NOVEL APPROACH TO COCHANNEL INTERFERENCE MINIMIZATION USING WILCOXON MULTILAYER PERCEPTRON NEURAL NETWORK

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***Abstract*—the purpose of this paper is based on, a novel wilcoxon learning machines technique used in artificial neural network equalizer, to mitigate the co-channel interference in the presence of additive white Gaussian noise (AWGN). Multilayer Perceptron Network, Radial Basis Function Network,Reurrent network, Functional link Artificial Neural Networks, Chebyshev Neural Networks, Fuzzy and Adaptive Neuro Fuzzy System have been successfully used in equalization. In this paper we proposed a MLP based equalizer trained using wilcoxon learning named as wilcoxon Multilayer Perceptron Neural network (WMLPNN). WMLPNN is a rank based statistics approach, in which weights and parameters of the network are updated using rules based on gradient descent principle. The Performance of the WMLPNN has been demonstrated through extensive computer simulations and compared with other neural networks equalizers in terms of convergence rate, computational complexity and bit error rate. The experiments results show the proposed method can effectively solve this class of problem.**

Keywords — Channel Equalizer; Artificial neural networks; Multilayer perceptron Neural network; Wilcoxon Multilayer Perceptron Neural Network; Linear channel; Back Propagation; Least mean Square; Recursive least squares.

I. INTRODUCTION

In wireless communication systems transmit high speed data over the communication channels. During this process the transmitted data is distorted, due to the effect of linear and nonlinear distortions. Linear distortion includes inter-symbol interference (ISI), co-channel interference (CCI) in the presence of additive white Gaussian noise (AWGN). Co-Channel Interference (CCI) occurs in cellular radio and dual-polarized microwave radio, for efficient utilization of the allocated channels frequencies by reusing the frequencies in different cells. When signals from different cells, sharing the same frequencies interfere with each other, co-channel interference arises. The non-ideal frequency response characteristic of the channel causes inter-symbol interference problem. Compensating all these channel distortion calls for channel equalization techniques at the receiver side[1,2]. Hence, adaptive channel equalizers played an important role in digital communication systems. Basically in an adaptive equalizer the current and past values of the received signal are linearly weighted by equalizer coefficients and summed to produce the output. The weights of equalizer are conventionally trained using least mean square (LMS) [1, 2, 4] and Recursive-least-squares (RLS) algorithm [1,2,5]. Generally linear equalizers show poor performance and hence nonlinear equalizers have been popular. ANN is a powerful tool in solving complex applications such as function approximation, pattern classification, nonlinear system identification and adaptive channel equalization. Conventionally an ANN based multi layer perceptron (MLP) [2,3,7,8] equalizer is trained the by error back propagation algorithm but it has a drawback of slow convergence. It has been seen that an optimal equalizer based on maximum a-posterior probability (MAP) criterion can be implemented using Radial basis function (RBF) network [2,3,4,9,10]. Different equalizers based on MLP for mitigation of co-channel interference have also been proposed. Here we proposed a MLP equalizer trained with wilcoxon learning algorithm [12-13] to mitigate co-channel problem.

The paper is presented in five sections following this section on introduction, Section II discusses the Communication system model consisting Co-channel interference; Section III discusses the Multilayer Perceptron Neural Network and Wilcoxon Multilayer Perceptron Neural Network. Section IV discusses the performance of MLP equalizer trained with Wilcoxon learning, and Section V provides the remark and conclusions.

II. SYSTEM DESCRIPTION

Figure.1 shows a digital communication system model where *x(t)* is the transmitted symbol sequence, $\eta(t)$ is additive white Gaussian noise, $y(k)$ is a received signal sequence sampled at the rate of the symbol interval T_s, $\hat{x}(k)$ is an estimate of the transmitted sequence $x(t)$ and d denotes the delay associated with estimation. The received signal is additionally corrupted by n-co-channel interference sources. The receiver has a copy

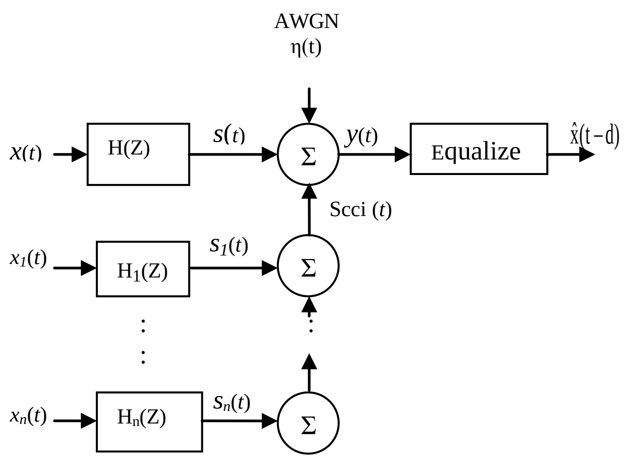

Figure. 1. Communication system model with Co-channel interference

of the training signal transmitted by the transmitter. The received signal sequence is defined by the following equation.

$$y(t) = s(t) + s_{CCI}(t) + \eta(t) \qquad \ldots\ldots (1)$$

Where $s(t)$ is the output of the desired channel, $Scc_I(t)$ is the co-channel interference component. The desired signal $s(t)$ and co-channel signal $Scc_I(t)$ are represent as

$$s(t) = \sum_{i=0}^{n_h} h(i)x(t-i) \qquad \ldots\ldots. (2)$$

$$s_{CCI}(t) = \sum_{j=1}^{k} \sum_{i=0}^{n_{h_j}-1} h_j(i)x_j(t-i) \qquad \ldots\ldots (3)$$

Where, $x(t)$ and $x_j(t)$ are the desired and co-channel data symbols respectively, $h(i)$ and $h_j(i)$ are the impulse responses of the desired channel and the j^{th} co-channel, having n_h and n_{hj} taps respectively, and k is the number of the interfering co-channels. Furthermore, the desired and co-channel data symbols and noise samples are assumed to be mutually uncorrelated. Without loss of generality the transmitted sequences can be assumed to be bipolar (± 1). The signal-to-noise ratio (SNR) and the signal-to-interference ratio (SIR) are defined as

$$SNR = \frac{\sigma_s^2}{\sigma_e^2} \qquad SIR = \frac{\sigma_s^2}{\sigma_{CCI}^2} \qquad \ldots\ldots.. (4)$$

Where $\sigma_e^2, \sigma_s^2, \text{and} \sigma_{CCI}^2$, are the noise variance, the signal power and the co-channel signal power respectively.

III. ARTIFICIAL NEURAL NETWORK

This section briefly describes the operation of a multi layer perceptron network and Wilcoxon Multilayer Perceptron Neural Network.

A. *Multi Layer Perceptron Network*

Artificial neural network based on MLP are feed forward nets with one or more layer of nodes between its input and output layers, and due to the nonlinearity activation function with each nodes the MLP is capable of forming arbitrarily complex decision function in the pattern space [2,3,7,8]. Figure.2 shows the block diagram of the MLP neural network. A three-layer MLP with enough number of nodes in the hidden layer **is** capable of approximating any arbitrary nonlinear mapping between the input and output space. The input pattern s(k) and its corresponding desired pattern d(k) are applied to the network.

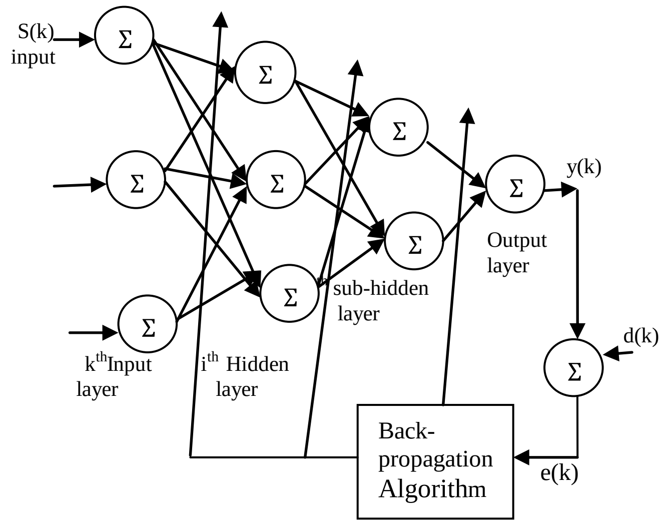

Figure: 2. block diagram of the MLP neural network

The MLP produces an output $y(k)$ is obtained as

$$y(k) = f\left(\sum_{j=0}^{n-1}(s_j w_j) + b\right) \qquad \ldots\ldots (2)$$

Where, b is the bias and w_j the weight matrix associated with input line j. Which is then compared with the desired pattern d(k) resulting an error signal $e(k)$ is obtained as

$$e(k) = d(k) - y(k) \qquad \ldots\ldots. (3)$$

The error signal is propagated back to the hidden layers. The weights and thresholds associated with the network are then updated using the back propagation (BP) algorithm [8]. This procedure is repeated till the mean square error (MSE) of the network approaches a minimum value. The MSE at k^{th} time index may be defined as

$$E(k)=\sqrt{\frac{1}{n}\sum_{j=1}^{n}\left[e_i(k)^2\right]} \qquad \ldots\ldots\ (4)$$

Where n is the number of nodes of the output layer and $\boldsymbol{e_j(k)}$ is the error associated with the j^{th} output node .

B. *Wilcoxon Multilayer Perceptron Neural Network*

Machine learning, namely learning from examples, has been an active research area for several decades, [12, 13]. WMLPNN is a rank based statistics approach, in which weights and parameters of the network are updated using rules based on gradient descent principle. In the wilcoxon learning machines the wilcoxon norm of a vector [12] is used as the objective function. To define the wilcoxon norm of a vector we need a score function $\varphi:[0,1]\rightarrow R$, i.e. is a function which is not decreasing function, associated with the score function and is defined by

$$a(i)=\varphi\left(\frac{i}{l+1}\right)\ldots\ldots i\in \underline{l} \qquad \ldots\ldots\ (8)$$

Where, $\underline{l}$ is a positive integer and define the function as a pseudo-norm function as

$$\|v\|w=\sum_{i=1}^{l}a(R(v_i))v_i=\sum_{i=1}^{l}a(i)v(i) \qquad \ldots\ldots\ (9)$$

Where,

$$v=[v_1,v_2\ldots\ldots v_l]^T\in R^l$$

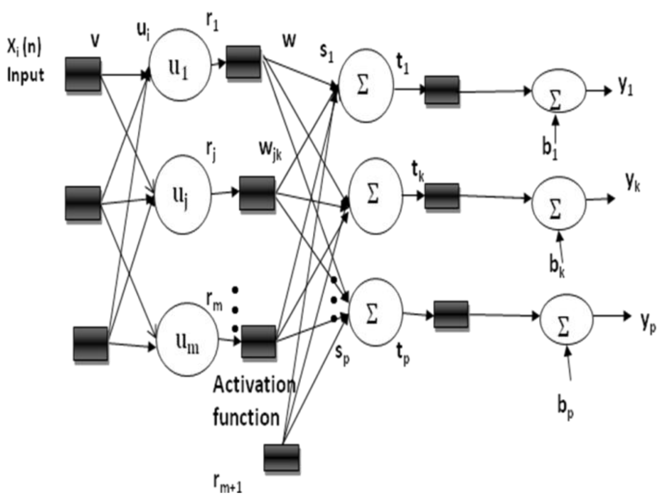

Figure.3. Block Diagram of Wilcoxon MLP neural network

In the general WMLPNN [13], There are one input layer with n+1 nodes, one hidden layer with m+1 nodes, and one output layer with nodes

$$x=[x_1,x_2\ldots\ldots x_n]^T\in R^n$$

$$z:=[z_1,z_2\ldots.z_n,z_{n+1}]^T=[x_1,\ldots\ldots.x_n 1]^T\in R^{n+1}$$

Used activation function is unipolar logistic function

$$r_j=f_{hj}(u_j)=\frac{1}{1+e^{-u_j}} \qquad \ldots\ldots\ (10)$$

The input and output of the output node are given by

$$S_k=\sum_{j=1}^{m+1}w_{kj}r_j \qquad r_{m+1}:=1 \qquad \ldots\ldots\ (11)$$

$$t_k=f_{ok}(S_k)\ldots\ldots k\in p \qquad \ldots\ldots\ (12)$$

The final output of the network is given by

$$y_k=t_k+b_k\ldots\ldots k\in p \qquad \ldots\ldots.\ (13)$$

Using incremental gradient descent algorithm. In this algorithm ψ_k are minimized in sequence represent as

$$\psi=\|P_k\|w=\sum_{q=1}^{l}a(q)[d_{qk}-t_{qk}] \qquad \ldots\ldots\ (14)$$

First, propose an updating rule for the output weights. It is given by

$$w_k=w_k-\eta\frac{\partial\psi_k}{\partial w_k},\ldots\ldots.k\in \underline{p},\ldots..\eta>0 \qquad \ldots\ldots\ (15)$$

Where,

$$\frac{\partial\psi_k}{\partial w_k}=\sum_{q=1}^{l}a(q)(-1)f'_{ok}(S_{(q)k})r_{(q)}=-\sum_{q=1}^{l}a(R_{(p_{qk})})f'_{ok}(S_{qk})r_q$$

Hence, the updating rule becomes

$$w_{kj}\leftarrow w_{kj}+\eta.\sum_{q=1}^{l}a(R_{(p_{qk})})f'_{ok}(S_{qk})r_{qj},\ldots\ldots.\ j\in\underline{m+1} \qquad \ldots\ldots\ (16)$$

Next, propose an updating rule for the input weights. It is given by

$$\frac{\partial\psi_k}{\partial w_k}=-\sum_{q=1}^{l}a(q)f'_{ok}(S_{(q)k})\begin{bmatrix}w_{k1}f'_{h1}(u_1)\\ w_{k2}f'_{h2}(u_2)\\ w_{km}f'_{hm}(u_m)\end{bmatrix}_{(q)}\times[z_1,z_2\ldots\ldots..z_n,z_{n+1}]_{(q)} \qquad \ldots\ldots.\ (17)$$

Hence, the updating rule becomes

$$v_{ji}\leftarrow v_{ji}+\eta.\sum_{q=1}^{l}a\left(R_{\left(p_{qk}\right)}\right)f'_{ok}(S_{qk})w_{kj}f'_{hj}(u_{qj})z_{qi} \qquad \ldots..\ (18)$$

The $b_k\ldots k\in\underline{p}$ is given the median of the residuals at the k^{th} output node is

$$b_k=\underset{1\le q\le l}{med}\{d_{qk}-t_{qk}\} \qquad \ldots..\ (19)$$

IV. Simulation Results and Discussion

The performance of the proposed equalizer was validated using simulation studies. Here performance of WMLPNN was compared with MLP equalizer and linear equalizer trained with BP algorithm. Initially the equalizers were trained with 1000 samples of training data and next the bit error rate (BER) performance was estimated using 100,000 samples. During the simulation were conducted under SIR of 10dB to 20dB and SNR of 0 to 30dB. The channel impulse response used in the experiment is presented in TABLE.1.

TABLE.1

LINEAR CHANNELS SIMULATED

Channel No.	Channel impulse response	Type of Channel
Ch1	$0.5+1.0Z^{-1}$	Non Minimum phase
Ch2	$0.26+0.93Z^{-1}+0.26Z^{-2}$	Maximum phase

A. Training Performance

During training the convergence of algorithm is evaluated from MSE at each iteration, for this study the training performance of equalizers were evaluated using ch1 was used as main desired channel and ch2 was used as the co-channel. Figure. 4 show the convergence characteristic of MLP, WMLPNN and RLS equalizer. MLP and WMLP the equalizer has 3-inpu nodes, 9-hidden nodes and one output node.

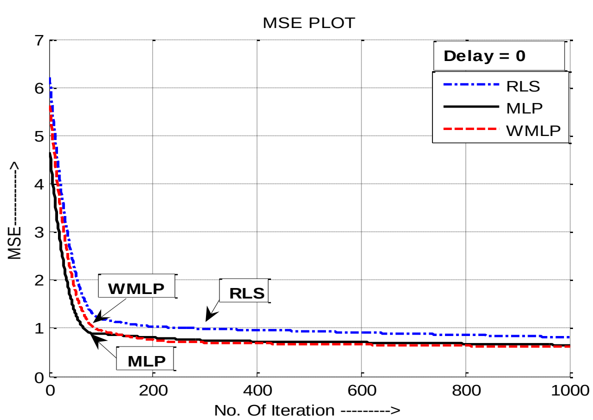

Figure.4 Convergence characteristic of RLS, MLP & WMLPNN equalizer for ch1 +CCI-ch2, SIR= 13dB, SNR30dB, Delay= 0.

From the simulation results it is seen that all equalizer are able to train their parameter. WMLPNN equalizer has a better trained from other equalizer.

B. BER Performance

The bit error rate (BER) performance provides the actual performance of the equalizer. The performance of WMLPNN was analyzed using BER as performance index. For this in the first study ch1 was used as the main channel and ch2 was used as co-channel with SIR=13dB and the structure is 3-9-1, the performance of all types of equalizer is presented in figure.5 (a) & (b) and figure.6 represent similar results using ch1 as main channel and ch2 as co-channel at SIR=15dB and the structure is 3-9-1.

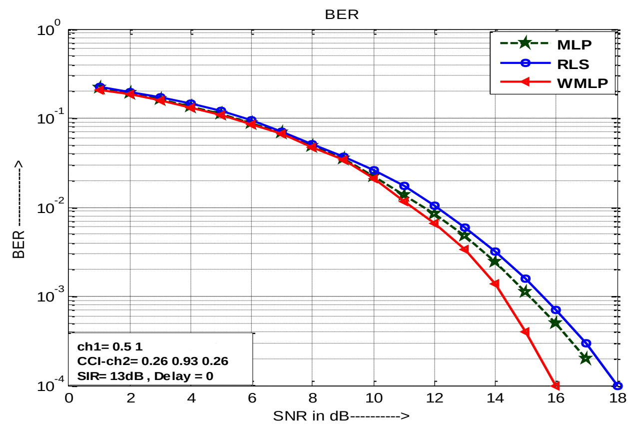

Figure.5 (a)

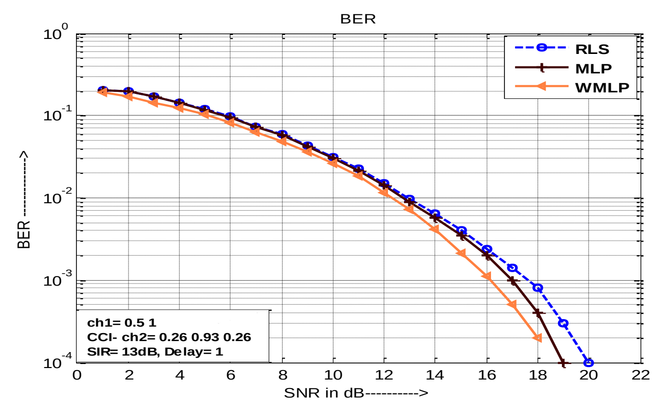

Figure.5(b)

Figure.5 (a), (b). BER performance of RLS (FIR=3rd order), MLPNN & WMLPNN (3-9-1) equalizer for ch1 +CCI-ch2, SIR= 13dB, SNR30dB, (a) Delay= 0, (b) Delay=1.

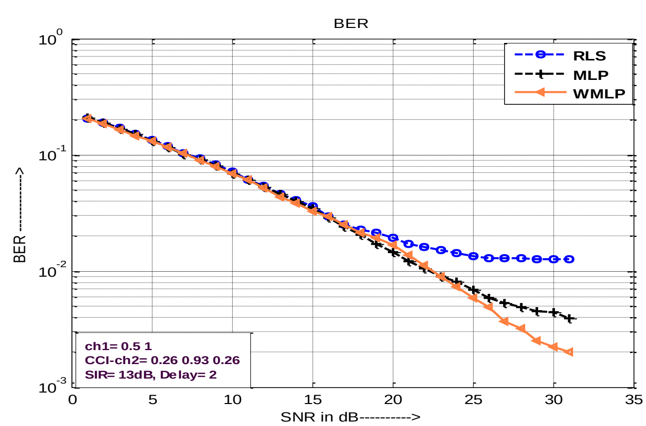

Figure.6. BER performance of RLS (3rd order), MLPNN & WMLPNN (3-9-1) equalizer for Ch1 +CCI-ch2, SIR= 15dB, SNR30dB, Delay= 2.

The above simulation results demonstrate that the WMLPNN equalizer posses capability for co-channel mitigation and performs better than MLP and RLS equalizer.

V. CONCLUSION

A multilayer perceptron neural network equalizer to combated co-channel interference is structurally complex. A MLP equalizer designed to treat co-channel interference as noise suffers from performance degration. The WMLPNN proposed here provides a performance superior to RLS, MLP equalizer which treat co-channel as noise. Simulation studies demonstrate this.

REFERENCES

[1]. S. U. H. Qureshi, “Adaptive Equalization,” IEEE, vol. 73, pp. 1349–1387, September 1985.

[2]. S. Haykin, Neural Networks – A Comprehensive Foundation. PHI publication: 2006.

[3]. M. Ibnkahla, Signal Processing for Mobil Communications Handbook, Ed. Boca Raton, FL: CRC Press, 2005.

[4]. J. G. Proakis, Digital Communications, 4^{th} edition. New York: McGraw-Hill Int., 2001.

[5]. Steven Van Vaerenbergh, Javier Via and Ignacio Santamaria, “Nonlinear System Identification Using a New Sliding-Window Kernel RLS Algorithm”, IEEE journal of communication, Vol.2, No.2, 3-May-2007.

[6]. Naveen Single and Joseph A. O’Sullivan, “Minimum Mean-Square-error Equalization using Priors for Two-Dimension Intersymbol Interference”, April 5, 2007

[7]. Gibson, G.J., S.Siu and C.F.N.Cowan,”Application of multilayer perceptrons as adaptive channel equalizer,” IEEE Int. Conf. Acoust., Speech, Signal Processing, Glasgow, Scotland, pp.1183-1186, 1989.

[8]. M. Meyer and G. Pfeiffer, "Multilayer perceptron based decision feedback equalizers for channels with intersymbol interference,”. IEEE Transactions,Vol 140, No 6, pp 420-424, Dec 1993.

[9]. Deng Jianping, Narasimhan Sundararajan, ”Communication Channel Equalization Using Complex-valued Minimal Radial Basis Function Neural Networks”, IEEE Transactions on neural networks, Vol.13, No.3, May 2002.

[10]. S. K. Patra and B. Mulgrew, “Fuzzy Implementation of Bayesian Equalizer in Presence of intersymbol and Co-channel Interference,” IEEE Transactions on Communication system, 1998.

[11]. C. C. Chuang, J. T. J eng, and P. T. Lin, “Annealing robust radial basis function networks for function approximation with outliers,” neuro-computing, vol.56, pp. 123-139, May 2004.

[12]. R. V. Hogg, J. W. McKean and A. T. Craig, Introduction to Mathematical Statistic, 6^{th} edition, Englewood Cliffs, NJ: Prentice-Hall, 2005.

[13]. S. Wan and L. E. Banta, “Parameter incremental learning algorithm for neural networks”, IEEE transaction, Neural Network.., vol.17, no. 6, pp. 1424-1438, November 2006.