신경회로망을 이용한 최적 탭 적응등화기 설계

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A design of optimal tap adaptive equalizer using neural networks

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요 약

오늘날 고속 통신의 요구와 통신 채널 환경의 악화로 채널에서 발생하는 심볼간의 간섭이 커져 강한 신호의 왜곡이 발생한다. 이러한 이유로 왜곡된 신호를 복원하기 위해 강력한 적응 등화기가 요구되고 있다.

채널을 등화하기 위한 적응 등화기로는 선형 등화기, 결정 궤환 등화기, MLSE (maximum likelihood sequence estimation) 등화기 등이 있다. 그런데 MLSE를 이용한 등화기는 많은 계산량과 하드웨어의 복잡성으로 인해, 실제적으로는 계산량이 적고 필터의 구조가 간단한 선형 등화기와 과거 심볼에 의한 간섭의 제거 능력이 뛰어난 결정 궤환 등화기가 사용되고 있다.

최근에는 비선형적 채널을 등화하기 위해 신경회로망의 비선형성과 학습 능력을 이용한 등화기가 개발되었다. 기존의 등화기는 고정된 탭(tap)을 사용하고 있다. 이러한 등화기는 심볼간 간섭과 노이즈의 변화에 빠르게 대처하지 못하고 또 수렴의 속도도 느려진다. 본 논문에서는 등화기의 탭이 채널을 통과한 신호의 특성에 따라 신경망의 구조가 최적으로 변하는 최적 탭 적응 등화기 모델을 제안하였다.

제안된 등화기는 신경회로망의 학습 능력의 특성을 이용하였다. 즉 신경회로망에 학습 한계 규정을 정하여 등화기의 입력 탭수를 최적화 하는 방법을 사용한다. 제안된 등화기와 기존의 등화기를 시뮬레이션을 통해 비교하고 수렴 속도와 BER을 통해 성능 향상을 보였다.

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1. 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 deconvoluing 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(NN) approach to equalization is well justified: In the first case, NN capability as universal function approximators could be exploited; In the second, it is well-known NN 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 NN proposed. this mothed employ to learning limitation character of NN. This paper is organized as follows, Section 2 introduce a general nonlinear channel model used in the equalization problem. Section 3,4 introduces a new mothed that increment input neuron. In Section 5, represented simulation result that conventional DFE and proposed DFE.

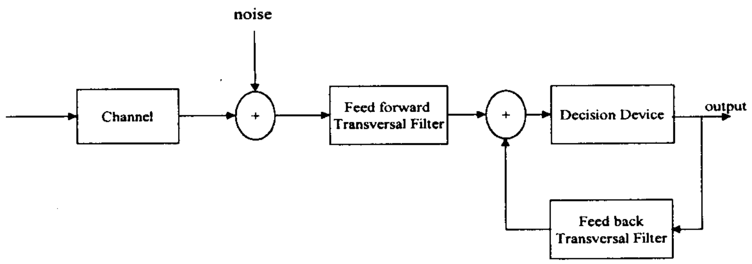

Fig 1. Channel equalizer structure(DFE).

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2. The nonlinear channel model

Fig. 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 be written as

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

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

A DFE 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.

In this paper, we propose the method of optimal structure for DFE 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.

3. 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.

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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 (2).

$$\Delta E = |E(n) - E(n+1)| \leq E(n+1) \cdot \theta_e \tag{2}$$

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

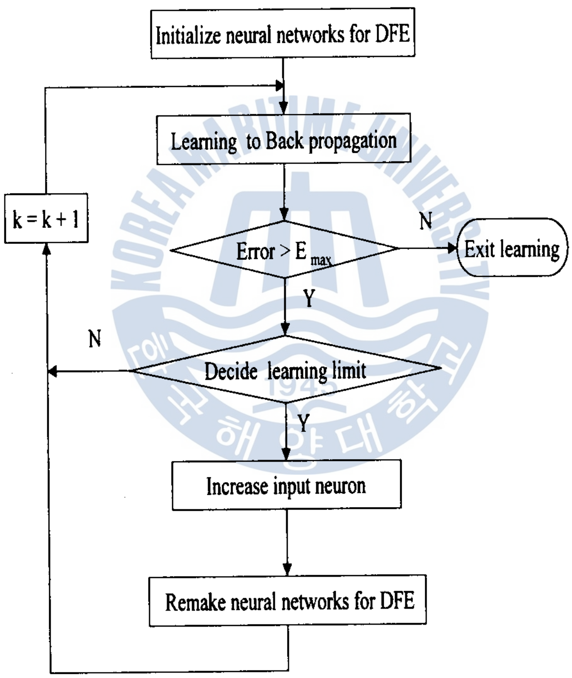

Fig. 2. The flowchart for increasing number of input neuron.

A learning limitation problem solution is weights change to increment neuron of input layer. weight of creation neuron is 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 2.

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4. The neuron increment method for Neural Networks

In a learning limitation condition equation (2), 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

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial h} \cdot \frac{\partial h}{\partial w}$$
$$= x \cdot (1 - y^2) \cdot \sum_{k=1}^{K} (d - y) \cdot (1 - y^2) \cdot w \tag{3}$$

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

$$\frac{\partial E_i}{\partial w_{pk}} = P_k \cdot x_p \tag{4}$$

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

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$$S_p = \sum_{k=1}^{K} \left| \frac{\partial E_k}{\partial w_{pk}} \right|,$$
$$S_q = \sum_{k=1}^{K} \left| \frac{\partial E_k}{\partial w_{qk}} \right|, \qquad (5)$$
$$\Delta S_{pq} = |S_p - S_q|$$

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 DFE 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.

The proposed DFE illustrated in Fig. 3.

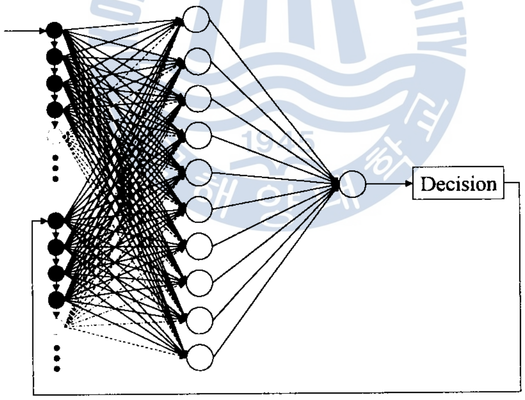

Fig. 3. The proposed Decision Feedback Equalizer based on the Neural Networks.

The proposed DFE more effect than conventional DFE in unknown channel for decreasing ISI.

5. Simulation results

In this section, the performance of proposed neural network equalizer is evaluated through simulation by comparing it with the conventional(fixed number of

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tap) equalizer. Channels used for simulations are simple intersymbol interference channels with additive white gaussian noise.

Example 1)

The used channel impulse response is as follow

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

The added noise is 10dB and modulation method utilized 4-QAM. Channel characteristics are included transmitted filter, channel and received filter. In this simulation, two methods are used; the proposed method and the conventional method. Figure 4 depicts convergence characteristics of equalizers. In figure 5.1, solid line is the proposed neural network equalizer and dotted line is the conventional neural network equalizer. We increase the number of input neurons by utilizing the derivative of the BER with respect to the weights of input layer. At convergence characteristics of the proposed decision feedback equalizer, the vibration happened between about 600 and 900 iteration by initial weights of incremented input neuron.

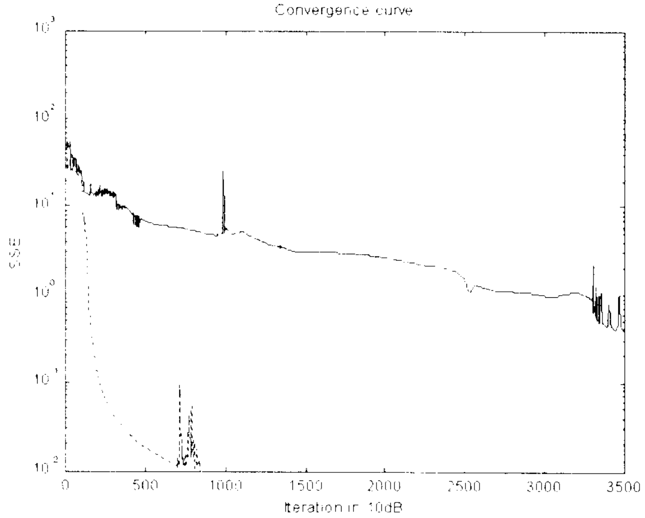

Figure 4 Convergence characteristics of equalizer (additive noise is -10dB).

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The tap number of proposed neural network equalizer is initialized with 10(5,5). After learning, the tap number of proposed neural network equalizer is 21(8,13 : 8 is the number of feedforward tap and 13 is the number of feedback tap). In the conventional neural networks decision feedback equalizer, the tap number is 15(5,10).

In figure 5, solid line is the result of proposed neural networks decision feedback equalizer, solid line with 'o' is conventional neural networks decision feedback equalizer and solid line with '*' is LMS type decision feedback equalizer. The tap number of LMS type decision feedback equalizer is 25(10,15).

The figure 4 and 5 show the proposed neural network equalizer has more excellent convergence speed and BER on variation SNR than conventional equalizer.

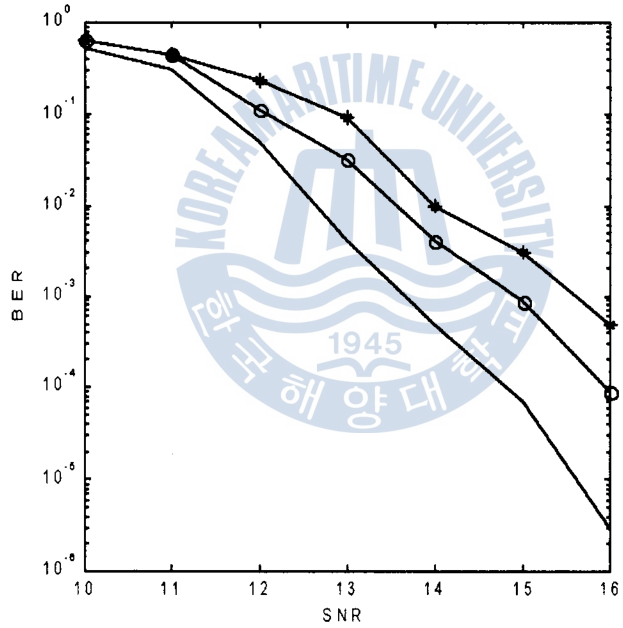

Figure 5 BER performance of equalizer with variation of SNR.

Example 2)

The used channel impulse response is as follow

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

Have the environment of channel is similar to example 1. And this channel is used high frequency environment. The tap number of proposed neural network

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equalizer initialized 10(5,5). After learning, the tap number of proposed neural network equalizer is 27(11,16). In the conventional neural network equalizer, the tap number is 15(5,10).

Figure 6 shows the channel characteristics on high frequency has less convergence properties than the channel characteristics of telephone and the proposed neural network equalizer has more excellent convergence speed and BER to SNR than conventional neural network equalizer and LMS type decision feedback equalizer. Figure 7 depicts BER on variation SNR. In figure 6, solid line is the result proposed neural networks decision feedback equalizer and dotted line is the conventional neural networks decision feedback equalizer.

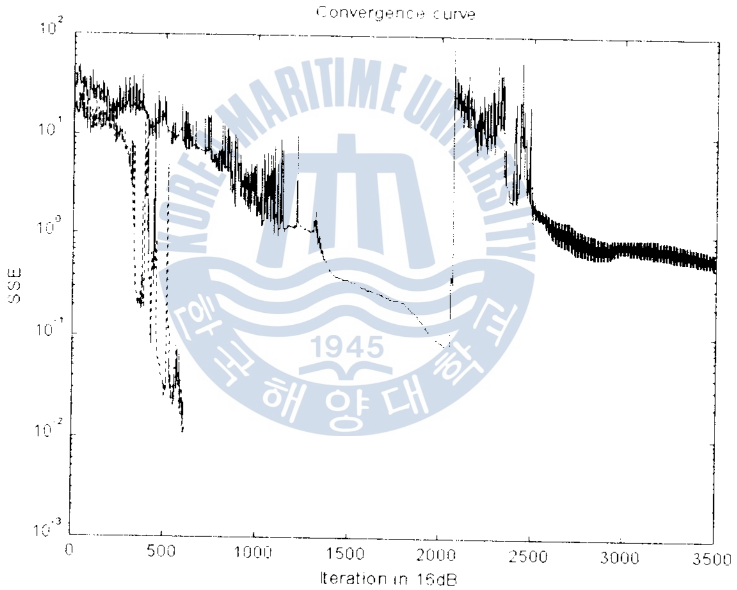

Figure 6 Convergence characteristics of equalizer (additive noise is -16dB).

Simulation results show the proposed neural network equalizer is more excellent than an equalizer with fixed number of tap when the channel characteristics are changed by time.

In figure 7, solid line is the result of proposed neural networks decision feedback equalizer, solid line with 'o' is conventional neural networks decision feedback equalizer and solid line with '*' is LMS type decision feedback equalizer. The tap number of LMS type equalizer are 25(10,15).

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6. Conclusions

This paper has introduced an adaptive decision feedback equalizer based on the complex back propagation structure that the number of tap is variant. This structure is capable of dealing with the 4-QAM signals over badly channel.

A signal processing of fixed number of tap(fixed tap) decision feedback equalizer in a conventional channel equalizer limits the performance of the system. To improve the system performance, this paper has proposed a new approach to adaptive equalization that makes use of optimal structure neural networks at channel characteristic.

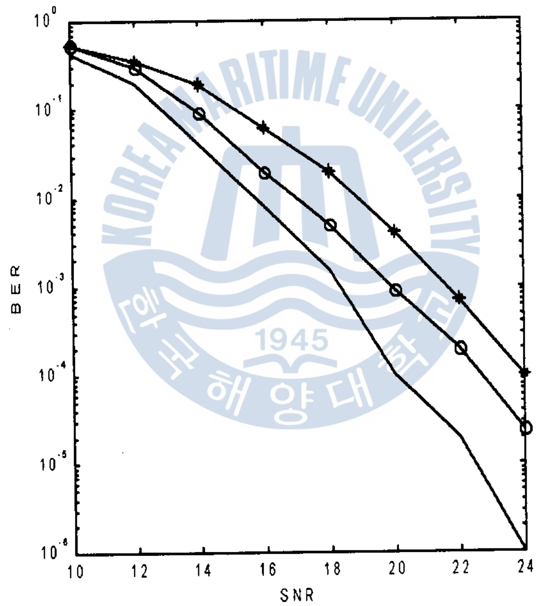

Figure 7 BER performance of equalizer with variation of SNR.

Improving the system performance, variable tap neural networks structures have been proposed for the channel equalization task.

When the proposed method is applied to the equalizer, we are obtained the improvement of 2dB ~ 4dB in channel characteristics of simulation results(example 1,2). And we confirmed that the performance of the variable tap neural networks based equalizer is improved convergence speed and BER substantially.

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