A Novel Bats Echolocation System Based Back Propagation Algorithm for Feed Forward Neural Network

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Abstract. Recently several research works have been done on supervised learning in Feed Forward Neural Networks based on different Swarm intelligence techniques rather than conventional Back Propagation algorithm. This paper discussed about the Bats Echolocation System based Back Propagation algorithm as a learning rule for Feed Forward Network. It was found that it increases the learning rate of the network. The performance of Bats Echolocation system based Back Propagation algorithm was validated by simulation and results were compared with conventional Back Propagation algorithm in terms of convergence speed.

Keywords: Feed Forward Neural Network, Swarm intelligence, Back Propagation algorithm, Bats Echolocation System.

1 Introduction

Swarm intelligence was a kind of computational intelligent technique, which had the ability to solve optimization problems [1], [2]. It was developed from the behavior of ants, bees, flocking of birds and fish schooling, where large group of individuals locate their food by coordinated motion [3], [4]. These techniques were found very useful to find a good solution for the system whose parameters are dynamically changing [5]. Bats Echolocation algorithm was proposed as a kind of Swarm intelligence technique called Bats Echolocation algorithm. It was used to increase the convergence speed of Back Propagation algorithm. Back Propagation algorithm was used to train the Artificial Neural Networks for the desired output [6]-[9]. This paper was organized in the following manner. Feed Forward Network was described with diagram and learning process was discussed. The Back Propagation Algorithm was then briefed and the simulation result of Back Propagation algorithm was discussed. Then, the Bats Echolocation system based BP algorithm was discussed. Finally the simulation result of the Bats Echolocation system based BP algorithm was discussed and compared with conventional Back Propagation algorithm.

V.V. Das, E. Ariwa, and S.B. Rahayu (Eds.): SPIT 2011, LNICST 62, pp. 61–69, 2012.

2 Feed Forward Network

The Feed Forward Networks generally possessed the input layer and output layer with hidden layers. The computational units in the hidden layer were called as hidden units. Intermediary computations were performed by these units on the input data before directing to output layer [7], [10]. The neurons in the input layer were linked with the hidden layer neurons, the weights on the links were referred as input-hidden layer weights. Similarly the hidden layer neurons were linked with the output layer neurons and the corresponding weights were referred as hidden-output layer weights. The architecture of Multilayer Feed Forward Network shown in Figure 1 with l neurons in the input layer, m neurons in the hidden layer and n neurons in the output layer.

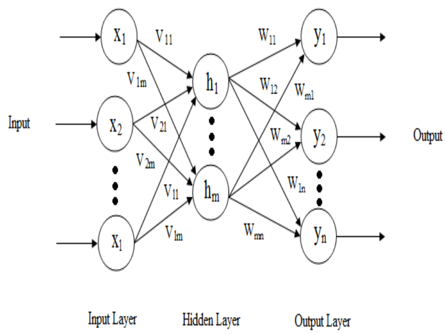

Fig. 1. Architecture of Multilayer Feed forward network

3 Learning Process

A Neural Network was a parallel distributed processor with the capability of storing experimental knowledge and made it available while it was in use [6], [11]. The experimental knowledge was acquired by learning process. Learning process was a kind of process by which network parameters were adapted to the environment through continuous stimulation. In general, learning processes were classified as (i) Supervised learning, (ii) Unsupervised learning [6],[12] and (iii) Reinforced learning [12],[13]. The proposed BP algorithm was a kind of supervised learning. Where the network output was compared with the target which was assigned by an external system. Then the network parameters were adapted (tuned) to reach the target [6], [7], [12].

3.1 Learning with Back Propagation Algorithm

The Back Propagation algorithmwas also called as generalized delta rule. In it, error in the output layer was back propagated to earlier ones in order to update the current input-hidden layer weights and hidden-output layer weights. By updating these weights, the network would learn to reach the target [7]. During learning process, The responses in the input layer was caused by the input , which in turn caused the response in the hidden layer, and then the response of hidden layer causes response in output layer. This response was compared with the target and the error was calculated. Now the algorithm propagated backwards to hidden layer forupdation of weights (updationin weights carried out based on rate of error changes in the output layer) in output layer, by this the error was minimized in the output [7]-[9]. Then the error was calculated in the error in the output and the new values were computed by its weights in the hidden layer. In the algorithm, the error was calculatedin the output the new values of weights were computed in each layer by backward movement to the input until the error was minimized in to a considerable value. Then the next input was selected and the same process was repeated.

3.2 Simulation Results of Back Propagation Algorithm in Feed Forward Network

The simulation results of Back Propagation algorithm were numerically analyzed and shown in table 1. The graphical representation of the simulation results were shown in figure 2.

Table 1. Simulation results of Back Propagation algorithm in Feed Forward Network for number of epochs

Epochs	Input vectors		Input-Hidden layer weights				Hidden-Output layer weights		Error
	I_1	I_2	V_{11}	V_{12}	V_{21}	V_{22}	W_1	W_2	
1	0.4	-0.7	0.1	0.4	-0.2	0.2	0.2	-0.5	0.13264
10	0.4	-0.7	0.0959	0.4266	-0.1927	0.1534	-0.041	-0.7267	0.0911
20	0.4	-0.7	0.1012	0.4584	-0.2021	0.0978	-0.2535	-0.9294	0.0613
30	0.4	-0.7	0.1110	0.4885	-0.2192	0.0452	-0.4184	-1.0904	0.0424
40	0.4	-0.7	01221	0.5153	-0.2387	-0.0019	-0.5485	-1.2192	0.0301
50	0.4	-0.7	0.1332	0.5388	-0.2580	-0.0429	-0.6528	-1.3235	0.0220
60	0.4	-0.7	0.1435	0.5591	-0.2761	-0.0785	-0.7378	-1.4093	0.0165
70	0.4	-0.7	0.1530	0.5768	-0.2927	-0.1094	-0.8083	-1.4808	0.0126
80	0.4	-0.7	0.1615	0.5921	-0.3076	-0.1362	-0.8675	-1.5412	0.0098
90	0.4	-0.7	0.1692	0.6055	-0.3211	-0.1597	-0.9179	-1.5928	0.0078
100	0.4	-0.7	0.1762	0.6174	-0.3333	-0.1804	-0.9614	-1.6375	0.0062
120	0.4	-0.7	0.1881	0.6371	-0.3541	-0.2149	-1.0322	-1.7105	0.0042
140	0.4	-0.7	0.1978	0.6529	-0.3712	-0.2426	-1.0874	-1.7678	0.0029
160	0.4	-0.7	0.2060	0.6658	-0.3854	-0.2651	-1.1316	-1.8137	0.0020
180	0.4	-0.7	0.2128	0.6764	-0.3974	-0.2837	-1.1677	-1.8513	0.0015
200	0.4	-0.7	0.2186	0.6853	-0.4075	-0.2993	-1.1976	-1.8824	0.0011
206	0.4	-0.7	0.2201	0.6877	-0.4102	-0.3035	-1.2055	-1.8908	0.0010

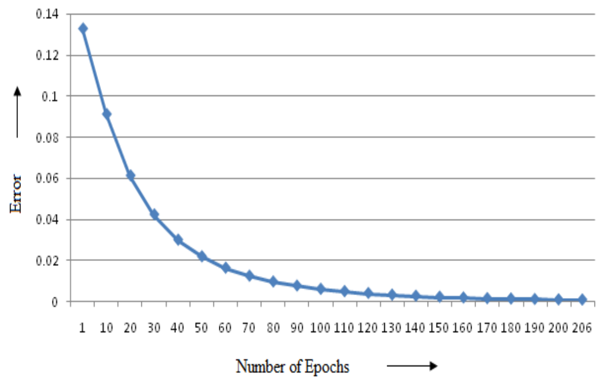

Fig. 2. Error Vs Number of epochs

The Back Propagation algorithm was very simple for implementation and also it had less computational complexity. But it was very slow in convergence [14], [15]. The simulation results, showed that, the target was achieved (expected output 0.1) after 206 epochs. It had 20 epochs to converge 0.02 (approximate) errors in order to reach the target. Particularly this case got worse when we deal the large network with difficult learning task [14]. Theconvergence speed of Back Propagation algorithm was improved by implementing the concept of Bats Echolocation system withinit. The network parameters were used to build the Feed Forward Network and the important parameters which were very essential to invoke the Back Propagation algorithm wre shown in table 2.

Table 2. Network parameters of Feed Forward Network with Back Propagation algorithm

Network parameters	Values
Number of Epochs	206
Number of neurons in input layer	2
Number of neurons in hidden layer	2
Number of neurons in output layer	1
Target	0.1
Input data	0.4,-0.7
Sigmoidal gain (α)	1
Learning rate coefficient (η)	0.6

4 Bats Echolocation System

Several animals in the world had the ability to navigate in the dark and locate the pray using sound waves, like cave swift lets, oil birds, cetaceans and bats. The ultrasonic sound bursts in the form of series of clicks was transmitted by Bats in 5 to 20ms duration at a rate of 10 Hz while searching for pray[16]. Once target of interest was detected, bats entered in to the approach mode. In this mode, the distance between the bats and pray was reduced. So the pulse repetition rates increased by bats up to 200 Hz in order to avoid overlapping of pulses which would create great loss in resolution [16], [18]. To get the information about angular position of pray, the bats used their sonar broadcast and their ears towards different targets. But this was not enough to identify the too close objects in the same direction. So, to increase their angular resolution the bats used sound pressure level difference and time difference of arrival between their ears[16]-[19]. By using this technique the bats were able to identify the too close objects with angular resolution of $\pm 2^{o}$to $\pm 5^{o}$. This paper proposed the Bats Echolocation System to improve the convergence speed of Back Propagation algorithm.

4.1 Implementation of Bats Echolocation System Based Back Propagation Algorithm in Feed Forward Network

In conventional Back Propagation Algorithm, the error was calculated based on the response in the output layer. But in Bats Echolocation based Back Propagation algorithm, the error was calculated with the response which was achieved by adding and subtracting the bats coefficient with the actual response in the output layer based on the target in order to increase the error convergence rate. This concept was achieved by the bats Echolocation system where ultrasonic sound bursts were initially transmitted by bats to identify the prey and its location judged by the difference in the repetition pulses. This behavior of bats was used in Back Propagation algorithm by adding and subtracting Bats coefficient with response of the output layer in order to got the output response which was closer to the target. This would leads to faster convergence in the Back propagation algorithm. The computational steps involved in the Bats Echolocation system based BP Algorithm, used to train the Feed Forward Network was as follows:

Step 1: The input and output patterns with respect to their maximum values were normalized.
Input pattern were represented as $\{I\}_{I\,(l*1)}$ and
Output pattern were represented as $\{O\}_{O\,(n*1)}$.

Step 2: The total number of hidden layer neurons were assumed in betweenl < m < 2l.

Step 3: $[V]^{0}$ = [input-hidden layer weights]
[W] 0 = [hidden-output layer weights] were assumed.
Assume $[\Delta V]\ 0 = [\Delta W]\ 0 = [0]$ (1)
The weights were initialized to small random values,$\lambda = 1$and threshold values set to be zero.

Step 4: For the training, one set of input and output were selected from the pattern. by using linear activation function,
$\{O\}\ I\ (l_{*1}) = \{I\}_{I\,(l*1)}$

Step 5: The inputs of the hidden layer were computed by

$$\{I\}_{H\,(m*1)} = [V]^{T}_{(m*l)} \{O\}_{I\,(l*1)} \quad (2)$$

Step 6: The hidden layer outputs were evaluated by the sigmoidal function as

$$\{O\}_H = \begin{Bmatrix} . \\ . \\ \frac{1}{\left(1+e^{-I_{Hi}}\right)} \\ . \\ . \end{Bmatrix}_{m*1} \tag{3}$$

Step 7: The input of the output layer were computed from,

$$\{I\}_{O\,(n*1)} = [W]^{T}_{(n*m)} \{O\}_{H\,(m*1)} \tag{4}$$

Step 8: The output layer outputs are evaluated by sigmoidal function as

$$\{O\}_{Ol} = \begin{Bmatrix} . \\ . \\ \frac{1}{\left(1+e^{-I_{Oj}}\right)} \\ . \\ . \end{Bmatrix} \tag{5}$$

Step 9: by adding and subtracting Bats coefficient O_{BC} with $\{O\}_{Ol}$

$\{O\}_{O1} = \{O\}_{Ol} + O_{BC}$

$\{O\}_{O2} = \{O\}_{Ol} - O_{BC}$ were computed

If $\{O\}_{O1} - \{O\}_{O2} < 0$, then $\{O\}_{O} - \{O\}_{O1}$

If $\{O\}_{O2} - \{O\}_{O1} < 0$, then $\{O\}_{O} - \{O\}_{O2}$

Step 10: The error for the i^{th} training set was calculated as

$$E^{p} = \frac{\sqrt{\sum\left(T_j - O_{Oj}\right)^2}}{n} \tag{6}$$

Step 11: {d} was calculated as

$$\{d\} = \begin{Bmatrix} . \\ . \\ (T_k - O_{Ok})O_{Ok}(1 - O_{Ok}) \\ . \\ . \end{Bmatrix}_{n*1} \tag{7}$$

Step 12: [Y] matrix was calculated from

$$[Y]_{(m*n)} = \{O\}_{H\,(m*1)} \langle d \rangle_{1*n} \tag{8}$$

Step 13: change in weights were evaluated from

$$[\Delta W]^{t+1}_{(m*n)} = \alpha\, [\Delta W]^{t}_{(m*n)} + \eta [Y]_{(m*n)} \tag{9}$$

Step 14: {e}, {d} and {X} were evaluated by

$$\{e\}_{(m*1)} = [W]_{(m*n)} \{d\}_{(n*1)} \tag{10}$$

$$\{d^*\} = \begin{Bmatrix} \cdot \\ \cdot \\ e_i(O_{Hi})(1-O_{Hi}) \\ \cdot \\ \cdot \end{Bmatrix}_{m*1} \quad (11)$$

$$[X]_{(l*m)} = \{O\}_{I(l*1)} \langle d^* \rangle_{(1*m)} = \{I\}_{I(l*1)} \langle d^* \rangle_{(1*m)} \quad (12)$$

Step 15: change in weightswere obtained by

$$[\Delta V]^{t+1}_{(l*m)} = \alpha\, [\Delta V]^{t}_{(l*m)} + \eta [X]_{(l*m)} \quad (13)$$

Step 16: The new weights were obtained by

$$[V]t+1 = [V]t + [\Delta V]\ t+1 \quad (14)$$

$$[W]t+1 = [W]t + [\Delta W]\ t+1 \quad (15)$$

Step 17: steps 4-16 were repeated till the error was reduced to tolerance value.

4.2 Simulation Results of Bats Echolocation System Based Back Propagation Algorithm in Feed Forward Network

Using the algorithm described above, the simulation results were obtained as shown in table 3. The graphical representations of simulation results were shown in figure 3. The parameters needed for Feed Forward Network with Bats Echolocation system based BP Algorithm were similar to Back propagation algorithm with Bats coefficient is 0.27.

Table 3. Simulation results of Bats Echolocation system based BP Algorithm in Feed Forward Network for number of epochs

Epochs	Input vectors		Input-Hidden layer weights				Hidden-Output layer weights		Error
	I_1	I_2	V_{11}	V_{12}	V_{21}	V_{22}	W_1	W_2	
1	0.4	-0.7	0.1	0.4	-0.2	0.2	0.2	-0.5	0.0089
10	0.4	-0.7	0.0987	0.4038	-0.1977	0.1933	0.1596	-0.5375	0.0070
20	0.4	-0.7	0.0977	0.4077	-0.1959	0.1865	0.1215	-0.5730	0.0055
30	0.4	-0.7	0.0970	0.4112	-0.1948	0.1804	0.0892	-0.6032	0.0043
40	0.4	-0.7	0.0967	0.4143	-0.1941	0.1749	0.0616	-0.6292	0.0034
50	0.4	-0.7	0.0964	0.4171	-0.1938	0.1700	0.0377	-0.6516	0.0027
60	0.4	-0.7	0.0963	0.4196	-0.1936	0.1656	0.0170	-0.6712	0.0022
70	0.4	-0.7	0.0963	0.4219	-0.1935	0.1617	-0.0012	-0.6883	0.0018
80	0.4	-0.7	0.0963	0.4239	-0.1936	0.1581	-0.0171	-0.7034	0.0015
90	0.4	-0.7	0.0964	0.4258	-0.1937	0.1549	-0.0311	-0.7167	0.0012
97	0.4	-0.7	0.0964	0.4269	-0.1938	0.1528	-0.0400	-0.7251	0.0010

The simulation results obtained from the Feed Forward Network with Bats Echolocation system based BP Algorithm showedthat the target was achieved in 97 epochs itself where as Back Propagation algorithm took 206 epochs and also this algorithm took only 10 epochs to converge with 0.015 error to reach the target. The convergence speed of the Bats Echolocation system based BP algorithm was 47.8 percent better than Back Propagation algorithm. The proper selection of the Bats coefficient (it depended on the error rate of the network) would increase the convergence speed of the Bats Echolocation system based BP algorithm.

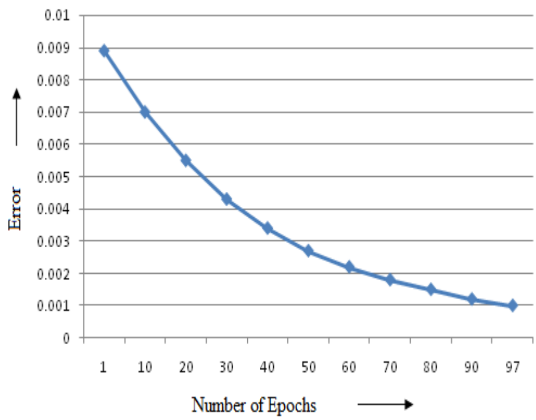

Fig. 3. Error Vs Number of epochs

5 Conclusion

The effectiveness of Bats Echolocation system based Back Propagation algorithm was proved by simulation results over the conventional Back Propagation algorithm for Feed Forward Network. The simulation results revealed that convergence speed of Bats Echolocation system based Back Propagation algorithm was 47.8 times better than conventional Back Propagation algorithm.

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