17-14

Chaotic Backpropagation Learning Algorithm in Feedforward Neural Network

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1. Introduction

The backpropagation (BP) learning algorithm has proved to be efficient in many engineering applications especially in pattern recognition and system control. Although the BP has been a significant research area of artificial neural network, this algorithm has a weakness for performing a poor convergence rate.

In this study, we propose a new modified BP learning algorithm by adding chaotic noise into weight update process. By computer simulations, we confirm that our proposed algorithm can give a better convergence rate in learning performance than the conventional BP algorithm.

2. Chaotic BP Algorithm

Slow convergence rate is the most common disadvantage of the BP learning algorithm. In the BP algorithm, the weights updates are proportional to the error propagating from output through the sigmoid function and through the weights. The convergence rate of the learning process can be improved by changing how the error propagates back through the network. Considering this, we add chaotic noise into weight update process during error propagation. The new modified weight update process for the BP algorithm can be described as follows where β is the noise amplitude.

$$\begin{aligned}\triangle_p w_{i,j}^{k-1,k}(m) &= -\eta \frac{\partial E_p}{\partial w_{i,j}^{k-1,k}} \\ &+ \zeta \triangle_p w_{i,j}^{k-1,k}(m-1) + noise_{i,j}(m),\end{aligned} \tag{1}$$

$$noise_{i,j}(m) = \beta_{i,j}(m)(x_{i,j}(m) - 0.5), \tag{2}$$

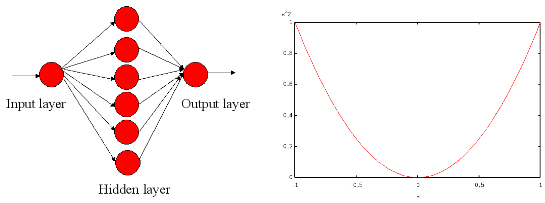
The chaotic noise is generated by the logistic map where α denotes the control parameter of chaos (Eq.(3)).

$$x_{i,j}(m+1) = \alpha x_{i,j}(m)(1 - x_{i,j}(m)), \tag{3}$$

3. Simulation Results

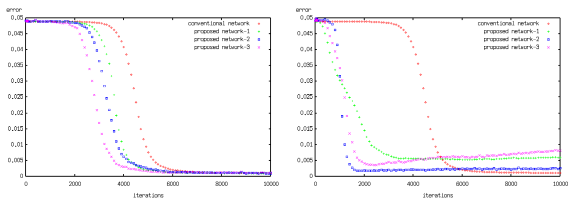
We consider the feedforward neural network produce outputs x^2 for input data x as one learning example. The sampling range of the input data is [-1.0, 1.0]. The learning rate and the inertia rate are fixed as $\eta = 0.02$ and $\zeta = 0.002$ respectively. The initial values of the weights are given between -1.0 and 1.0 at random. The learning iterations is set to 10000 and 6 neurons are prepared in the hidden layer. The network structure and learning example are shown in Fig. 1.

We investigate the learning efficiency by adding the chaotic noise into different position of weight update process ; a) Proposed network-1 (from input layer to hidden layer only), b) Proposed network-2 (from hidden layer to output layer only) and c) Proposed network-3 (both of them). We also compare the learning performance with the conventional method where there is no chaotic noise application at all. Figure 2 show the learning performance of all proposed and conventional network respectively when the noise amplitude β is fixed as 0.01. Here, we make two comparisons between fully developed chaos noise and intermittency chaos noise. The logistic map is used to generate the chaotic noise where $\alpha = 4.00$ shows the fully-developed chaos and $\alpha = 3.82676$ shows the intermittency chaos.



(a) Network structure (b) Learning example

Figure 1: Network structure and learning example.



(a) $\alpha = 4.0$. (b) $\alpha = 3.82676$.

Figure 2: Learning curve for amplitude noise $\beta = 0.01$.

Both figures show that the presence of noise during weight update process gives a better convergence rate compared to the conventional method. From the simulation result, we confirm that when the chaotic noise is applied to both sides of weight update process (Proposed network-3), the learning process gain better performance compared to other positions. Furthermore, the intermitency chaos shows a large difference in learning performance when the noise amplitude is set to 0.01 and the fully-developed chaos gives a slight improvement only for the learning performance.

4. Conclusions

In this study, we proposed a new modified BP learning algorithm by adding chaotic noise into weight update process. By computer simulations, we confirmed that the addition of chaotic noise during weight update process can give a better convergence rate and faster learning performance compared to the conventional BP algorithm.