpropagation Feed Forward ANN model and BFOA trained Feed Forward ANN model.

Table 2 Performance Comparison of Cascade Forward SCG Backpropagation ANN and BFOA-ANN

	Evaluation					
	SCG-Cascade Forward ANN			BFOA- Cascade Forward ANN		
	Accuracy	Mean Absolute Error	Root Mean Square Error	Accuracy	Mean Absolute Error	Root Mean Square Error
1st Iteration	77.5610	0.2244	0.4737	79.0244	0.2098	0.4580
2nd Iteration	78.0488	0.2195	0.4685	81.4634	0.1854	0.4305
3rd Iteration	78.5366	0.2146	0.4633	80.9756	0.1902	0.4362
4th Iteration	75.1220	0.2488	0.4988	79.0244	0.2098	0.4580
Mean Value	77.3171	0.226825	0.476075	80.12195	0.1988	0.445675

Table 2 shows the result after applying data sets on SCG Backpropagation Cascade Forward ANN model and BFO trained Cascade Forward ANN model.

4.2 Result Analysis

The improvement in performance of BFOA-ANN over normal neural networks is given in table below.

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Table 3 Improvement in the Prediction Accuracy of the ANN Model and BFO-ANN Model

Prediction Model	Evaluation			
		Accuracy	Mean Absolute Error	Root Mean Squared Error
Feed Forward ANN vs. BFO-Feed Forward ANN	Feed Forward ANN Model	76.95125	0.2317	0.481275
	BFO-FF-ANN Model	79.5061	0.20245	0.449875
	Improvement %	2.55485	0.02925	0.0314
Cascaded-Forward ANN vs. BFO Cascaded-Forward ANN	Cascaded ANN Model	77.3171	0.226825	0.476075
	BFO Cascaded ANN	80.12195	0.1988	0.445675
	Improvement %	2.80485	0.028025	0.0304

This table shows the comparison of accuracy between the scaled Conjugate gradient back propagation trained Artificial Neural Network (ANN) and neural network optimised using Bacterial foraging optimisation algorithm (BFO-ANN). BFO-

ANN model gives an improvement of 2.55% and 2.8 % in accuracy in feed forward and cascade forward ANNs respectively which means BFO-ANN model provides more accurate prediction. These comparisons are shown graphically in Figure 1, 2 and 3.

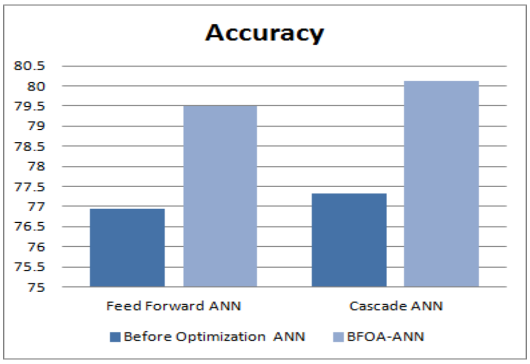

Figure 1 Comparison: Accuracy

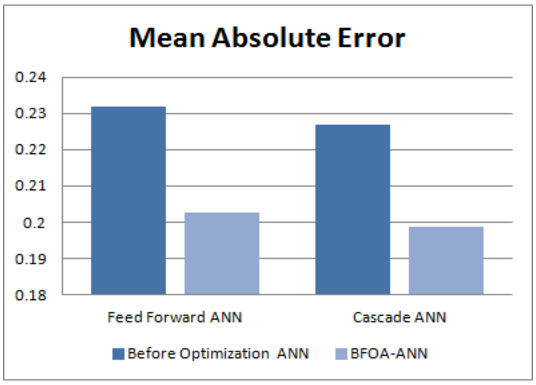

Figure 2 Comparison: Mean Absolute Error

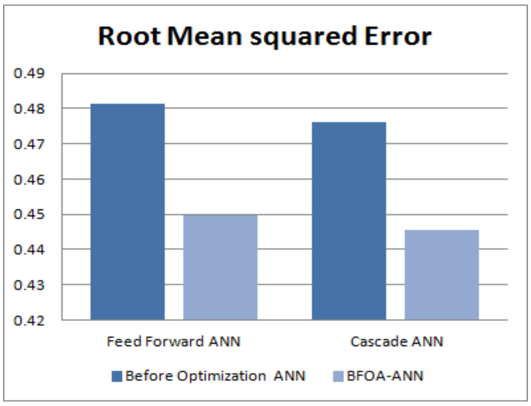

Figure 3 Comparison: Root Mean Square Error

The performance plots of ANN training are shown Figure 4 to Figure 7. In Figure 4 and Figure 5, the performance plot of SCG trained Feed Forward ANN and BFOA Feed Forward ANN is shown respectively. In Figure 6 and Figure 7, the performance plot of SCG Back propagation and BFOA trained cascade Forward ANN is shown respectively

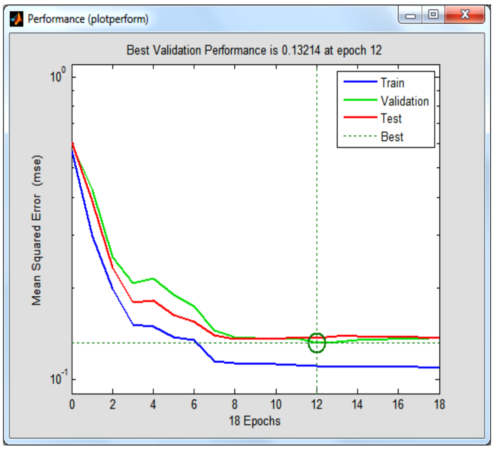

Figure 4 Performance plot of SCG Backpropagation trained Feed Forward ANN

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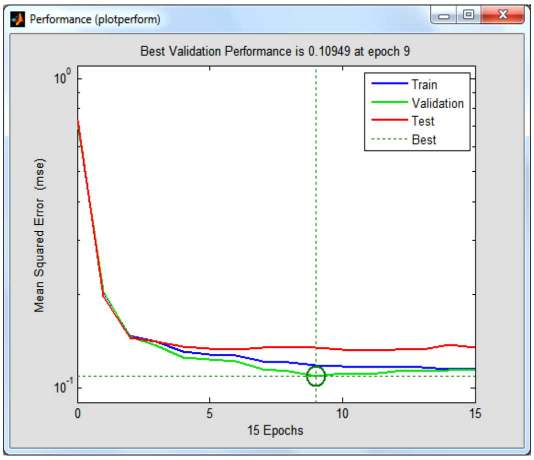

Figure 5 Performance plot of BFOA trained Feed Forward ANN

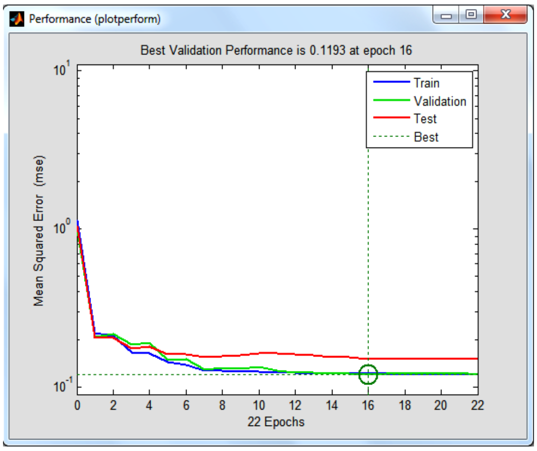

Figure 6 Performance Plot of SCG Backpropagation trained Cascade forward ANN

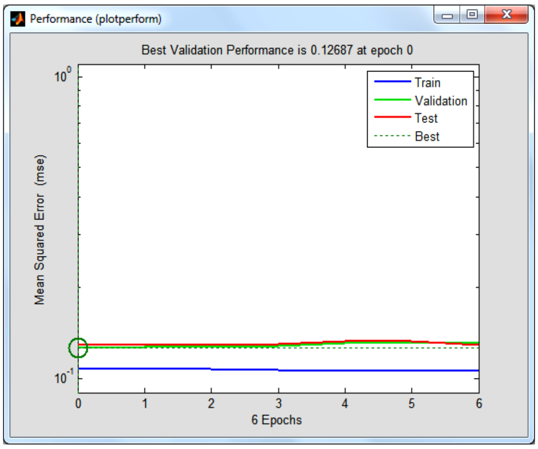

Figure 7 Performance Plot of BFOA trained Cascade forward ANN

5. CONCLUSION

The bacterial foraging optimization algorithm was able to train the artificial neural network with high classification accuracy. The accuracy of BFO trained artificial neural network was improved by 2.55% and 2.8 % in feed-forward and cascade-forward neural networks respectively. Thus, the Bacterial Foraging Optimization is an effective training algorithm for artificial neural networks.

6. REFERENCES

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