A Study of Sudden Noise Resistance Based on Four-Layer Feed-Forward Neural Network Blind Equalization Algorithm

Yanqi Kang[1] and Liyi Zhang[2]

[1] College of Mining Engineering, Taiyuan University of Technology, Taiyuan Shanxi 030024, China
[2] College of Information Engineering, Tianjin University of Commerce, Tianjin 30072, China
tykangyq@126.com

Abstract. In the study of feed-forward neural network blind equalization algorithm, three-layer BP neural network structure is usually adopted .In this paper, iterative formula of four-layer feed forward neural network blind equalization algorithm was deduced by way of adding hidden layers and computer simulations of its properties on sudden noise resistance were done. The experimental results demonstrate that three-layer and four-layer neural network have similar inhibitory action and the fault tolerance to the sudden noise, but four-layer neural network surpasses three-layer in steady-state residual error aspect.

Keywords: Blind Equalization Algorithm, Four-layer Feed-forward Neural Network, Sudden Noise, Steady-state Residual Error.

1 Introduction

Neural network as a discipline involved in neural science, information science, and computer science has been widely applied in pattern recognition, system control, and etc [1].It has been a research hotspot due to its strong ability to learn and its robustness [2]. The multilayer feed forward neural network is currently one of the most widely used ones of all sorts of neural networks [4]. The blind equalization algorithm [3-5] based on the feed-forward neural network usually adopts a three-layer neural network structure, namely from the input layer to the hidden layer to the output layer. The three-layer network structure has a fast convergence speed, but the sudden noise signals greatly influence steady-state residual error and bit error rate and therefore reduce the quality of communication. In this study, four-layer feed forward neural network is applied in blind equalization algorithm, the comparison between its function and that of the three-layer are made by computer simulations. The experimental results show that the four-layer has a better performance.

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2 Blind Equalization Algorithm of Four-Layer Feed Forward Neural Network

2.1 Four-Layer Feed Forward Neural Network Model

Fig. 1 shows a four-layer feed forward neural network structure.

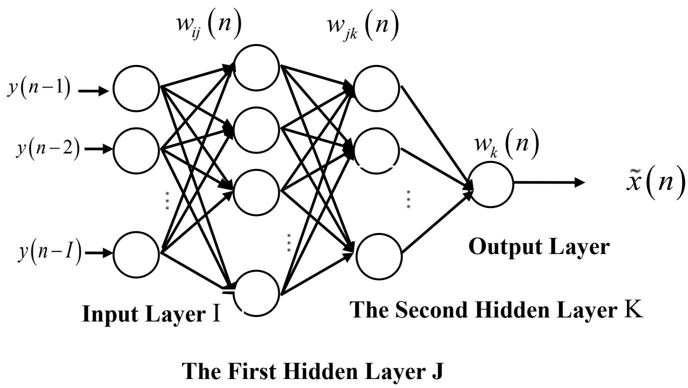

Fig. 1. The topology structure of the four-layer feed forward neural network blind equalizer

In the figure, there is only forward output in neural network, and neurons are connected by weight value [6]. The connection weight value between the input layer and the first hidden layer is $w_{ij}(n)(i=1,2,\cdots,I;\, j=1,2,\cdots,J)$, the connection weight value of the first and second hidden layer is $w_{jk}(n)(k=1,2,\cdots,K)$, the connection weight value of the second hidden layer and the output layer is $w_K(n)$. "u and v " stands for input and output of Neurons. Their superscripts stand for layer, the subscripts for neurons of the same layer. $y(n-i)$ stands for the input of the neural network, $\tilde{x}(n)$ is output of the neural network. Then the state equation of the feed-forward neural network is as follows:

$$u_i^I(n)=y(n-i) \tag{1}$$

$$v_i^I(n)=u_i^I(n)=y(n-i) \tag{2}$$

$$u_i^J(n)=\sum_{i=1}^{I} w_{ij}(n)v_i^I(n)=\sum_{i=1}^{I} w_{ij}(n)y(n-i) \tag{3}$$

$$v_i^J(n)=f_1\left(u_i^J(n)\right)=f_1\left(\sum_{i=1}^{I} w_{ij}(n)\,y(n-i)\right) \tag{4}$$

$$v_k^K(n) = f_2\left(u_k^K(n)\right) = f_2\left(\sum_{j=1}^{J} w_{jk}(n) v_j^J(n)\right) \tag{5}$$

$$v_k^K(n) = f_2\left(u_k^K(n)\right) = f_2\left(\sum_{j=1}^{J} w_{jk}(n) v_j^J(n)\right) \tag{6}$$

$$u(n) = \sum_{k=1}^{K} w_k(n) v_k^K(n) \tag{7}$$

$$v(n) = \tilde{x}(n) = f_3\left(u(n)\right) = f_3\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) \tag{8}$$

2.2 The Iterative Form of Four-Layer Feed-Forward Neural Network Blind Equalization Algorithm

The key to solve problems by the use of feed-forward neural network based on blind equalization is to choose a suitable transfer function. Because the transfer function determines the relationship between input and output of the entire network, it also determines the output. The transfer function in this study is [7]

$$f_1(x) = f_2(x) = f_3(x) = f(x) = x + \alpha \sin \pi x \qquad \alpha > 0 \tag{9}$$

According to the traditional constant-modulus (CMA) algorithm and feed-forward neural network training methods, a new cost function is redefined as follows:

$$J(n) = \frac{1}{2}\left[\left|\tilde{x}(n)\right|^2 - R_2\right]^2 \tag{10}$$

In the equation, R_2 is the same to the traditional CMA[8], i.e.

$$R_2 = E\left\{\left|x(n)\right|^4\right\} / E\left\{\left|x(n)\right|^2\right\} \tag{11}$$

In Blind equalization algorithm, the network weight value's iteration formula generally uses the steepest gradient descent method formation, namely

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \eta \frac{\partial J(n)}{\partial \mathbf{w}(n)} \tag{12}$$

$$\frac{\partial J(n)}{\partial w(n)} = 2\left[\left|\tilde{x}(n)\right|^2 - R_2\right] \frac{\partial \tilde{x}(n)}{\partial w(n)} \tag{13}$$

In the equation, η is the length of the iteration step.

The four-layer feed-forward neural network contains two hidden layers and two output layers, so its value iteration formula is different from that of three layers'.

(1) Weight Value Iteration Formula of the Output Layer

$w_K(n)$ is the connection weight value between the output layer and the second hidden layer, the weight value iteration formulas are as follows:

$$w_k(n+1) = w_k(n) - 2\eta_1\left[\left|\tilde{x}(n)\right|^2 - R_2\right]\frac{\partial \tilde{x}(n)}{\partial w_k(n)} \tag{14}$$

$$\frac{\partial \tilde{x}(n)}{\partial w_k(n)} = f'\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) v_k^K(n) \tag{15}$$

$$w_k(n+1) = w_k(n) - 2\eta_1\left[\left|\tilde{x}(n)\right|^2 - R_2\right] f'\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) v_k^K(n) \tag{16}$$

In the equation, η_1 is the length of the iteration step of the output layer.

(2) Weight Value Iteration Formula of the First and Second Hidden Layer

$w_{jk}(n)$ is the connection value between the first and second hidden layer, the weight value iteration formulas are as follows:

$$w_{jk}(n+1) = w_{jk}(n) - 2\eta_2\left[\left|\tilde{x}(n)\right|^2 - R_2\right]\frac{\partial \tilde{x}(n)}{\partial w_{jk}(n)} \tag{17}$$

$$\frac{\partial \tilde{x}(n)}{\partial w_{jk}(n)} = f'\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) f'\left(\sum_{j=1}^{J} w_{jk}(n) v_j^J(n)\right) w_k(n) v_j^J(n) \tag{18}$$

$$\begin{aligned} w_{jk}(n+1) &= w_{jk}(n) - 2\eta_2\left[\left|\tilde{x}(n)\right|^2 - R_2\right] \\ &\quad \times f'\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) f'\left(\sum_{j=1}^{J} w_{jk}(n) v_j^J(n)\right) w_k(n) v_j^J(n) \end{aligned} \tag{19}$$

In the equation, η_2 is the length of the iteration step of the first and second hidden layer.

(3) Weight Value Iteration Formula of Input Layer and the First Hidden Layer

$w_{jk}(n)$ is the connection value between input layer and the first hidden layer, their weight value iteration formulas are as follows:

$$w_{ij}(n+1) = w_{ij}(n) - 2\eta_3\left[\left|\tilde{x}(n)\right|^2 - R_2\right]\frac{\partial \tilde{x}(n)}{\partial w_{ij}(n)} \tag{20}$$

$$\begin{aligned}\frac{\partial \tilde{x}(n)}{\partial w_{ij}(n)} = & f'\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) f'\left(\sum_{j=1}^{J} w_{jk}(n) v_j^J(n)\right) \\ & \times f'\left(\sum_{i=1}^{I} w_{ij}(n) y(n-i)\right) w_k(n) w_{jk}(n) y(n-i)\end{aligned} \tag{21}$$

$$\begin{aligned}w_{ij}(n+1) = & w_{ij}(n) - 2\eta_3\left[\left|\tilde{x}(n)\right|^2 - R_2\right] f'\left(\sum_{k=1}^{K} w_k(n) v_k^K(n)\right) \\ & \times f'\left(\sum_{j=1}^{J} w_{jk}(n) v_j^J(n)\right) f'\left(\sum_{i=1}^{I} w_{ij}(n) y(n-i)\right) \\ & \times w_k(n) w_{jk}(n) y(n-i)\end{aligned} \tag{22}$$

In the equation, η_3 is the length of the iteration step of first and second hidden layer.

3 Computer Simulations of Four-Layer Feed-Forward Neural Network Blind Equalization Algorithm

In order to test the validity of the four-layer feed-forward neural network blind equalization algorithm in resistance of sudden noise, signal-to-noise ratio was 20dB at the very beginning of simulation. When iteration became 20,000 times, signal-to-noise ratio reduced to 3dB. When it went through 100 code elements, signal-to-noise ratio came back to the 20dB.

Shown in Fig. 2 (a) and Fig. 2 (b) are the sudden noise resistance convergence curves of typical phone channel and ordinary channel gotten from four-layer feed-forward

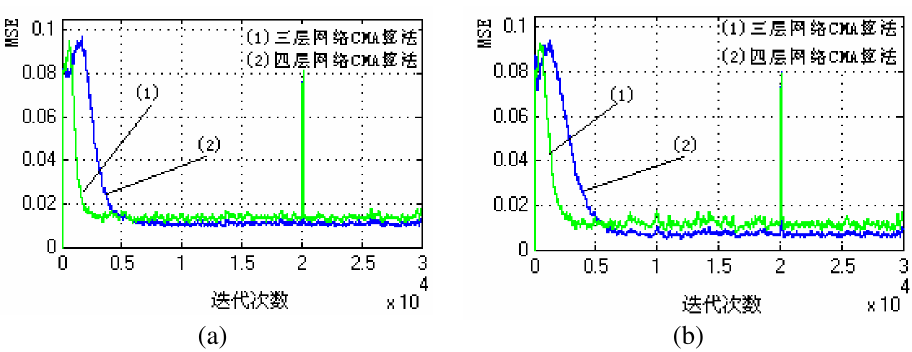

Fig. 2. Sudden noise resistance convergence curves of 8PAM signal in a typical phone channel (a) and ordinary channel (b)

neural network blind equalization algorithm and traditional three-layer feed-forward neural network for 8PAM signal blind equalization algorithm. As can be seen from the graph, the two algorithms all have good inhibition and fault tolerance to sudden noises, but four-layer neural network surpasses three-layer in steady-state residual error aspect while its convergence speed is slower.

4 Conclusions

Due to the defects of the traditional three-layer feed-forward neural network blind equalization algorithm in its influence on the steady-state residual error, this study deduced iterative formula of four-layer feed-forward neural network blind equalization algorithm by way of adding hidden layers and compared the difference by computer simulations between its function in sudden noise resistance and that of three-layer feed-forward neural network blind equalization algorithm. The experimental results demonstrated that three-layer and four-layer neural networks had similar inhibitory action and the fault tolerance to the sudden noise, but four-layer neural network surpassed three-layer network in steady-state residual error aspect while its convergence speed was slower.

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