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ISI & BURST NOISE INTERFERENCE MINIMIZATION USING WILCOXON GENERALIZED RADIAL BASIC FUNCTION EQUALIZER

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***Abstract*- This paper presents a novel technique in channel equalization. Wireless communication system is affected by inter-symbol interference, co-channel interference and Burst noise interference in the presence of additive white Gaussian noise. Different equalization techniques have been used to mitigate these effects using Artificial Neural Networks based Multilayer Perceptron Network, Radial Basis Function, Recurrent Network, Fuzzy and Adaptive Neuro fuzzy System, and also using linear adaptive LMS, RLS system. In this paper we proposed a RBF based equalizer which is trained using wilcoxon learning method. The equalizer presented shows considerable performance gain. Simulation studies have been conducted to demonstrate the performance of wilcoxon training for this class of problem.**

Keywords*— Channel Equalizer, Artificial neural networks, Multilayer perceptron network, Radial basis function, wilcoxon generalized radial basis function network, Linear channel, Back Propagation, Least mean Square, Recursive least squares.

I. INTRODUCTION

Today's 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) and nonlinear distortion includes Burst noise interference. The non-ideal frequency response characteristic of the channel causes inter-symbol interference problem, and burst noise is a heigh intensity noie which occures for short duration of time, its affect the signal consequitively, Compensating all these channel distortion calls for channel equalization techniques at the receiver side.

Adaptive channel equalizers have played an important role in digital communication systems [1-2]. Adaptive equalization at the receiver removes the effects of ISI and BNI. Basically 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 trained using least mean square (LMS) [3] and Recursive-least-squares (RLS) algorithm [4]. Figure.1 shows a digital communication system model where s(n) is a transmitted symbol sequence, $\eta(n)$ is additive white Gaussian noise, b(n) denoted as burst noise is a heigh intensity noie which occures for short duration of time, its affect the signal consequitively, $y(n)$ is a received signal sequence sampled at the rate of the symbol interval T_s and $\hat{s}(n)$ is an estimate of the transmitted sequence s(n). The received signal sequence is defined by the following equation.

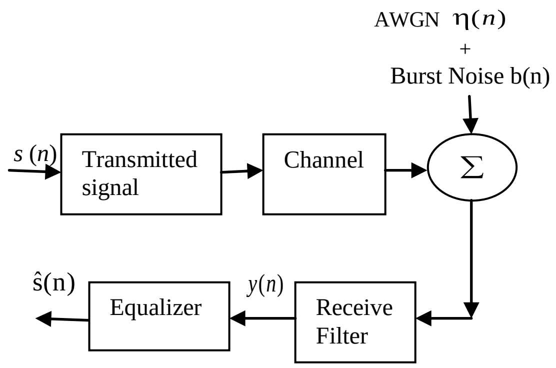


Figure. 1. Digital communication system model

$$y(n)=\sum_{i=0}^{r-1} x_i(n)s(n-i)+\eta(n)+b(n) \quad \ldots\ldots (1)$$

Where, $0 \le i \le r-1$, 'n' represents the sampling time at the receiver, (r-1) is the channel length and $x_i(n)$ is represents the impulse response of the channel. It is assumed that channel is FIR. Generally linear equalizers show poor performance and hence nonlinear equalizers have been popular. ANN [2] 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) [6] 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 [7-11]. Here the RBF centers are fixed using K-mean clustering and weights trained using LMS. Different equalizers based on RBF for mitigation of ISI and BN interference have also been proposed [11]. Here we proposed a RBF equalizer trained with wilcoxon learning algorithm [12, 14] to mitigate ISI and BN interference problem.

The paper is presented in four sections, following this Section on introduction; Section II discusses the Radial basic function and Wilcoxon Generalized Radial basic function equalizer. Section III discusses the performance of the RBF equalizer trained with Wilcoxon learning, and Section VI provides the remark and conclusions.

II. ARTIFICIAL NEURAL NETWORK STRUCTURE

This section describes the artificial neural network equalizers structures, Radial basis function (RBF) equalizer and Wilcoxon Generalized Radial basis function equalizer (WGRBFE).

A. *Radial Basic Function Equalizer*

The RBF network was originally developed for interpolation in multidimensional space [7- 11] .The schematic of this RBF network with *m* inputs and a scalar output is presented in Figure. 2

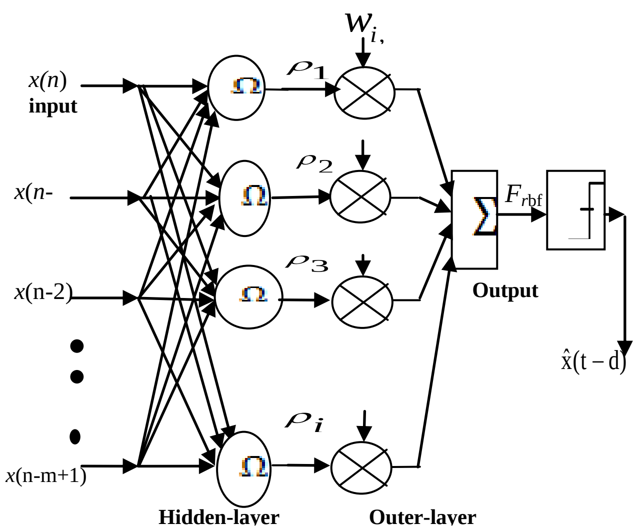


Figure.2. Structure of the Radial basis function network

This network can implement a mapping F_{rbf}: $R^m \to R$ by the function

$$F_{rbf}\{x(n)\} = \sum_{i=1}^{r_h} w_i \phi(\| x(n) - \rho_i \|).......x(n) \in R^m \quad ......(2)$$

Where $x(n)$ is the input vector, is the given kernel function from R+ to R, $w_{i,}....1 \le i \le r_h$ are weights and $\rho_i \in R^m$ are known as RBF centers. The centers of the RBF networks are updated using k-means clustering algorithm. Gaussian kernel is the most popular form of kernel function for equalization application represented as

$$\phi(\gamma) = \exp(\frac{\gamma}{-\sigma_{r_h}^2}) \quad .... (3)$$

Here, the parameter $\sigma_{r_h}^2$ controls the radius of influence of each basis functions and determines how rapidly the function approaches $0..with..\gamma$. Equalization applications the RBF inputs are presented through a TDL. Training of the RBF networks involves setting the parameters for the centers ρ_i, spread σ_η^2 and the linear weights w_i RBF the spread parameter, $\sigma_{r_h}^2$ is generally set to channel noise variance σ_η^2 this provides the optimum RBF network as an equalizer. In the RBF network the weights can be updated using simple least-means-square (LMS) algorithm can be done sequentially and the network offers a nonlinear mapping, maintaining its linearity in parameter structure at the output layer

B. *Wilcoxon Generalized Radial Basic Function Equalizer*

Machine learning, namely learning from examples, has been an active research area for several decades, [12,14]. WGRBFN 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 [13] is used as the objective function. To define the wilcoxon norm of a vector we need a score function $\varphi : [0,1] \to R$, i.e. is a function which is not decreasing function, associated with the score function and is defined by

$$a(i) = \varphi\left(\frac{i}{l+1}\right)......i \in \underline{l} \quad .... (4)$$

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

$$\|v\|w = \sum_{i=1}^{l} a(R(v_i))v_i = \sum_{i=1}^{l} a(i)v(i) \quad .... (5)$$

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

In the general GRBFN [14], we will consider a commonly used class of approximating functions with Gaussian basis functions define as $g : R^n \rightarrow R^p$

$$x = [x_1, x_2......x_n]^T \in R^n \quad y = [y_{1,} y_{2,} ....y_p]^T \in R^p$$

Then, the predictive function *f* is a nonlinear map given by

$$y_k = f_k(x) = \sum_{j=1}^{m} w_{kj} \exp[-\sum_{i=1}^{n} (x_i - c_{ji})^2 / v_{ji}] + b_k ,....k \in \underline{p} \quad .... (6)$$

Where w_{kj} is the connection weight from the j^{th} hidden node to the k^{th} output, c_{ji} is the center of the j^{th} basis function, v_{ji} is the i^{th} variance of the j^{th} basis function, $v_{ji} = 2\sigma_{ji}^2 > 0$ b_k is the bias term given as

$$b_k = \underset{1 \le q \le l}{med} \{d_{qk} - t_{qk}\} \quad ...... \quad (7)$$

In this network, there is one input layer with *n* nodes, one hidden layer with *m* node and one output layer with *p* nodes. We have p bias terms at the output nodes.
Define, for $i \in \underline{n}, j \in \underline{m}, k \in \underline{p}$

$$u_j = \sum_{i=1}^{n} (x_i - c_{ji})^2 / v_{ji}, r_j = \exp(-u_j), t_k = \sum_{j=1}^{m} w_{kj} r_j \quad ...... \quad (8)$$

In WGRBFN the parameters can be updated using following rules

$$w_{kj} \leftarrow w_{kj} + \eta . \sum_{q=1}^{l} a(R(\rho_{qk})) r_{qj}, \ j \in \underline{m} \quad ..... \quad (9)$$

$$c_{ji} \leftarrow c_{ji} + \eta . w_{kj} . \sum_{q=1}^{l} a(R(\rho_{qk})) r_{qj} \frac{2(x_i - c_{ji})^2}{v_{ji}^2} \quad .... \quad (10)$$

$$v_{ji} \leftarrow v_{ji} + \eta . w_{kj} . \sum_{q=1}^{l} a(R(\rho_{qk})) r_{qj} \frac{(x_{qi} - c_{ji})^2}{v_{ji}^2} \quad .... \ (11)$$

Where $\eta > 0$ is the learning rate. The WGRBF equalizer perform almost similar like an optimal RBF network.

III. SIMULATION STUDIES

The performance of the proposed equalizer was validated using simulation studies. Here performance of WGRBF equalizer was compared with RBF equalizer and linear equalizer trained with LMS algorithm and using KMean's Clustering algorithm updates the center of the RBF and WGRBF equalizer. 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. the simulation conducted under SNR of 0 to 30dB and the burst noise 5% of 100 samples consequitively affect the input signal with 10dB. 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	$1 + 0.5\ Z^{-1}$	Minimum phase
Ch2	$0.26+0.93Z^{-1}+0.26Z^{-2}$	Mixed phase

A. *MSE Performance Study*

The training performances of equalizers were demonstrated using ch2. The convergence of algorithm is evaluated from MSE at each iteration for this study. The MSE was plotted at each iteration is shown in Figure.3 RBF and WGRBF equalizer has 2-input and 16-centers. From the simulation result it is seen that all equalizer are able to train their parameter. WGRBF equalizer has a better trained from other equalizer.

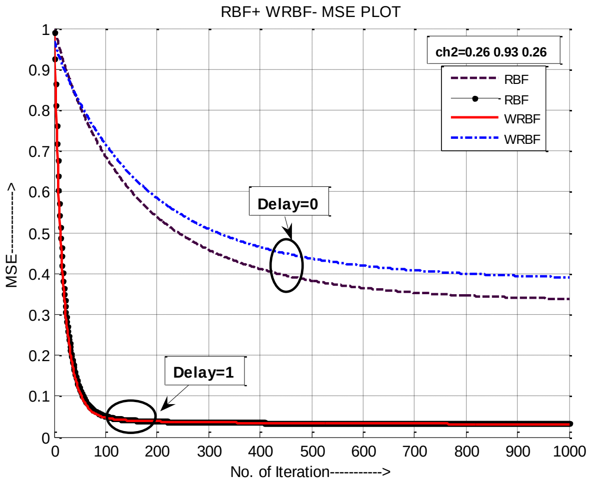
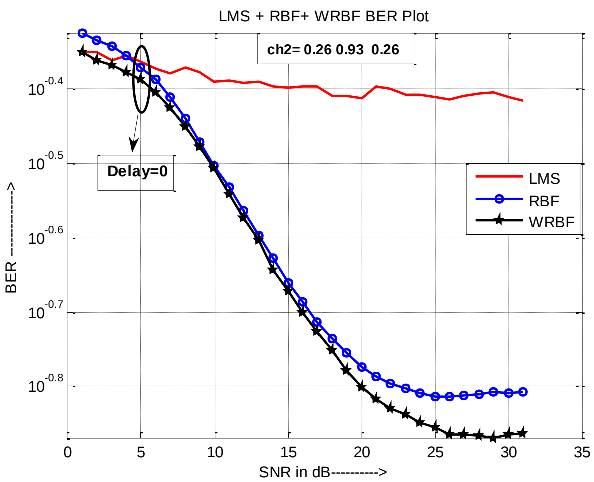
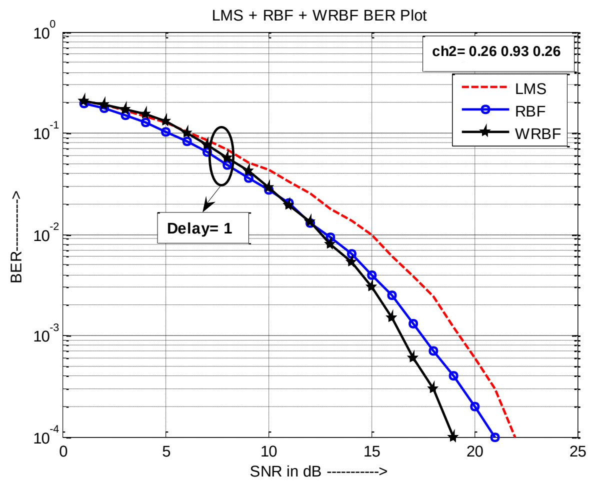


Figure.4. Convergence characteristic of WGRBF and RBF equalizer for Ch2, the burst noise 5% of 100 samples consequitively affect the input signal SNR=30dB, Delay= 0, 1.

B. *BER Performance Study*

The bit error rate (BER) performance provides the actual performance of the equalizer. The performance of WGRBF equalizer was analyzed using BER as performance index. For this in the first study ch2 was used as channel, here the burst noise 5% of 100 samples consequitively affect the input signal with AWGN and ISI, consider the structure of RBF, WGRBF equalizer is 2- input, 16-center, and 1-output and SNR of 0 to 30dB. The performance of all types of equalizer is presented in figure.5 respectively. Figure.6 represents the BER performance of ch1, here the structure of RBF and WGRBF equalizer is considered as 2-input, 8- center, and 1-output and SNR of 0 to 30dB. From the simulation results it is seen that WGRBF performs similar to RBF and sometimes better.





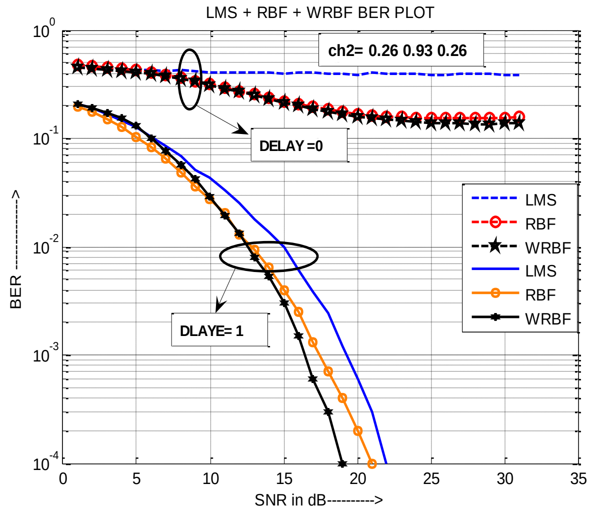


Figure.5. BER performance of the LMS+RBFN +WGRBFN equalizer for ch2 , the burst noise 5% of 100 samples consequitively affect the input signal, SNR= 30dB, Delay= 0, 1.

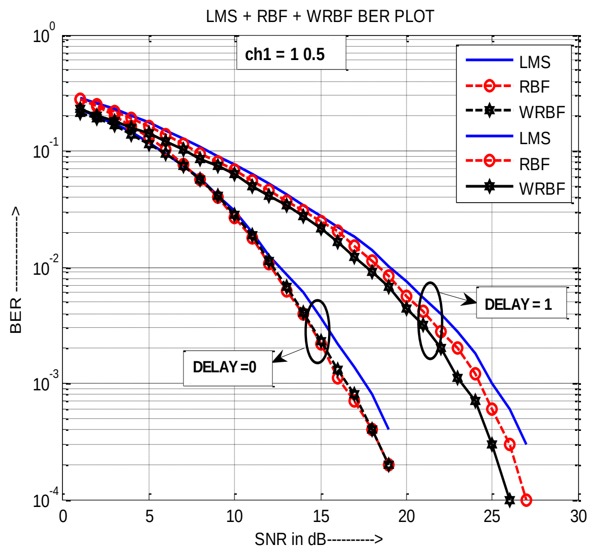


Figure.6. BER performance of the LMS+RBFN +WGRBFN equalizer for ch1 , the burst noise 5% of 100 samples consequitively affect the input signal, SNR= 30dB, Delay= 0, 1.

IV. CONCLUSION

A radial basis function equalizer to combated burst noise and inter-symbol interference is structurally complex. A RBF equalizer designed to treat inter-symbol and burst noise interference as noise. The WGRBF proposed here provides MSE performance superior to RBF equalizer and BER performance similar and better than RBF and LMS equalizer. Simulation studies demonstrate this.

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