A Study on the Decision Feedback Equalizer using Neural Networks

Sung Hyun Park and Sang Bae Lee
Dept. of Electro. & Comm. Eng, Korea Maritime Univ.
E-mail : sh_park@hanmail.net

ABSTRACT

A new approach for the decision feedback equalizer(DFE) based on the back-propagation neural networks is described. We propose the method of optimal structure for back-propagation neural networks model. In order to construct an the optimal structure, we first prescribe the bounds of learning procedure, and then, we employ the method of incrementing the number of input neuron by utilizing the derivative of the error with respect to an hidden neuron weights. The structure is applied to the problem of adaptive equalization in the presence of intersymbol interference(ISI), additive white Gaussian noise. From the simulation results, it is observed that the performance of the propose neural networks based decision feedback equalizer outperforms the other two in terms of bit-error rate(BER) and attainable MSE level over a signal ratio and channel nonlinearities.

Ⅰ. Introduction

Adaptive channel equalization has been found to be very important for effective digital data transmission over linear dispersive channels. In high speed data transmission, the amplitude and phase distortion due to variation of channel characteristics to which the data signal will be subjected is to be suitably compensated[1].

The equalization problem can be viewed from two different viewpoints. Traditionally, equalization has been considered equivalent to inverse filtering of channel; this corresponds to deconvolving the received sequence in order to reconstruct the original message, Therefore, the combination of channel and equalizer should be as close as possible to an ideal delay function[2].

A difference approach considers equalization as a "classification" problem[3][4], in which the objective is separation of the received symbols in the output signal space.

From both points of view, the neural networks(neural networks) approach to equalization is well justified. In the first case, neural networks capability as universal function approximators could be exploited. In the second, it is well-known neural networks ability to perform classification tasks by forming complex nonlinear decision boundaries.

In this paper, a new approach for the decision feedback equalizer based on the neural networks proposed. This mothed employ to learning limitation character of neural networks. neural networks used to complex multilayer perceptron.

This paper is organized as follows. Section Ⅱ introduce a general nonlinear channel model used in the equalization problem. Section Ⅲ represented complex multilayer perceptron adaptation algorithm. Section Ⅳ,Ⅴ introduces a new mothed that increment input neuron. In Section Ⅵ, represented simulation result that conventional decision feedback equalizer based on the neural networks and proposed decision feedback equalizer.

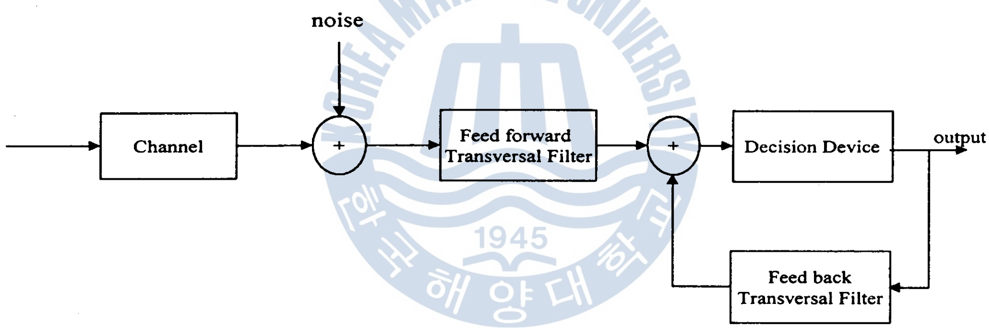

Figure 1. Channel equalizer structure(decision feedback equalizer).

Ⅱ. The nonlinear channel model & equalizer

Figure 1. depicts a typical channel equalizer. The combined effect of the transmitted filter and the transmission medium is included in the 'channel'. A widely used model for a linear dispersive channel is the finite impulse response (FIR) model. The output of the FIR channel may rewritten as

$$a(n) = \sum_{i=0}^{N_h - 1} h(i) \cdot t(n-i) + q(n) \qquad (1)$$

where h(i) are the channel taps and N_h is the length of the channel impulse response.

A decision feedback equalizer consists of a feedforward part and a feedback part. In a general conventional design, it is fixed tap length(tap numbers), the time variable noise and distortion not concern. Therefore, when the signal with a heavy noise and distortion are transmitted the communication system, a fixed tap number equalizer appear bad performance. this characteristics is to view a LMS equalizer and a general neural networks equalizer[8].

The structure of decision feedback equalizer based on the neural networks is shown in Figure 2. This neural networks equalizer is composed of the feedforward tapped delay line, the decision feedback tapped delay line, and the multilayer feedforward neural networks. The in-phase and the quadrature components of the feedforward and feedback are applied to the multilayer feedforward neural networks, which has a three layer, namely, input layer, hidden layer and output layer[9][10]. The output of the neural networks id applied to the decision element, and the output is then fed into decision feedback. The weights are adjusted by back propagation algorithm.

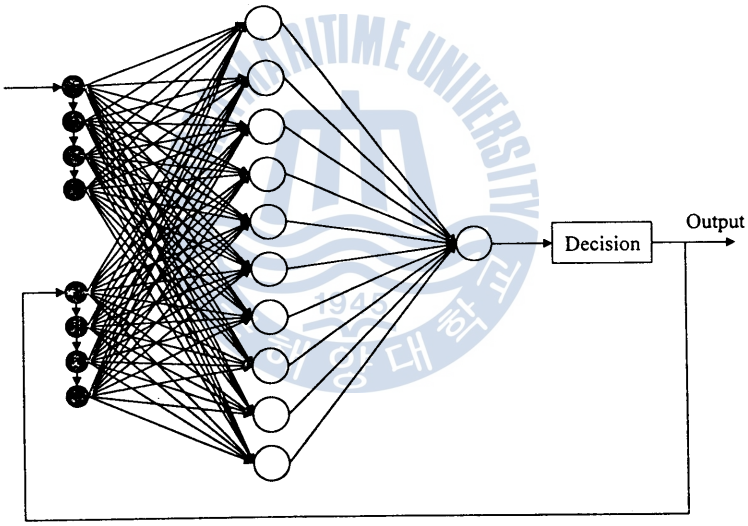

Figure 2. The structure of decision feedback equalizer based on the neural networks

The input signals to each neuron are the output signals from the other neurons, combined by weights. As for multilayer feedforward neural networks, the signals, which are input to the neurons in hidden layer, are the output signals of input layer neurons. Also, the signals, which are input to the neurons in output layer, are the output signals of hidden layer neurons. F(x) is an output function of a neuron and generally has nonlinear characteristics.

y_i is given by

$$y_i = F\left(\sum_{i=1}^{n} w_{ij} \cdot x_i \right) \tag{2}$$

Since F(x) is a nonlinear function, it can be seen that the input/ output of a neuron shown in equation (2) has nonlinear characteristics. In neural networks, the desired nonlinear characteristics of a neuron and the weight of a weight, combining with a neuron. Suppose the output function of neurons in input layer and output layer employs the linear function, namely, F(x) = x.

The weights must be updated to be adaptive to compensate the distortion so that the error between the input and output of decision element can be minimized. In back propagation algorithm, the error evaluation function E given by

$$E = \frac{1}{2} \sum_j |d_j - z_j|^2 \tag{3}$$

is minimized by steepest descent method. In equation (3), z_j is the output od neural networks, in other words, it is the output signal of an output layer neuron; and d_j is a teacher signal, or the output of the decision element. The update formula of the weight by back propagation algorithm becomes

$$w_{j,i}(n+1) = w_{j,i}(n) + \eta \delta_j(n) y_i(n) \tag{4}$$

where η, which is a small and positive constant, is the updating coefficient. Also, $w_{j,i}(n)$ is the weight from neuron i to neuron j, and $y_i(n)$ is the output signal of neuron i. $\delta_j(n)$ is the error signal that error signal that is generated in neuron j.

The error signal is giving by

$$\delta_j(n) = \begin{cases} (d_j(n) - y_j(n)) F'\left(\sum_j w_{j,i}(n) y_i(n)\right), \\ \text{neuron j belongs to Output Layer} \\ F'\left(\sum_i w_{j,i}(n) y_i(n)\right) \sum_k \delta_k(n) w_{k,j}(n), \\ \text{otherwise} \end{cases} \tag{5}$$

where $d_j(n)$ is a teacher signal and $F'(x)$ is the derivative for x in the output function F(x). The known training signal is used as a teacher signal while the neural networks equalizer is in acquisition and the output of the decision element is used as a teacher signal for tracking.

The conventional neural network, sigmoidal function defined as

$$F(x) = \frac{(1-e^{-x})}{(1+e^{-x})} \tag{6}$$

is used as an output function. For employing the back propagation algorithm, it is required that the output function has a derivation, because the back propagation algorithm has to evaluate equation (4) and (5).

In this paper, we propose the method of optimal structure for decision feedback equalizer using back propagation. In order to construct an the optimal structure, we first prescribe the bounds of learning procedure, and then, we employ the method of incrementing the number of input neurons(Tap) by utilizing the derivation of error with respect to an hidden neuron weights.

III. Complex multilayer perceptron algorithm

Before a complex multilayer perceptron represented, first, multilayer neural networks structure represented briefly. Figure 3. shows multilayer neural networks[6][7].

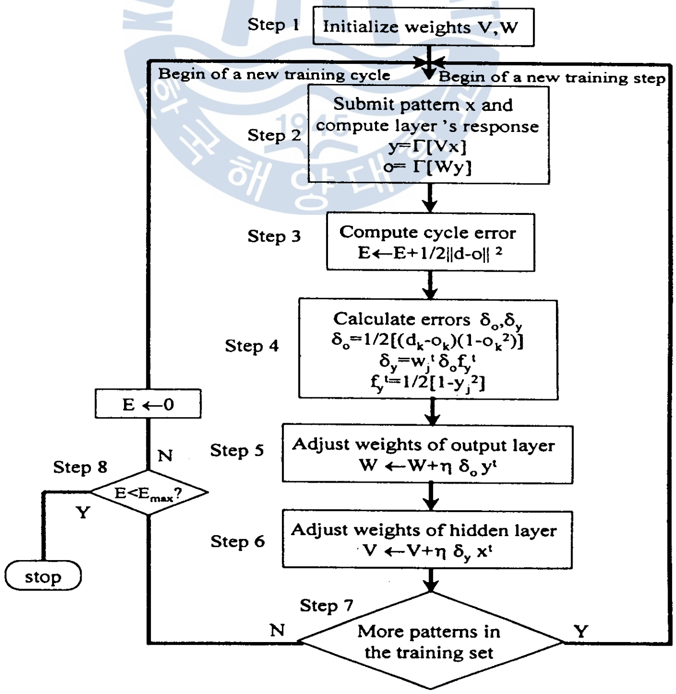

Figure 3. Universally multilayer perceptron structure

The applications of multilayer perceptron in equalization problem so far, have been limited to binary {0, 1} or bipolar {-1, 1} valued data and real valued channel models.

For complex channel models and QAM signals, we use complex connection coefficients to get the weighted sum to which a complex transfer function is added. Where transfer function is sigmoid functions with the real and imaginary parts. This weighted sum are evaluated separately. Using the steepest descent mothed, we get the complex adaptation algorithm of our new decision feedback equalizer[5][7][9].

The stepwise algorithm of complex multilayer perceptron is described as follows :

1). Initialize weights and biases.

Set all weights and biases to small complex random values.

2) Present input and desired outputs.

Present input vector $\vec{x}(0), \vec{x}(1), \ldots, \vec{x}(n)$ and desired output $\vec{d}(0), \vec{d}(1), \ldots, \vec{d}(n)$ where n is the total number of training patterns.

3) calculate actual outputs :

$$x_i^{(l+1)} = f\Big(\sum_{j=1}^{N_l} w_{ij}^{(l)} x_j^{(l)} + \theta_i^{(l)}\Big)$$
$$y_i^{(l+1)} = x_i^{(M)} = f\Big(\sum_{j=1}^{N_{M-1}} w_{ij}^{(M-1)} x_j^{(M-1)} + \theta_i^{(M-1)}\Big) \qquad (2)$$

4) Adapt weights and biases :

$$w_{ij}(n+1) = w_{ij}(n) + \mu \delta_i x_j^* \qquad (3)$$

where x_j' = output of neuron j or input to neuron i

$$\delta_i = \begin{cases} (d_i - y_i) f^{*'} & \text{output layer} \\ f^{*'} \sum_k w_{ik}^* & \text{input layer} \end{cases} \qquad (4)$$

Ⅳ. A learning limitation rule of Neural Networks

Where channel equalization with unknown channel employ neural networks, We must know that a Neural Networks Structure make a decision for arbitrarily complex regions by channel passed signal. But it is difficult to know. Therefore, we new neural networks structure proposed.

Generally in error back propagation learning, learning error represented characteristic that the early stage of learning progress rapidly decrease and as increasing learning iteration, learning error slackly decrease. Such characteristic, for a mediation of threshold value of learning limitation rule apply to adaptive constant when neural networks is learning.

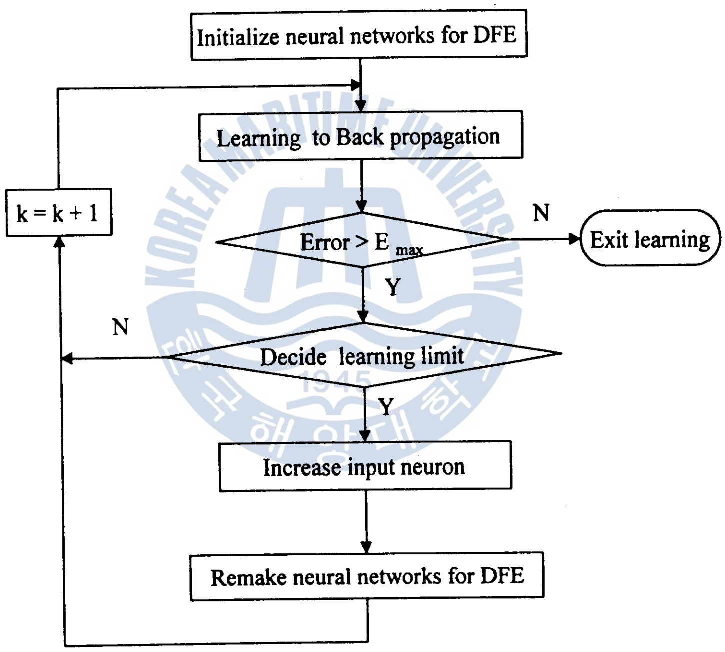

Figure 4. The flowchart for increasing number of input neuron.

A neural networks don't raised learning that error variety rate of learning iteration small than a threshold value. Thus the neural networks is viewed that reached learning limitation state.

A learning limitation rule condition of a error back propagation algorithm represented as the equation (5).

$$\Delta E = |E(n) - E(n+1)| \leq E(n+1) \cdot \theta_e \quad (5)$$

where E(n) is the learning error of n iteration, θ_e is adaptive constant.

A learning limitation problem solution is weights change to increment neuron of input layer. The weights of creation neuron are given a initiation value. An already existing neuron weight have to acquired weight value through learning process.

A input layer neuron increasing algorithm flowchart by learning limitation is shown in Figure 4.

V. The neuron increment method for Neural Networks

In a learning limitation condition equation (5), a error decrement rate have to influence of weight between input layer and hidden layer. Therefore, a error sensitivity of weight determine number of increment neuron.

A definition error sensitivity of weight by means of chain rule represented as follows

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial h} \cdot \frac{\partial h}{\partial w} = x \cdot (1-y^2) \cdot \sum_{k=1}^{K}(d-y) \cdot (1-y^2) \cdot w \quad (6)$$

where $P = (1-y^2) \cdot \sum_{k=1}^{K}(d-y) \cdot (1-y^2) \cdot w$

y : output of output layer,
d : desired value,
K : the number of hidden neuron,
x : output of input layer,
w : weights between input layer and hidden layer,
h : output of hidden layer.

this equation can be rewritten as follows

$$\frac{\partial E_i}{\partial w_{pk}} = P_k \cdot x_p \quad (7)$$

where E_i : i neuron error of output layer,
w_{pk} : weight between input layer and hidden layer,
x_p : output of input layer.

A error sensitivity represented as follows

$$S_p = \sum_{k=1}^{K} \left| \frac{\partial E_k}{\partial w_{pk}} \right|,$$
$$S_q = \sum_{k=1}^{K} \left| \frac{\partial E_k}{\partial w_{qk}} \right|, \qquad (8)$$
$$\Delta S_{pq} = |S_p - S_q|$$

where ΔS_{pq} : error sensitivity difference between S_p and S_q.

The most value ΔS_{nm}(nm is a error sensitivity that input layer between n-th node and m-th node) select in ΔS. A selected ΔS increase at input layer neuron. Where decision feedback equalizer structure divide into feedforward part and feedback part. Thus, if position of the selected ΔS is feedforward part then increasing input layer neuron at feedforward part else position of the selected ΔS is feedback part then increasing input layer neuron at feedback part.

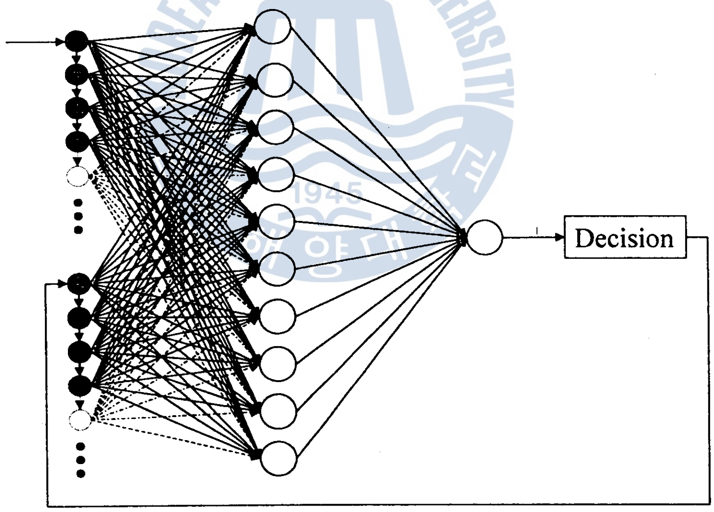

Figure 5. The proposed Decision Feedback Equalizer based on the Neural Networks.

The proposed decision feedback equalizer illustrated in Figure 5. Applying to neural networks of adaptive equalization used to complex multilayer perceptron.

The proposed decision feedback equalizer more effect than conventional decision feedback equalizer in unknown channel for decreasing ISI.

Ⅵ. Simulation Results

In this section, the performance of proposed neural networks decision feedback equalizer id evaluated through simulation by comparing it with the conventional neural networks decision feedback equalizer. Channels used for simulations are simple ISI channels with additive white gaussian noise.

Channel impulse response 1 is as follow

$$0.04 + 0.05Z^{-1} + 0.07Z^{-2} - 0.21Z^{-3} - 0.5Z^{-4} + 0.72Z^{-5} + 0.36Z^{-6} + 0.21Z^{-7} + 0.03Z^{-8} + 0.07Z^{-9}$$

where noise is 10dB, modulation method is 4-QAM. Where channel characteristics include transmitted filter, channel and received filter.

Fig. 5. depicts convergence characteristics of equalizers. This equalizers structure is proposed method and conventional back propagation. At convergence characteristics of proposed decision feedback equalizer, the vibration curve among 600 ~ 900 iterations are caused by initial weights of increment neuron.

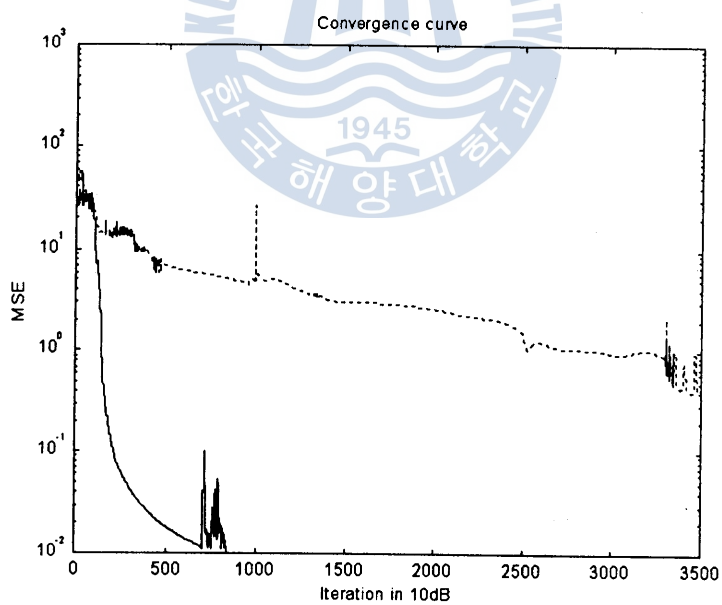

Fig 6. Convergence characteristics of equalizer. additive noise= -10dB, solid line is proposed neural networks decision feedback equalizer, dotted line is conventional neural networks decision feedback equalizer.

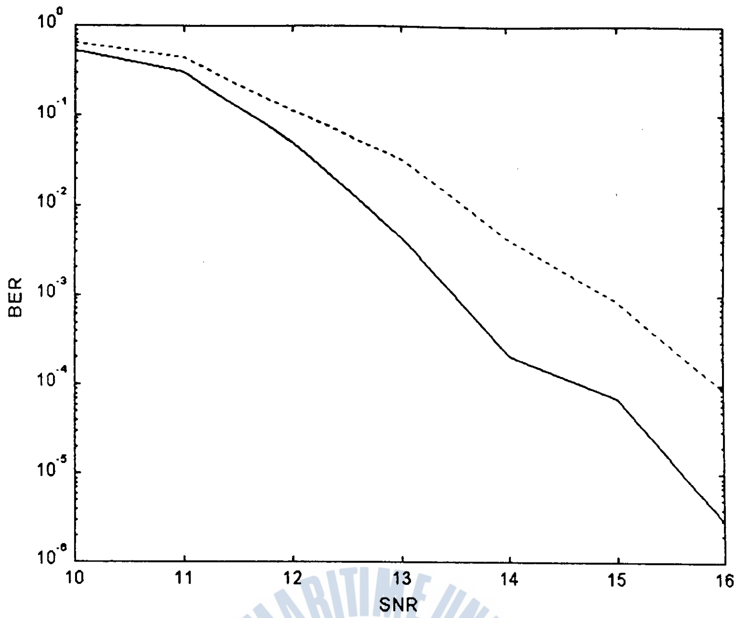

Fig. 7. BER performance of equalizer with variation of SNR.(sliod line is proposed neural networks decision feedback equalizer, dotted line is conventional neural networks decision feedback equalizer).

The proposed neural networks decision feedback equalizer initialized 10(5,5)-15-1, after learning, final structure of proposed neural networks decision feedback equalizer is 21(8,13 : 8 is the number of feedforward tap, 13 is the number of feedback tap)- 15-1. conventional neural networks decision feedback equalizer is 15(5,10)-15-1.

Shown the Fig. 5,6 we are known that proposed neural networks decision feedback equalizer more convergence speed and BER on variation SNR than conventional neural networks decision feedback equalizer.

Channel impulse response 2 is as follow

$$0.227 + 0.406Z^{-1} + 0.688Z^{-2} + 0.406Z^{-3} + 0.227Z^{-4}$$

where channel environment condition is similar to channel 1. And this channel is high frequency environment.

The proposed neural networks decision feedback equalizer initialized 10(5,5)-15-1, after learning, this proposed neural networks decision feedback equalizer is 27(11,16)-15-1. The conventional neural networks decision feedback equalizer is 15(5,10)-15-1.

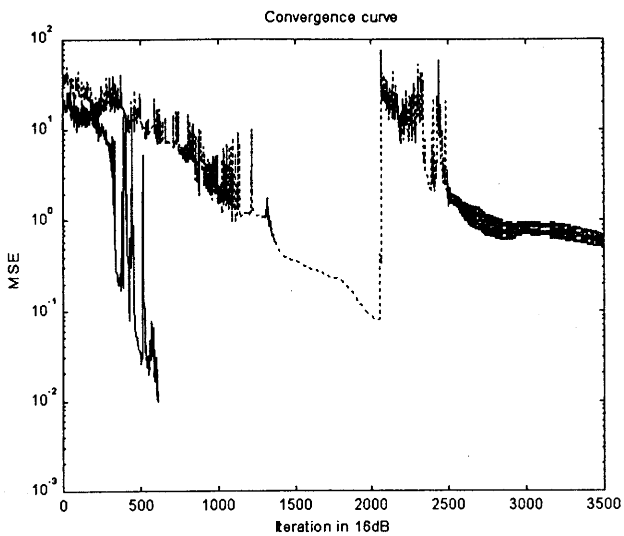

Fig. 8. Convergence characteristics of equalizer additive noise= -16dB, solid line is proposed neural networks decision feedback equalizer, dotted line is conventional neural networks decision feedback equalizer.

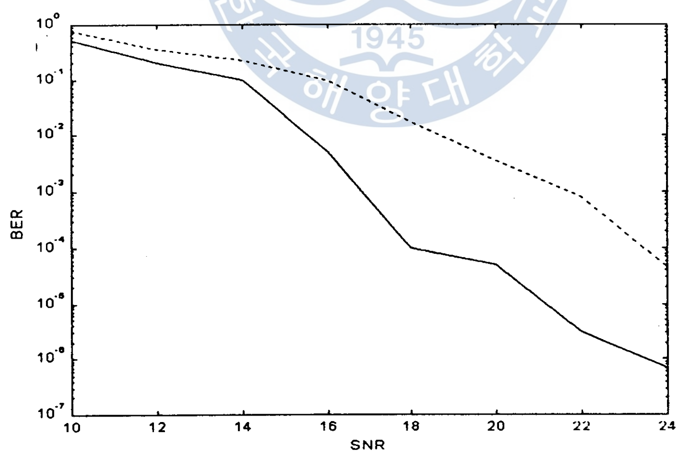

Fig. 9. BER performance of equalizer with variation of SNR.(sliod line is proposed neural networks decision feedback equalizer, dotted line is conventional neural networks decision feedback equalizer).

In Fig. 7, we are shown that high frequency channel characteristics badly effect an convergence of error. Also, we are known that proposed neural networks decision feedback equalizer more fast convergence speed and BER on variation SNR than conventional neural networks decision feedback equalizer.

A equalizer with fixed tap effect than proposed equalizer for variation of channel characteristic.

Ⅶ. Conclusions

This paper has introduced a new approach to adaptive equalization that makes use of optimal structure neural networks at channel characteristic In previous research, equalizers used to fixed input tap for channel equalization. However, there are tendency that mean square error(MSE) slowly converges and that produce poor bit error rate(BER) when badly noise and dispersion add to channel. However, a proposed equalizer improved more performance than a fixed tap equalizer at solving these problem.

Reference

[1] S. U. H. Qureshi, Adaptive Equalization, Proc. IEEE. vol. 73, No. 9, September 1985, pp. 1349-1387.

[2] J. G. Proakis, Digital Communication, Third Edition, McGraw-Hill, 1995.

[3] G. J. Gibson, S. Siu, and C. F. N. Cowan, The application of nonlinear structure to the reconstruction of binary signals, IEEE Trans. Signal Processing, vol. 39, Aug. 1991

[4] M. Peng, C. L. Nikias, and J. G. Proakis, Adaptive Equalization with Neural networks : New multilayer perceptron structure and their evaluation, Proc. of the 1992 internal. conf. on Acou., speech, and signal proc., vol 2, 3/23/92.

[5] H. Leung, S. Haykin, The complex backpropagation algorithm, IEEE Trans. Signal Processing, vol. 39, No. 9, Sept. 1991, pp. 2101-2104.

[6] S. Haykin, Neural Networks : A Comprehensive Foundation, Macmillan College publishing, 1994.

[7] S. Haykin, Adaptive Filter Theory, 3rd. ed., Prentice Hall, 1996.

[8] J. G. Proakis, M. Salehi, Contemporary Communication Systems Using MATLAB, PWS publishing Comp., 1997.

[9] B. Yuhas, Neural Networks in Telecommunications, Kluwer Academic Publishers, 1994.

[10] J. C. Patra, R. N. Pal, A functional link artifical neural network for adaptive channel equalization, Signal processing 43, 1995, pp. 181-195.