ADAPTIVE CHANNEL EQUALIZATION USING NEURAL NETWORK

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Abstract **This paper applies neural networks to the adaptive channel equalization of a bipolar signal passed through a dispersive channel in the presence of additive noise. The paper describes two neural networks which might be considered as adaptive equalizers. The simulation results confirm that the neural network equalizers offer a performance which exceeds that of linear structures. More specifically, this paper highlights the effects of delay order on BER performance for nonlinear structures.**

I. Introduction

In this paper we applies the application of nonlinear structures as adaptive channel equalizers and demonstrate the advantage which they offer over the linear transversal equalizer (LTE) [1], especially in a highly noisy environment. Channel equalization is a suboptimal technique employed to combat the effects of intersymbol interference (ISI) and noise, which corrupt the transmission of signals across a communication channel (Fig. 1). The task of the equalizer is to reconstruct the transmitted sequence with the minimum probability of misclassification, i. e.: $\tilde{s}(t) = s(t-d)$, where *d* is the delay. The channel is usually modeled by a FIR filter with the following transfer function: $H(z) = \sum_{i=0}^{n_h-1} h_i z^{-i}$, where h_i is the channel impulse response and n_h is his length. In Fig.1 the transmitted symbol *s(t)* is taken from the set $\{\pm 1\}$; it forms an independent and identically distributed sequence, and *e(t)* is an additive Gaussian noise with zero mean and variance σ_e^2.

It is well-known [1] that block detection equalization based on the principle of Maximum Likelihood Sequence Estimator (MLSE) will provide the best classification performance when the channel is completely known. Its implementation complexity is one of the main reasons for using other symbol-decision class equalizers with simpler implementation, but with poorer performance. If we consider the equalization problem as a geometric classification problem [2] we remark that the optimal decision boundary is sometimes nonlinear. This points us to one of the shortcomings of the LTE which necessarily forms decision boundaries which are hyperplanar and therefore leads to a significantly poorer bit-error rate (BER) in highly noisy environment. In this case we are led to a problem of noise enhancement so that if we increase the order of the LTE, the final power of the noise increases and this tends to diminish any advantage gained by increasing the LTE order. We can overcome these difficulties by utilizing neural networks as channel equalizers.

II. Nonlinear architectures

In this section we give a brief description of the architecture and capabilities of the multilayer perceptron (MLP) and the radial basis function (RBF) networks in equalization problem, confirming the results of Chang and Mulgrew [1,2].

In the MLP the neurons are arranged in layers as depicted in Fig.2 (a network with only one hidden layer). We shall describe the architecture of a perceptron by a sequence of integers $n_0, n_1, \ldots n_k$ where n_0 is the dimension of the input of the network, and the number of nodes in each layer, ordered from input to output, are $n_1, \ldots, n_k$.

RBF is a two-layer network comprising a hidden layer and an output layer (Fig. 3), and it has been shown to be capable of universal approximation as is the case for the MLP network [4]. The hidden layer contains *n* neurons, which calculate the Euclidean distance between a vector center $\mathbf{c}_i$ and an input vector $\mathbf{y} = \left[y(t)\ y(t-1)\ \ldots.\ y(t-m+1) \right]^t$. The result is passed through a nonlinear function to generate the hidden node output, Φ_i, normally chosen to be Gaussian functions $\Phi_i = \exp\left(-\frac{\left\| \mathbf{y} - \mathbf{c}_i \right\|^2}{r_i^2} \right)$, where r_i is called the width.

The output layer is computed by a weighted linear combination of the *n* neurons of the hidden layer. The overall response is a mapping: $f\ (\mathbf{y}) = \sum_{i=1}^{n} w_i \Phi_i$, where w_i are the weights. It has been shown [2] that RBF realizes an implementation of the optimal Bayesian equalizer if the parameters of the network are well chosen (i. e., the number of hidden neurons *n* is equal to the number of desired channel states: $n = 2^{m+n_h-1}$, the RBF centers are placed at desired channel states: $\mathbf{c}_i = \left[\bar{y}_i(t)\ \bar{y}_i(t-1) \ldots \bar{y}_i(t-m+1) \right]^t$ and all the widths are twice as large as noise variance). In our work, the training of RBF was done using a two-step approach: in the first step a supervised clustering procedure [2] was used to optimize the location of the centers and all the widths were set at $r_i = r = \frac{d_m}{\sqrt{2 \cdot n}}$, where d_m is the maximum distance between the chosen centers. In the second step, the second layer weights were trained using the least mean squares (LMS) algorithm.

III. Simulation Study

In the following simulation, the decision delay was fixed to 1. Simulations were conducted in order to illustrate the difference in performance between linear and nonlinear equalizers.

The channel used in our simulations is a discrete microwave channel modeled as a FIR filter, where only three components are selected in relation to a maximum peak distortion criterion. Its transfer function is: $H_1(z) = -0.0875 + 0.7901z^{-1} - 0.5989z^{-2}$. This discrete-time channel model is obtained by sampling the analog two-ray propagation model, and generally, it has a non-minimum phase characteristic [5]. We used a roll-off parameter equal to 0.3 in cosines-raised filter system and a transmission rate equal to 24 Mbit/sec. Phase-offset is not considered and the sampling optimum epoch is used [5]. We designed a 6-14-10-1 MLP network with the following parameters values and a 6-256-1 RBF network, with inputs $y(t), y(t-1),..., y(t-5)$. We have chosen six inputs by analogy with the linear Wiener filter where six has been shown to be the minimum number of inputs necessary to obtain the best performance. The number of hidden layers and neurons for the MLP has been determined experimentally after several tries. Concerning the RBF, the number of hidden centers leads to the architecture that realizes the bayesian equalizer [6]. However, some techniques are possible to reduce the complexity of nonlinear equalizers. One of them is the Variable Selection using the Statistical Sensitivity Analysis (VS-SSA)[3, 6]. This method allows the selection of an appropriate input variable subset which can reduce the complexity of the nonlinear structures without significant degradation in equalization performance, as was shown in [6].

For measuring the performance of our structures we used $BER_L = \log_{10}BER$, for 100000 test samples. The BER of the trained RBF network, the MLP network, the order-6 Wiener filter are plotted for comparison (Fig. 4). We can see the superiority of nonlinear techniques, and we observed an acceptable performance for 17 dB for nonlinear structures. The results were better for RBF structure than for MLP structure (Fig. 4).

III.1 The effect of delay

In the following simulation we will impose different delay orders for the RBFN structure. The equalizer order was chosen to be 4. The following two channels, showing the same magnitude but different phase responses, were used:

$$H_2(z) = 0.5429 - 0.1369z^{-1} - 0.9125z^{-2}$$
$$H_3(z) = 0.9125 + 0.1369z^{-1} - 0.5429z^{-2}$$

Simulations were conducted using 2 values of signal-noise ratio (SNR) with delay order d = 0,…,5 in order to study the effects of delay order on BER_L performance. In each case, we trained a different RBF in order to minimize the cost function $E\{[\bar{s}(t) - s(t-d)]^2\}$, where $E\{\bullet\}$ is the statistical operator. In fact, the Bayesian decision function depends also on delay order and there is at least one minimum value of this function which can be attained by different delay orders.

The results show that the optimum delay order which results in the best BER performance is different for each channel model even though these channels exhibit the same magnitude response. For example, for SNR=16 dB, the optimum delay for H_2 is 4, while it is 2 for H_3 (Fig. 5). Experiments also show that for the same channel the optimum delay may depend on the SNR. Note also that for different SNR conditions, the performance of the RBF equalizer can result in significantly different levels of classification performance (Fig. 5). The experiments showed that effects of the delay on the BER_L performance were the same for the MLP structure.

IV. Conclusion and Perspectives

In this paper we confirm the results of previous authors that is the MLP and RBF network can offer advantages over linear structures in the design of adaptive equalizers. However the selection of optimal parameters for a MLP equalizer need further studies. We highlighted the effects of delay order on BER_L performance for nonlinear structures. It is obvious that significant improvement to the equalizer's performance can be achieved over an equalizer which operates with a fixed delay order if the optimum delay could be calculated. We will focus on that in a future work.

V. References

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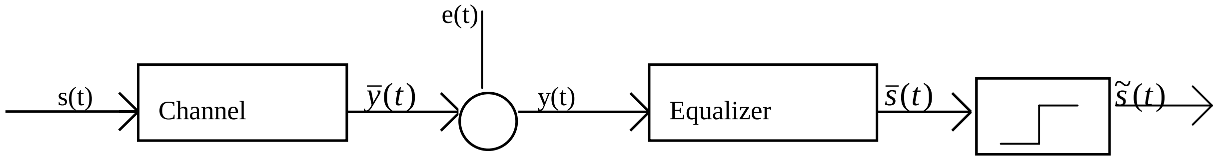

Fig. 1 Discrete-time model of a data transmission system.

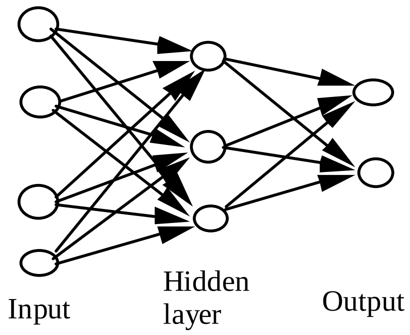

Fig. 2 Structure of multilayer perceptron (MLP)

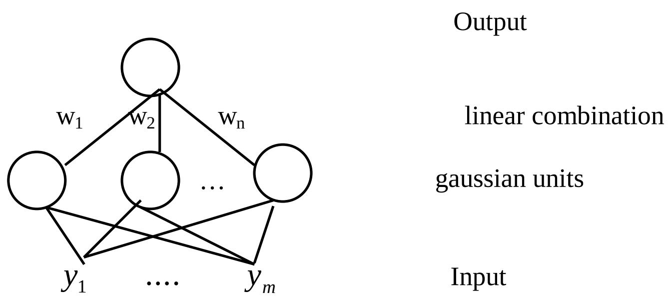

Fig. 3 Radial Basis Function Network (RBFN).

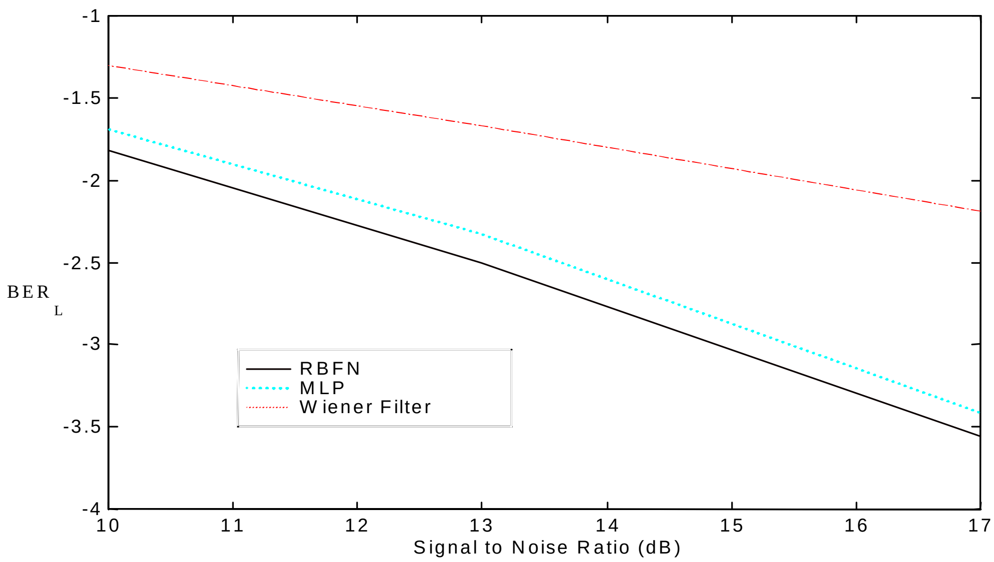

Fig. 4. $H_1(z)$ BER_L for RBF, MLP and Wiener Filter (The order of the Wiener filter equalizer was 6)

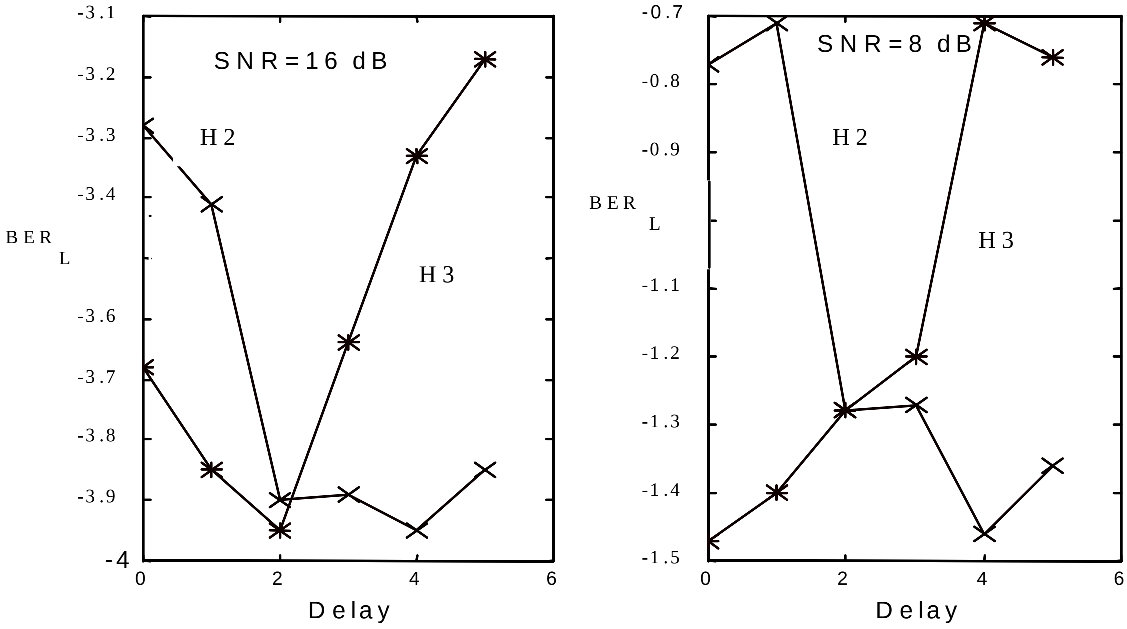

Fig.5 BER_L versus Delay for two SNR values for H_2 e H_3 channels.