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Channel Equalization using Weiner filter

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***Abstract*—Many digital communication systems suffer from the problem of inter symbol interference (ISI), which may arise from the common phenomenon of multipath propagation, thus to achieve reliable communication in these situations, channel equalization is necessary. This paper presents how to reduce ISI, for that first we are calculating the optimal channel weight vector of wiener filter. The purpose of the wiener filter is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal.**

Keywords:- ***Equalizer, Channel Equalizer ISI, Decision Feed Back Equalization, LMS.***

I. INTRODUCTION

Digital transmission has tremendous impact on the human civilization due to the development in digital communication technology. With expanding communication networks, as we move towards a more information centric world and the demand for very high speed efficient data transmission over communication channels increases, communication system engineers face ever-increasing challenges in utilizing the available bandwidth more efficiently so that new services can be handled in a flexible way.

Many digital communication systems suffer from the problem of inter symbol interference (ISI), which may arise from the common phenomenon of multipath propagation, thus to achieve reliable communication in these situations, channel equalization is necessary.

The demand for high data rates has increased the requirement of equalization techniques so that the effects of channel may be reduced. Channel equalization is used to improve the received signal quality in telecommunication especially in digital communication system.

In the proposed method, first the optimal channel weight vector of wiener filter is calculated. The basic concept behind wiener filter is to minimize the difference between filter output and some desired output. This minimization is based on the least mean square error approach which adjusts the filter coefficient to reduce the square of the difference between desired and actual waveform after filtering. Then these weight vectors will be updated by multiplicative neural network using a bisigmoidal activation function so as to get output signals approximately equal to the desired signal.

1. BRIEF REVIEW OF THE PREVIOUS WORK DONE

Most of the digital communications channels suffer from inter symbol interference due to non ideal nature of the channel. In real time application ISI with a additive white Gaussian noise creates severe problem at the receiver, in order to obtain reliable transmitted signal equalizer is required at the receiver end. As per researches non linear equalizer exhibit better performance than linear equalizer, forward neural network architecture with optimum number of nodes has been used to achieve adaptive channel equalization in [1]. Forward neural network architecture with optimum no. of nodes has been used to achieve adaptive channel equalization and Summation at each node is replaced by multiplications which result in powerful mapping [2]. Contribution of FIR filter in neural network has been described in [3], also Novel Adaptive DFE with the combination of FIR filter & functional link neural network (CFFLNNDFE) is introduced. Further improve

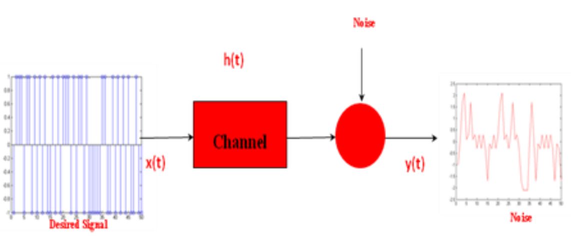
the performance of the non linear equalizer to drive novel simplified, modified, normalized LMS algorithm. In paper [4] Conditional Fuzzy Clustering-Means (CFCM) has been proposed, a collection of estimated centers is treated as set of pre-defined desired channel, states & used to extract channel output states. This Modification of CFCM makes it possible to search for the optimal desired channel states of an unknown channel. The desired channel states, the Bayesian equalizer is implemented to reconstruct transmitted symbols.

In paper [5] applications of artificial neural networks (ANNs) in modeling nonlinear phenomenon of channel equalization has been described in detail. The Author has been used different feed forward neural network (NN) based equalizers like multilayer perception, functional-link ANN, radial basis function, and its variants are reviewed. Feedback-based NN architectures like recurrent NN equalizers. Training algorithms has been compared in terms of convergence time and computational complexity for nonlinear channel models. In paper [6], A novel fully complex multiplicative neural network(MNN) algorithm has been proposed to extract

Quadrature Amplitude Modulation (QAM) signals when passed through a non linear channel in the presence of noise. The training algorithm for the multilayer feed forward fully complex MNN has been derived. The equalizer is tested on 4, 16 & 32 QAM signal and compared with split complex feed forward MNN equalizer. High order feed forward neural network architecture with optimum number of nodes used for adaptive channel equalization in [7]. The equalizer has been tested on Rayleigh fading channel with BPSK signals and performance comparison with recurrent radial basis function(RRBF) neural network show that the proposed equalizer provides compact architecture and satisfactory results in terms of bit error rate performance at various levels of signal to noise ratios for a Rayleigh fading channel. In Paper [9] authors used new approach Neural Networks as a classifier for equalization of communication channels. The classical gradient based methods suffer from the problem of getting trapped in local minima. And the stochastic methods which can give a global optimum solution need long computational times. Also used a novel method in which the task of an equalizer is decentralized by using a FIR filter for studying the channel characteristics. In paper [9] Authors proposed a new neuron model based on a polynomial architecture and considering all the higher-order terms.

3. CHANNEL EQUALIZATION

In communication system transmitter sends information over an RF channel which distorts the transmitting signal before it reaches the receiver. Equalization is the process of recovering the data sequence from the corrupted channel samples.



$$y(t) = \underbrace{x(t)h_0(t)}_{\text{Desired Signal}} + \underbrace{\sum_{k=1}^{m} x(t-k)h_k(t)}_{\text{ISI}} + \underbrace{n(t)}_{\text{Noise}} \quad (1)$$

Figure 1 Communication Channel

3.1 PURPOSE OF EQUALIZATION

Equalization reduces Inter Symbol Interference (ISI) as much as possible to maximize the probability of correct decisions. Channel distortion arises in many communication systems and the distortion increases as the data rate compression in time or in space is increased within a fixed bandwidth channel. It happens in telephone channel, cellular mobile radio and fiber optical channel; this phenomenon is called the ISI.

ISI is an unavoidable consequence of both wired and wireless communication systems which reduce the quality of the received signal as measured by Bit Error Rate (BER).

3.1.1 CAUSES OF INTER SYMBOL INTERFERENCE (ISI)

- Band limited nature of channel
- Symbol rate is higher than the bandwidth.
- Channel multipath reflection
- Crucial channel spacing
- Multipath effects

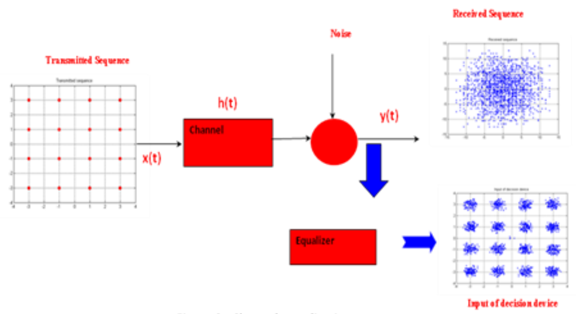


Figure 2 Channel equalization

4. PROPOSED METHODOLOGY

In the proposed method, first the optimal channel weight vector of wiener filter is calculated by the estimation of correlation and cross correlation of input and desired noiseless signal. The basic concept behind wiener filter is to minimize the difference between filter output and some desired output. This minimization is based on the least mean square approach which adjusts the filter coefficient to reduce the square of the difference between desired and actual waveform after filtering. Then these weight vectors will be updated by multiplicative neural network using a bisigmoidal activation function.

4.1. PROPOSED STRUCTURE FOR CHANNEL EQUALIZATION

When a corrupted input signal is filtered with wiener filtered, it provides weighted output y(n) . Error detector checks for the difference between desired signal and the output signal and if this error is within a Bit error Rate Range, weights are updated by multiplicative neuron network. Bisigmoidal activation function is used within the MNN.

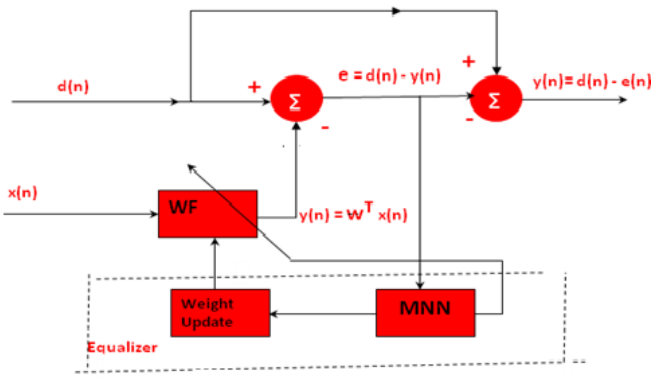


Figure-3 Channel Equalizer Using W F

4.2 WIENER FILTER

Wiener filter is the basis of adaptive filter theory. It is the optimal filter that most adaptive filtering algorithms attempt to achieve. The generalization to the complex case is straightforward. Consider the situation in fig. 4 where d(n) is the desired signal and x(n) is the input signal. The input x(n) is processed by a filter so that the output is y(n).

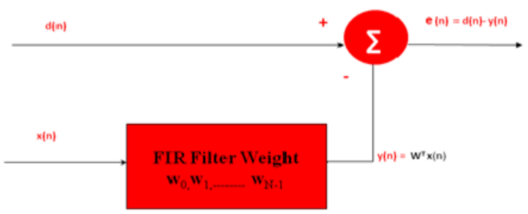


Figure-4 Wiener Filter

4.2.1. CALCULATION OF OPTIMAL WEIGHT

The goal is to find the impulse response coefficients of this filter so that the expected value of the squared errors squared error. $E\{e^2(n)\}$ is minimized. For FIR

$$Y(n) = w_0 x(n) + w_1 x(n-1) + ----- + w_{N-1} x(n-N+1) \qquad (1)$$

$$Y(n) = w^T x(n) \qquad (2)$$

$$w^T = [w_0, w_1 --- w_{N-n}]$$

$$x[n]\; x(n-1) ----- x(n-N+1)$$

The function to be minimized is called the cost function or objective function given as

$$J(w) = E\{e^2(n)\}$$
$$= E\{[d(x) - y(n)]^2$$
$$J(w) = E\{d^2(n) - 2d(n)y(n) + y^2(n) \qquad (3)$$

Now we can substitute for y(n) from (2). Note that since y(n) is a sum of product, $y^2(n)$ can be written as

$$w^T x(n) x^T(n)\; w$$

With this substitution and using the fact that the expectation operation is linear, equation (3) can be written as,

$$J(w) = E\{d^2(n) - 2E\{d(n) w^T x(n)\} + E\{w^T x(n)\, x^T(n) w \qquad (4)$$

The function to be minimized is called the cost function or objective function given as Since the filter weight vector w is not a random variable, the cost function reduces to

$$J(w) = E\{d^2(n) - 2w^T E\{d(n)x(n)\}$$
$$+ w^T E\,\{x(n)\, x^T(n)\} w \qquad (5)$$

We assume d(n) has zero mean. The first term in (5) is equal to σ^2_d, variance of d(n).

Also can define

$$P = E\{d(n)x(n)\} = [p^{(0)} p^{(1)} --- p^{(N-1)}]^2 \qquad (5.1)$$

as the cross correlation between the desired signal and the input signal vector. In the third term in (5), we easily recognize the correlation matrix

$$\mathbf{R} = E\{x(n) x^T(n)\} \qquad (5.2)$$

The cost function now becomes

$$J(w) = \sigma_d^2 - 2w^T p + w^T R w \qquad (6)$$

The second term in (6) is linear in terms of the filter coefficients, and the third term is quadratic. Hence the overall cost function is quadratic also called convex.

A Convex function has a unique minimum point, which can be easily solved for by taking the gradient with respect to w and setting it to zero. To see this process, it is instructive to study the case of a 2-tap wiener filter. The cost function in this case is

$$J(w_0, w_1) = E\{d^2(n) - 2E\{d(n)y(n)\} + E\,\{y^2(n)\}$$
$$= \sigma_d^2 - 2w_0 p(0) - 2w_1 p(1) + w_0^2 r(0) + 2w_0 w_1 r(1) + w_1^2 r(0) \qquad (7)$$

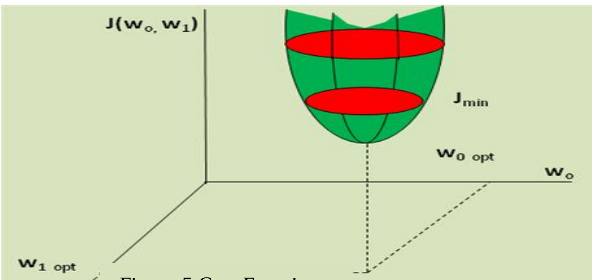


Figure-5 Cost Function

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With the cross-correlation and autocorrelation as constants, this cost function is clearly a quadratic function in w_0 and w_1. The minimum is at the bottom of the "bowl." The derivatives of the cost function with respect to the two weights are

$$\frac{\partial J}{\partial w_0} = -2p(0) + 2w_0 r(0) + 2w_1 r(1) \qquad (8)$$

$$\frac{\partial J}{\partial w_1} = -2p(1) + 2w_0 r(1) + 2w_1 r(0) \qquad (9)$$

The gradient,

$$J\nabla(W0, W1)$$

Can then be written in matrix format as

$$\nabla J(w_0, w_1) = \begin{bmatrix} \dfrac{\partial J}{\partial w_0} \\ \dfrac{\partial J}{\partial w_1} \end{bmatrix} \qquad (10)$$

$$J(w) = -2p + 2Rw \qquad (11)$$

By setting this gradient to zero, we get the Wiener filter

$$w_{opt} = R^{-1} p \qquad (12)$$

We have used the subscript "opt" to denote the optimal weight vector.

4.3 WEIGHT UPGRADATION USING MNN

Neural network Solves problem by self origination, It has massive parallel distributed structure & has ability to learn. It is mostly used in Non-linear, I/O mapping etc. In this work weights are updated with MNN for which Bipolar Sigmoidal activation function is used at each node. Proposed network can solve complicated problem and require less number of parameters as compared to the existing conventional models.

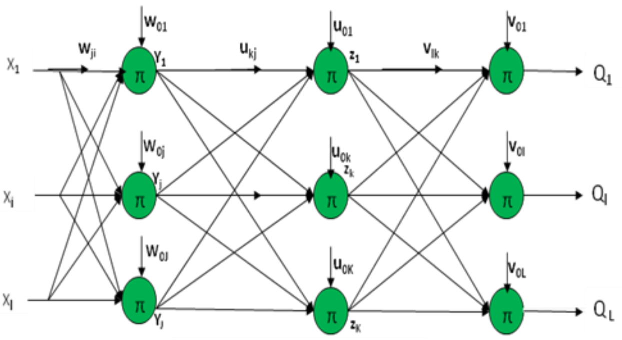

Figure-6 Multiplicative Neural Netwok

4.3.1 BIPOLAR SIGMOIDAL (TAN SIGMOID) ACTIVATION FUNCTION

Bipolar sigmoid is most powerful & most authentic activation function. According to tan sigmoid activation function:

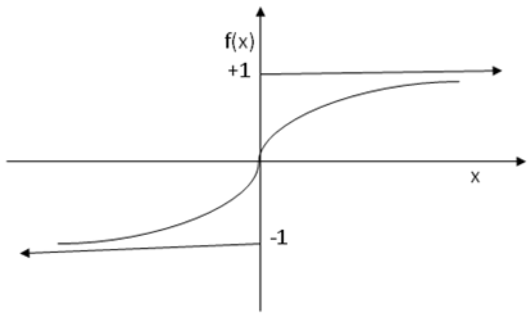

Figure-7 Tan Sigmoidal (Bipolar) Activation Function

For Multiplicative Neural Network in figure -5 we can write various equations connecting input, weights, activation function and output as:

$$net\ j = \prod_{i=1}^{I} (w_{ji}\ x_i + w_{oj})$$

$$y_j = f(net\ j)$$

$$net\ k = \prod_{j=1}^{J} (u_{kj}\ y_j + u_{0k})$$

$$z_k = f\ (net\ k)$$

$$net\ l = \prod_{k=1}^{K} (v_{lk} z_k + v_{ol})$$

$$Q_l = f\ (net\ l)$$

Now mean square error is given by-

$$E = \frac{1}{2PL} \sum_{l=1}^{L} \sum_{p=1}^{P} (Q_{lp}^{t} - Q_{lp}^{a})^2$$

For minimum error-

$$\frac{dE}{dw_{ji}} = \frac{dE}{d(Q_{lp}^t - Q_{lp}^a)} * (-1) * \frac{dQ_{lp}^a}{d\ netl} * \frac{d\ netl}{dz_k} * \frac{dz_k}{d\ netk} * \frac{d\ netk}{dy_j} * \frac{d\ y_j}{d\ netj} * \frac{d\ netj}{dw_{ji}}$$

$$\frac{dE}{dw_{ji}} = \frac{-1}{PL}\sum_{l=1}^{L}\sum_{p=1}^{P}(Q_{lp}^{t}-Q_{lp}^{a})*\{1-(Q_{lp}^{a})^{2}\}*\{1-(z_k)^{2}\}*\{1-(y_j)^{2}\}$$

$$*\frac{netl*netk*netj*x_i}{(v_{lk}z_k+v_{0k})*(u_{kj}y_j+u_{oj})*(w_{ji}x_i+w_{oi})}$$

Now weights can be updated as-

$$w_{ji}(new) = w_{ji} + \Delta w_{ji}$$

$$\Delta w_{ji} = \eta \frac{dE}{dw_{ji}}$$

$$w_{ji}(new) = w_{ji} + \eta \frac{dE}{dw_{ji}}$$

Additive weights w_{0j}, u_{0k} *and* v_{0l} *as shown in fig.*7 *can be taken directly from ref.* [2]

$$\Delta w_{oj} = \eta \frac{\Delta w_{ji}}{y_j}, \Delta u_{ok} = \eta \frac{\Delta u_{kj}}{z_k}, \Delta v_{ol} = \eta \frac{\Delta v_{lk}}{Q_l^a}$$

$$w_{0j}(new) = w_{0j} + \eta \frac{\Delta w_{ji}}{y_j}$$

$$u_{ok}(new) = u_{0k} + \eta \frac{\Delta u_{kj}}{z_k}$$

$$v_{0l}(new) = v_{0l} + \eta \frac{\Delta v_{lk}}{Q_l^a}$$

5. Results

Input	**Input with Noise**	**Output**	**SNR**
1	1.17	1.0607	16.4745
0	0.05	0.042	23.8095
1	0.89	0.95	20

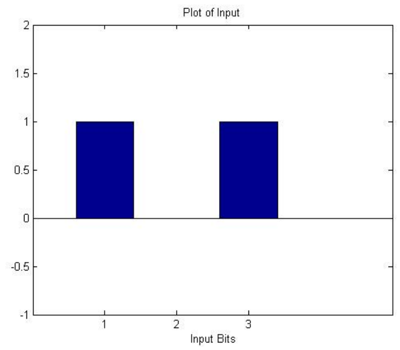

Figure-8

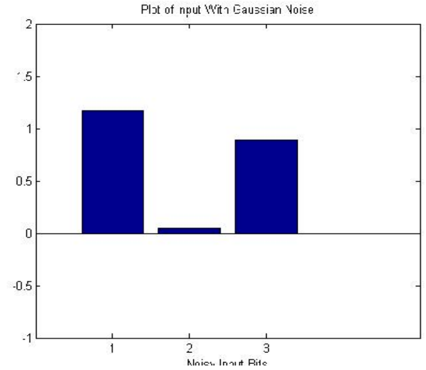

Figure-9

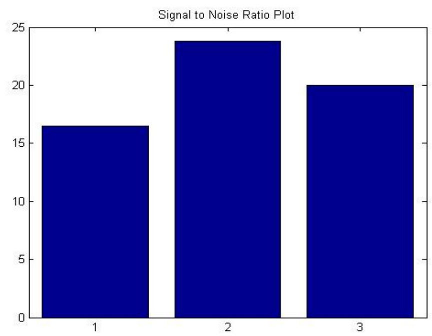

Figure-10

For digital data variation of signal to noise ratio has been obtained from 15 to 25 db

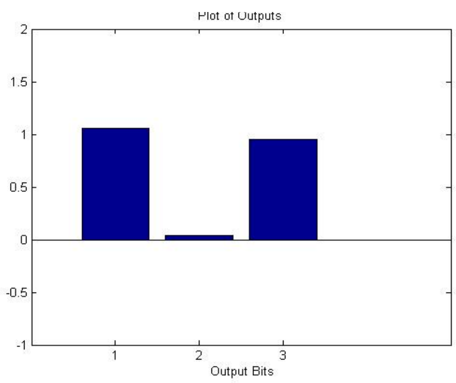

Figure-11

6. CONCLUSION

The Proposed model for channel equalization has been verified for speech signal. It has been observed that output SNR increases with increase in input SNR. Bit error rate also decreases with increase in the output SNR.

7. FUTURE WORK TO BE DONE

Verification of the proposed model for channel equalization for more number of input continuous signals like speech signals of approximately same frequency.

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