A Study on the Decision Feedback Equalizer using Neural Networks

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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(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 Ⅱ introduce a general nonlinear channel model used in the equalization problem. Section Ⅲ,Ⅳ introduces a new mothed that increment input neuron. In Section Ⅴ, represented simulation result that conventional DFE and proposed DFE.

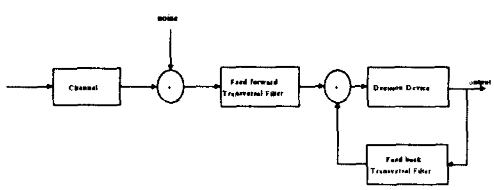

Fig 1. Channel equalizer structure(DFE).

Ⅱ. 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 ne written 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 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.

Ⅲ. 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.

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).

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

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

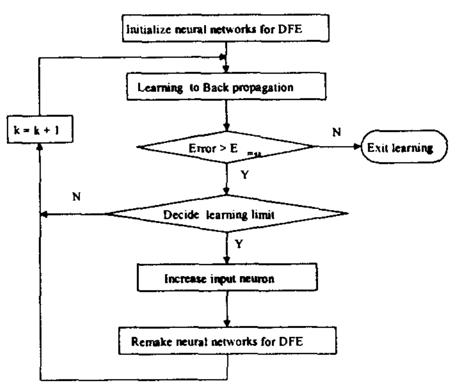

Fig. 2. The flowchart for increasing number of input neuron.

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.

Ⅳ. 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

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial h} \cdot \frac{\partial h}{\partial w}$$

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

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

$$\frac{\partial E_i}{\partial w_{pk}} = P_k \cdot x_p \qquad (4)$$

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

$$S_p = \sum_{k=1}^{K} \left| \frac{\partial E_k}{\partial w_{pk}} \right|,$$

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

$$\Delta S_{pq} = |S_p - S_q|$$

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 ⊿S is Feedforward part then increasing input layer neuron at Feedforward part else position of the selected ⊿S is Feedback part then increasing input layer neuron at Feedback part.

The proposed DFE illustrated in Fig. 3.

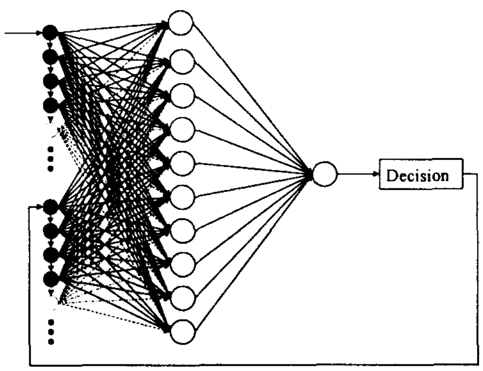

Fig. 3. The proposed Decision Feedback Equalizer based on the Neural Networks.

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

V. Simulation results

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

channel impulse response 1 is as follow

[0.04 0.05 0.07 -0.21 -0.5 0.72 0.36 0.21 0.03 0.07]

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

Fig. 4. depicts the learning characteristics of the equalizer based on the neural networks (proposed method and conventional back propagation)

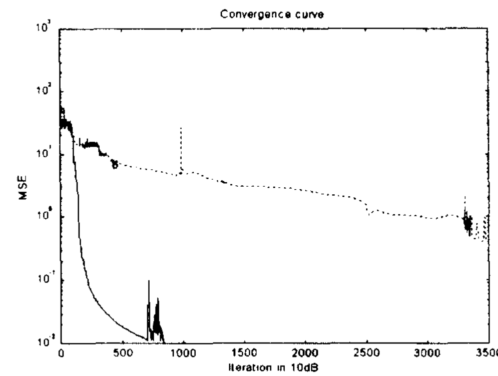

Fig 4. Convergence characteristics of equalizer additive noise= -10dB, solid line is proposed NN DFE, dotted line is conventional NN DFE.

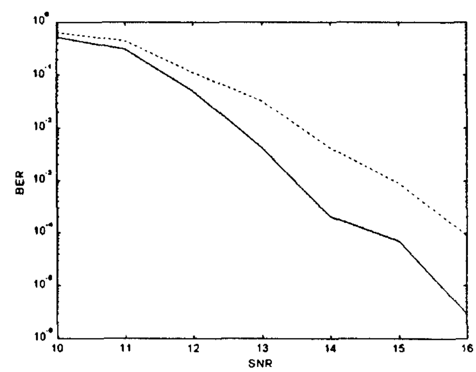

Fig. 5. BER performance of equalizer with variation of SNR.(sliod line is proposed NN DFE, dotted line is conventional NN DFE).

the proposed NN DFE initialized 10(5,5)-15-1, after learning, proposed NN DFE is 21(8,13)-15-1. conventional NN DFE is 15(5,10)-15-1. Shown the Fig. 4,5, we are known that proposed NN DFE more convergence speed and BER on variation SNR than conventional NN DFE.

channel impulse response 2 is as follow

[0.227 0.406 0.688 0.406 0.227]

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

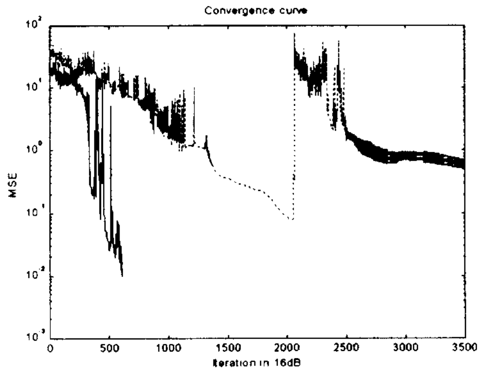

Fig. 6. Convergence characteristics of equalizer additive noise= -16dB, solid line is proposed NN DFE, dotted line is conventional NN DFE.

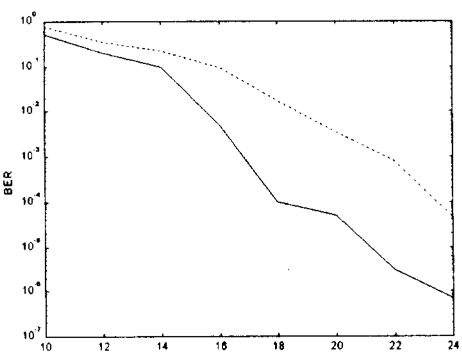

Fig. 7. BER performance of equalizer with variation of SNR.(sliod line is proposed NN DFE, dotted line is conventional NN DFE).

The proposed NN DFE initialized 10(5,5)-15-1, after learning, this proposed NN DFE is 27(11,16)-15-1. the conventional NN DFE is 15(5,10)-15-1.

In Fig. 6, we are shown that high frequency channel characteristics badly effect an convergence of error.

Also, we are known that proposed NN DFE more fast convergence speed and BER on variation SNR than conventional NN DFE.

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

Ⅵ. 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.

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