Review Paper on Additive Noise Filtering in Digital Communication using Neural Network

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Abstract – In this paper we proposed reduction of noise at the receiver end using multiplicative neural network techniques. We compared the improved result of bit error rate in terms of mean square error convergence curve at different stage of peak signal to noise ratios. Multiplicative neural network is very effective approach with low complexity. The outcome is analyzed by variation in M-array quadrature amplitude modulation technique.

Keywords: Quadrature amplitude modulation (QAM), Peak signal to noise ratio (PSNR), Bit error rate (BER).

I. INTRODUCTION

In Present world the Quadrature amplitude modulation (QAM) is use in both an analog or digital modulation scheme. It transfer two analog message or two digital bit streams, by changing an amplitudes of two carrier waves, using the amplitude-shift keying (ASK)digital modulation scheme or amplitude modulation (AM) analog modulation scheme. The tow carrier waves usually sinusoids, are out of phase with each other by 90^0 and are thus called Quadrature carriers or Quadrature. The modulated waves are summed, and the final waveform is a combination of both phase-shift keying (PSK) and amplitude-shift keying (ASK) or of phase modulation (PM) and amplitude modulation. In digital QAM signal, a finite number of at least two phases and at least two amplitudes are used. PSK modulators are often designed using the QAM principle, but it is not considered as QAM since the amplitude of the modulated carrier signal is constant. QAM is used widely as a modulation scheme for digital communication system[1].

In a high speed digital data transmission in communication channel effectively, the adverse effect of dispersive channel causing inter symbol interference (ISI), the nonlinearities introduced by modulation of demodulation process and the noise generated in system are to be suitable compensated. In such cases, nonlinear equalizer structures may be contently employed with added advantage in terms of lower bit error rate (BER) and lower mean square error (MSE) and higher convergence rate than those of a linear equalizer [2].

Artificial neural network (ANN) can perform complex mapping between its input and output space and are capable of forming complex decision regions with nonlinear decision boundaries further , because of nonlinear characteristics of the ANN, these network of different architecture have found successful application in channel equalization[3] .

When significant noise is added to the transmitted signal linear boundaries are not optimal. The received signal at each sample instant may be considered as a nonlinear function of the past values of the transmitted symbols. Further, since the nonlinear distortion varies with time and from place to place, effectively the overall channel response becomes a nonlinear dynamic mapping and the problem is tackled using classification techniques. As shown in a wide range of engineering applications, neural network (NN) has been successfully used for modeling complex nonlinear systems and forecasting signal with relatively simple architecture [4]-[5].]. A wide range of neural architectures are available for modeling the nonlinear phenomenon of channel equalization. Feed forward networks like multilayer perceptron (MLP) which contain an input layer, an output layer and one or more hidden layers possess nonlinear processing capabilities and universal approximation characteristic and have been successfully implemented as channel equalizers [7]-[9]. The back propagation which is a supervised learning algorithm is used as a training algorithm [10]. These neuron models process the neural inputs using the summing operation. Recently, higher-order networks have drawn great attention from researchers due to their superior performance in nonlinear input-output mapping, function approximation, and memory storage capacity. Some examples are Product unit neural network (PUNN), Sigma-Pi network (SPN), Pi-Sigma network (PSN) etc. They allow neural networks to learn multiplicative interactions of arbitrary degree. Multiplication plays an important role in neural modeling of biological behavior and in computing and learning with artificial neural networks. The multiplicative neuron contains units which multiply their inputs instead of summing them and thus allow inputs to interact nonlinearly. Multiplicative node functions allow direct computing of polynomials inputs and approximate higher order functions with fewer nodes. Thus they may present better approximation capability and faster learning times than the classical MLP because of their capability of processing higher-order information from training data [11]-[13].

II. CHANNEL EQUALIZATION BY NEURAL NETWORK

The block diagram of adaptive equalization in figure 1 is described as follows. The external time dependant inputs consist of the sum of the desired signal d(k), the channel nonlinearity NL and the interfering noise v(k). The adaptive filter has a finite impulse response (FIR) structure. The impulse response is equal to the filter coefficients. The coefficients for a filter of order p are defined

$$W_k=[\ W_k(0),\ W_k(1),\ldots\ldots\ldots,\ W_k(p)]^T \quad (1)$$

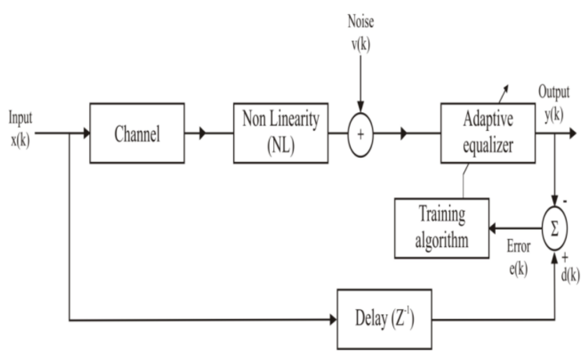


Fig.1 Block diagram of an adaptive equalizer

A predefined delayed version of the original signal forms the training sequence to provide reference points for the adaptation process. The criterion for optimization is a cost function or the error signal which is the difference between the desired and the estimated signal given by

$$e(k) = d(k) – y(k) \quad (2)$$

The desired signal is estimated by convolving the input signal with the impulse response expressed as

$$d(k) = W^T_k\ x(k) \quad (3)$$

where $x(k)=[x(k),x(k-1),\text{-------------}x(k-p)]^T$ is the input signal vector. The filter coefficients are updated at every time instant as

$$W_{k+1} = W_k + \Delta W_k \quad (4)$$

ΔW_k is a correction factor for the filter coefficients.

The optimization algorithm can be linear or nonlinear. Figure 2 shows a feed forward multiplicative neural network (MNN).

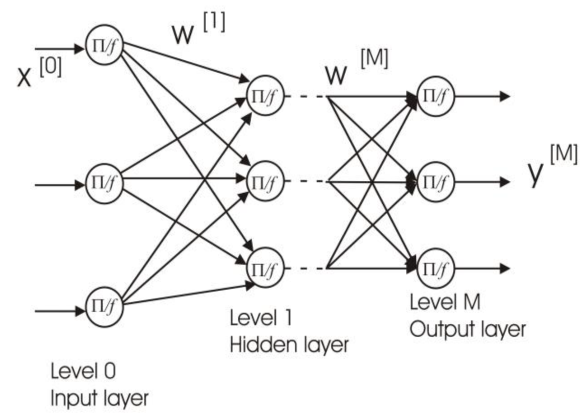


Fig.2 Multiplicative neural network.

The block diagram of a channel equalizer using MNN is shown in figure 3. The transmitter sends a known training sequence to the receiver. A sequence of 3000, equiprobable, 4-QAM complex valued symbol set, in which the input signal takes one of 4 different values given by all possible combinations of { -1, 1} + j*{ -1, 1}, where j = sqrt(-1) is generated. In the absence of the noise the output signal occupies well-defined M states of the M-QAM signal constellation. When the signal is passed through the nonlinear channel, it becomes a stochastic random process. Decision boundaries can be formed in the observed pattern space to classify the observed vectors between 4 classes. For equalization, the adaptive filter is used in series with the unknown system on the test signal by minimizing the squared difference between the adaptive equalizer output and the delayed test signal. The task of the equalizer is to set its coefficients in such a way that the output is a close estimate of the desired output . Depending on the value of the channel output vector, the equalizer tries to estimate an output, which is close to one of the transmitted values. The neural equalizer separately processes the real and imaginary part using the multiplicative, split complex, neural network models [14]-[15]. This can be viewed as 2 real valued activation functions for processing the in phase and quadrature component of the 4QAM signal. The split complex approach is generally used to avoid singular points and critical selection of network parameters like the weights, bias, learning rate and momentum factor.

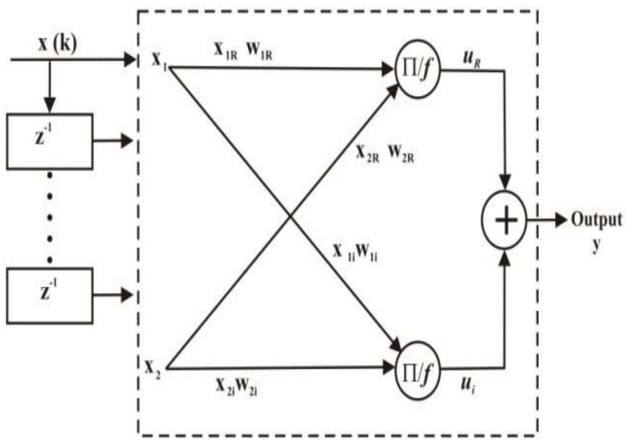


Fig.3 Multiplicative neural network based channel equalizer.

The real R and imaginary I parts of the input signal are split as.

$$F(x(t)) = f(x_{1R}(t),x_{2R}(t)) + i\ f(x_{1I}(t),x_{2I}(t))$$

Where the input $X_1(t) = x_{1R}(t) + i\ x_{1I}(t)$ and

$$X_2(t) = x_{2R}(t) + I\ x_{2I}(t)$$

III. Previous Work

To get surveyed by this work is conducted through some paper, after review of these papers the aimed methodology is proposed.

Jagdish C. Patra and Ranendra N.Pal was analyze that application of artificial neural networks (ANN) to adaptive channel equalization in a digital communication system with 4-QAM signal constellation is reported in this paper. A recent computationally efficient single layer functional link ANN (FLANN) is proposed in this purpose. This network has a very simple structure in which the nonlinearity is introduced by any functional expansion in the input pattern by trigonometric polynomials. Because of input pattern enhancement, the FLANN is capable to forming arbitrarily nonlinear decision boundaries and can perform complex pattern classification tasks. Which is Considering channel equalization as a nonlinear classification problem, the FLANN has been utilized by nonlinear channel equalization. The performance of the FLANN is also compared with two other ANN structures [a multilayer perceptron (MLP) and a polynomial perceptron network (PPN)] along with the conventional linear LMS-based equalizer for different linear and nonlinear channel models. The effect of eigenvalue ratio (EVR) of input correlation matrix on the equalizer performance has been studied. The comparison of computational complexity was involved for this, the three ANN structures is also provided[14].

Testsuya hoga nd Johanthon A.Chambers , was analyzed that in many pattern have classification problem ,to overcome it an intelligent neural system is required which can learn the newly encountered but misclassified patterns incrementally while keeping a good classification performance over the past patterns stored in the network. a require pattern correction scheme is proposed using adaptively trained generalized regression neural networks (GRNNs). The scheme is based upon both network growing and dual-stage shrinking mechanisms. In the network growing phase, a subset of the misclassified patterns in each incoming data set is reiterative added into the network until all the patterns in the incoming data set are classified correctly. Then, the redundancy in the growing phase is removed in the dual-stage network shrinking. Both long- and short-term memory models are considered in the network shrinking, which are motivated from biological working of the brain. The learning capability of the projected scheme is investigated through large simulation studies[15].

Jawad ali shah was describes the adaptive channel equalization of a non-linear recursive channel has been investigated. The channel equalizer is uses non-linear mapping of Gaussian radial basis function(RBF), to overcome by this problem when a binary antipodal signal is transmitted by the nonlinear recursive channel. The Gaussian RBF based tapped delay line (TDL) neural network used as channel equalizer , is first given a training sequence to calculate the centers in an under the supervision manner using k-means clustering algorithm. The weights of the neural network are adaptively adjusted by using recursive least square (RLS) algorithm. The performance of the trained equalizer has been tested to compute the bit error rate (BER) at various SNR levels and for many different number of unseen neurons. At last the proposed equalizer is compared with perceptron classifier and back propagation nural networks[16].

Kavita burse was proposed that A novel feed forward multiplicative neural network architecture with optimum number of nodes is used for adaptive channel equalization.The replacement of summation at each node by multiplication results in more powerful mapping because of its capability of processing higher-order information from training data. Performance comparison with Chebyshev neural network show that the proposed equalizer provides satisfactory results in terms of mean square error convergence curves and bit error rate performance at various levels of signal to noise ratios. A high order feed forward neural network equalizer with multiplicative neuron is proposed to use of multiplication allows direct computing of polynomial inputs and approximation with fewer nodes. Performance comparison in terms of convergence rates and BER performance suggest the better classification capability of the proposed MNN equalizer over CFLANN[17].

IV. PROPOSED METHODOLOGY

In the initial step of multiplicative filtering method of channel equalization of multiplicative neural network. In this process the input signal consist of the sum of desired signal , the channel non linearity and the interfering noise. A predefined delayed version of the original forms the training sequence to provide reference points for the adaptation process.

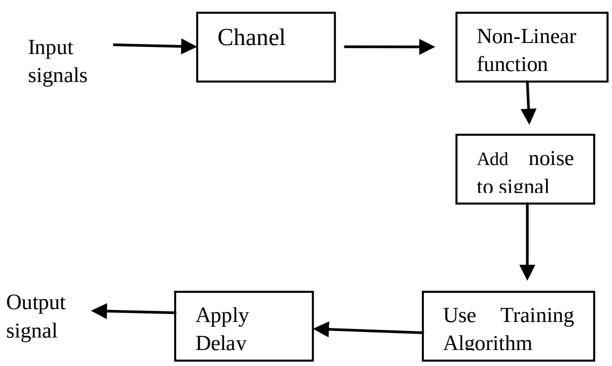


Fig.4 Flowchart of multiplicative neural network.

The transmitter send a known signal to the receiver. When our signal is passed through the nonlinear channel, it will be selected by a random process for channel equalization the adaptive filter is used in a series with the test signal to minimizing the difference between the adaptive equalizer outputs and delayed to the test signal. Depending on the value of channel output signal the channel equalizer tries to estimate an output which is close to one of the transmitted signal. The equalizer use in neural network is separately process the real and imaginary part using the multiplicative neural network. This can be viewed real and complex value separately.

The back propagation based learning has been used by a transmitting algorithm. The algorithm is first developed for single hidden layer network which is then extended for multilayer neural network. The collecting function is considered as a multiplication of linear function in different bipolar dimensions of space. In each node we use a bipolar sigmoidal activation function.

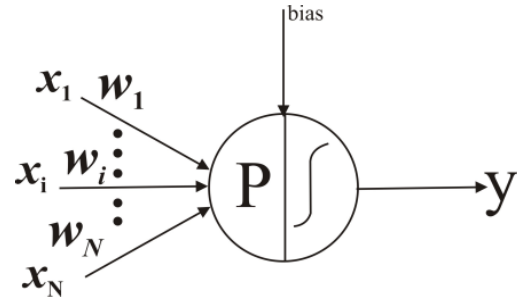
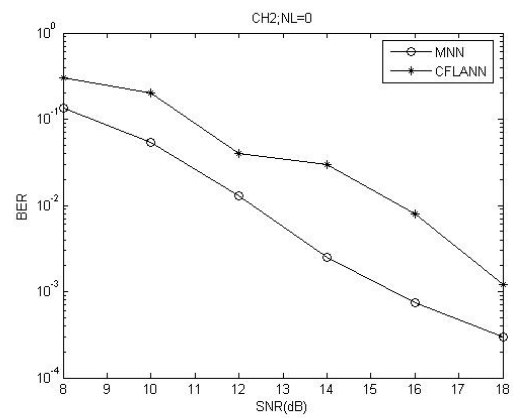
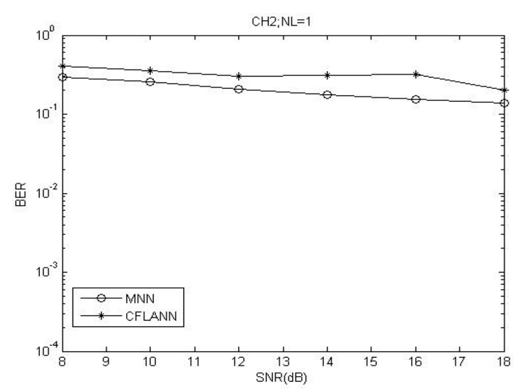


Fig.4 Working of multiplicative neuron

V. SIMULATION/EXPERIMENTAL RESULTS

In this section the multiplicative neural network equalizers has have a faster speed of convergence and have a vary smaller steady state MSE, than chebyshav functional link artificial neural network (CFLANN) in either linear or nonlinear environment. In the CFLANN neural network equalizer ht input is expanded and the number of output node is in reduced where in case of multiplicative neural network the structure is one of the smaller size . the bit error rate performance for various comparison of SNR is plotted in figure mention in below .





VI. Conclusion

The objective of this paper is undoubtedly the improvement of bit error rate. in literature survey there are various image compression techniques used along with different kind of algorithm. In our work we would use the 16 array QAM signal. After the comparison of 4 array QAM signal this method gives better performance than other method

VII. Future Scopes

In future support the multiplicative neural network can be used to equalize the same kind of nonlinear recursive channels. The MNN has that advantages that the number of hidden neurons and their center are determined automatically by the number of support vectors and their values respectively. With the use of multiplicative neural network it will allows multiplication of direct computing of polynomial input.

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