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A Simple Recurrent Neural Network Equalizer Structure

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Abstract

This paper describes a one-processing-neuron recurrent neural network for application in channel equalization using variations on the RTRL (Real Time Recurrent Learning) algorithm for training the neural network. The structure is very simple and its computational demand is very low due to the use of only one processing neuron in its architecture. Simulation results are presented including several cases involving BPSK, 8PSK and 16PSK modulation schemes in additive Gaussian noise.

1. Introdution

1.1. The Equalization Problem

Several digital communication channels, particularly those using higher transmission rates are subject to intersymbol interference and additive noise. This interference is caused by the bandlimited characteristics of the channel that causes the spread of the transmitted pulses. Moreover, several channels are severely disturbed by non-linear distortion as in the case of satellite communications, or by the occurrence of fading as in mobile communications. Therefore, the use of special devices to compensate those disturbances is needed. According to the degree of the disturbance, it may be necessary to make use of more sophisticated techniques in the equalizer design.

1.2. Transmission Modeling

A radio transmission system usually consists of three parts. At one end is the transmitter. The transmitter accepts information from a source, transforms it into a form that can be transmitted and sends it over a *Radio Frequency* (RF) channel. The channel possibly distorts the transmitted signal before it reaches the receiver. It is then the receiver's task to decide what signal was transmitted, and to turn it into understandable information. If everything goes well, the information the receiver delivers should coincide with the information fed into the transmitter.

Figure 1: Components of a Transmission System

1.3. General Structure of an Equalizer

The general structure of a typical equalizer is depicted in figure 2. Details on the equalization problem and typical structures can be found in [9]. The received signal corrupted by additive noise and distorted by the channel is filtered or processed by the equalizer and a built in decision mechanism produces an estimate for the transmitted symbol with a possible delay.

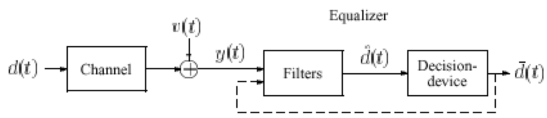

Figure 2**:** The structure of an equalizer

Due to the use modulation the signals involved in the transmission model are of complex nature and are known as complex envelopes [9].

2. The Neural Equalizer Structure

Neural networks are being used in many areas of engineering and other sciences and represent a reasonably new technology that can be used in channel equalization. Many communication researchers followed that approach and produced successful results using neural equalizers [1-6]. Within the field of neural networks, recurrent nets can offer very promising results as their inherent time-varying characteristics can enhance the properties of a dynamical system represented by a recurrent neural network [10].

This paper presents a very simple recurrent neural network structure with only one processing neuron as depicted in Figure 3.

The structure may have in fact more than two neurons but the second and subequent neurons are the so called input neurons and do not process information as the first neuron : the processing neuron. The only function of the input neuron is to multiply the input by a weight w_{2i} (i = 1,N).

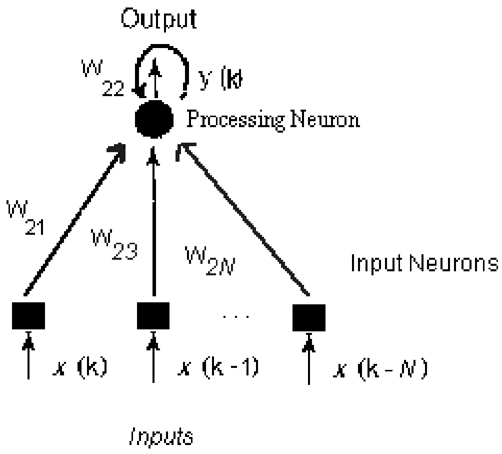

Figure 3: One Processing Neuron Recurrent Neuron Equalizer Structure

The neural network architecture may have one or more input neurons (receiving the signal to be processed by the equalizer) and one processing neuron (the main processing unit in the equalizer). The scheme results in a computational simple structure and yet efficient in equalizing channels as indicated by the simulation results.

The neural input at instant kT (where T is the symbol interval) is the signal to be equalized, i.e the channel output. The equalized output, i.e. the (processing) neural output is given by the equations

$$\begin{aligned} s(k+1) &= w_{21}(k)x(k) + w_{22}(k)y(k) + \\ &+ \sum_{i=3}^{N} w_{2i}(k)x(k-(i-2)T) \end{aligned} \tag{1}$$

$$\begin{aligned} y(k+1) &= \tanh(\mathrm{Real}(s(k+1))) + \\ &+ j\tanh h(\mathrm{Imag}(s(k+1))) \end{aligned} \tag{2}$$

where tanh(.) is the hyperbolic tangent function, j = $\sqrt{-1}$ and Real(.) and Imag(.) denote the real and imaginary parts of a complex number respectively.

The equalizer weights { w_{2i} } are obtained by training the recurrent neural network using variations on the RTRL (Real Time Recurrent Learning) techniques [7] based on RTRL training [1,8,10].

A summary of the training procedure is given below.

Define for the q-th neuron, the sensitivity terms, P_{RR}, P_{RI}, P_{IR}, P_{II} as

$$\begin{aligned} P^q_{RR\,ij} &= \left\{ \frac{\partial y_{R\,ij}}{\partial w_{R\,ij}} \right\} & P^q_{RI\,ij} &= \left\{ \frac{\partial y_{R\,ij}}{\partial w_{I\,ij}} \right\} \\ P^q_{IR\,ij} &= \left\{ \frac{\partial y_{I\,ij}}{\partial w_{R\,ij}} \right\} & P^q_{II\,ij} &= \left\{ \frac{\partial y_{I\,ij}}{\partial w_{I\,ij}} \right\} \end{aligned} \tag{3}$$

where the subscripts R and I denote real and imaginary parts respectively.

The objective function is also defined as

$$\begin{aligned} J(k) &= |E(k)|^2 = |d(k) - y(k)|^2 = \\ &= |e_R(k) + ie_I(k)|^2 \end{aligned} \tag{4}$$

where d(k) is the desired symbol (known in the learning phase).

The recursive equations for (3) are

$$\begin{aligned} &\begin{bmatrix} P^q_{RR\,ij} & P^q_{RI\,ij} \\ P^q_{IR\,ij} & P^q_{II\,ij} \end{bmatrix}(k+1) = \begin{bmatrix} \sec h^2(s_{R\,q}) & 0 \\ 0 & \sec h^2(s_{I\,q}) \end{bmatrix}(k) \\ &x\left(\sum_{m=1}^{Ninputs} \begin{bmatrix} w_{Rqm} & -w_{Iqm} \\ w_{Iqm} & w_{Rqm} \end{bmatrix} \begin{bmatrix} P^m_{RR\,ij} & P^m_{RI\,ij} \\ P^m_{IR\,ij} & P^m_{II\,ij} \end{bmatrix}(k) \right. \\ &\left. + \delta_{mq} \begin{bmatrix} x_{R\,j} & -x_{I\,j} \\ x_{I\,j} & x_{R\,j} \end{bmatrix}(k) \right) \end{aligned} \tag{5}$$

The weight update equation is:

$$\begin{aligned} &w_{ij}(k+1) = w_{ij}(k) \\ &+\alpha \sum_{k=1}^{Ninputs} \left(\begin{bmatrix} e_{Rk} & e_{Ik} \end{bmatrix} \begin{bmatrix} P^k_{RR\,ij} & P^k_{RI\,ij} \\ P^k_{IR\,ij} & P^k_{II\,ij} \end{bmatrix} \begin{bmatrix} 1 \\ j \end{bmatrix}(k) \right) \end{aligned} \tag{6}$$

where α is the learning rate parameter [10].

The initial values for the sensitivities are usually set to zero.

3. Simulation Results and Conclusions

The neural equalizer described in this paper was simulated using representative channel responses. Simulations included BPSK, 8PSK and 16PSK systems for several channel responses. The first channel used had a tranfer function in z-transform notation given by $H_1(z) = 1 + 0,7\ z^{-1}$., corresponding to a simple linear minimum phase channel with no zeros in the unity circle. This channel response was used by Kechriotis et all. [1] .For this type of channel linear equalizers perform well, particularly those with parameters adapted by recursive least squares algorithms [9]. The one-neuron recurrent neural equalizer can be viewed as a variation of the RTRL equalizer proposed by Kechriotis et all. by the use of training techniques such as the teacher forcing method [10] for a faster convergence. Basically, this method uses a replacement of the actual output of the processing neuron, during training of the network, with the corresponding desired response (or the target signal) in the computation of the dynamic behavior of the network, whenever that desired ouput is available. According to Williams and Zipser [11] the beneficial effects of teacher forcing are possibility of faster training and corrective mechanism during training.

Training can be achieved using only 50 or 100 symbols in contrast of 2000 used in [1]. The results were obtained based on 500 different realizations using 10^4 symbols for each value of SNR . The weights were initialized to small random values with a maximum value of 10^{-3} and a learning rate of 0.5. The bit error rates are shown in figure 4. Other results, for BPSK only, are shown in figure 5 for a partial response channel having a double zero on the unit circle with $H_2(z) = 1 -2z^{-1} + z^{-2}$. This response was also used in [1]. It can be seen that the one-neuron equalizer despite its very simple structure performs quite well compared to standard equalizers using RLS (Recursive Least Squares) techniques that might need as many as 20 taps in their structure. In all cases the equalizer used 3 input neurons plus the processing neuron yielding a structure with 4 neurons.

For future developments on the present paper, the author is working on the equalization problem using a structure similar to the one here presented for time varying channels using WSS-US (Wide Sense Stationary – Uncorrelated Scattering) channel models which are very suitable for modeling time-varying channels. This application is of high interest for cellular communications environments.

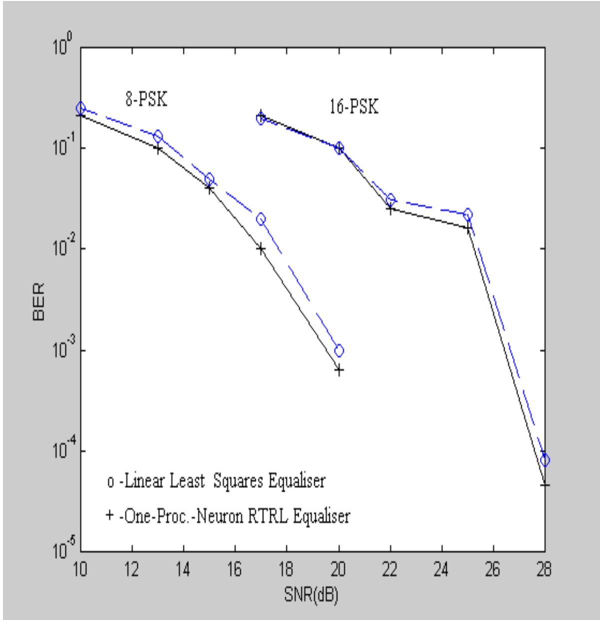

Figure 4: Bit Error Rate for Channel Response $H_1(z)=1+0.7z^{-1}$

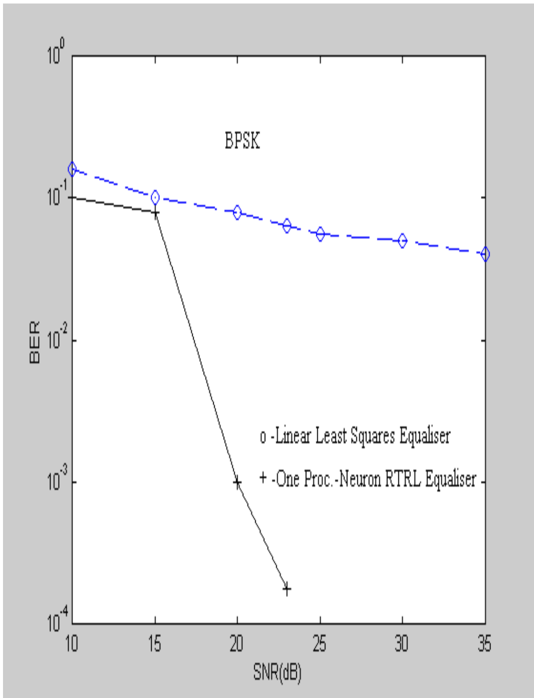

Figure 5: BER for Channel Response $H_2(z^{-1})=1-2z^{-1}+2z^{-1}$

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