Adaptive Channel Equalizer using Combination of FIR and Functional Link Artificial Neural Network for Complex Signals

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Abstract— This paper proposes an adaptive nonlinear channel equalizer by using combination of finite impulse response (FIR) filter and functional link artificial neural network (FLANN) network (CFFLANN) capable of equalizing complex multilevel signals. The equalizer is designed to remove linear and nonlinear distortion produced by nonlinear channel. FLANN section removes the nonlinear distortions and FIR section removes linear distortions. Equalizer uses modified least mean square (MLMS) algorithm to adapt its tap weights. This system has less complex structure and high convergence speed. Performance of the equalizer is evaluated by two parameters-mean square error (MSE) and bit error rate (BER).

Keywords— Adaptive equalizer, finite impulse response (FIR) filter, functional link artificial neural network (FLANN), nonlinear channel.

I. INTRODUCTION

In digital data transmission over a communication channel, various types of distortions like ISI caused by dispersive channel, the nonlinearity introduced by modulation and demodulation process and noise, put adverse effect. To overcome these distortions, various equalizing techniques including linear and nonlinear equalizers have been reported in recent years. Due to the simple structure and fast convergence speed, linear channel equalizer based on finite impulse response (FIR) or lattice structure is widely used. But the performance of the linear equalizers is limited especially when the nonlinear distortions exist. In such case, the nonlinear equalizers based on nonlinear signal processing may be used with the benefits of lower bit error rate (BER), lower mean squared error (MSE), and higher convergence rate than those of the linear equalizers.

Researchers proved that Neural networks (NNs) are the systems that can perform complex mapping between its input and output space and are capable of forming complex decision regions with nonlinear decision boundaries. Furthermore, due to nonlinear characteristics of the NN, networks of different architectures have been successfully applied in channel equalization.

A Neural network structure that is called functional link artificial neural network (FLANN) is proposed by Pao (1989), and is a single-layer neural network structure capable of forming arbitrarily complex decision regions by generating nonlinear decision boundaries. In this network, the input space is expanded by employing nonlinear functions which results in higher dimensional space, and hence, capability of the nonlinear approximating is enhanced. Adaptive channel equalizer based on a single-layer polynomial perceptron network (PPN) is reported by Chen et al. (1990), where the original input pattern is expanded employing polynomials and cross-product terms of the pattern and then, this expanded pattern is utilized for the equalization problem and, the performance of this network over linear equalizers has been found very superior. Radial basis function (RBF) network, which provides an attractive alternative to MLP, has been utilized for the purpose of channel equalization by Chen et al. (1991). Several RBF networks with modified structure have been proposed and validated the superior performance to the MLP and MLP decision feedback. Since the RBF network needs a large number of hidden nodes to achieve acceptable system performance, it is not quite suitable for the implementation of hardware and cannot help in simplifying the hardware design. Although a series of adaptive filters based on a single-layer NN using real-valued and complex-valued adaptive algorithms are proposed by Goh and Mandic (2007), their nonlinear processing speed is not too good. To speed up the convergence and improve the network performance, a new Jacobian matrix for optimal learning of single-layer NNs is proposed by Peng et al. (2008). However, it would result in the heavy computational complexity and be confronted with the stability problem. The key advantage of the FLANN over other network architecture is that the nodes on the hidden layers can be left out, which reduces computational complexity and computational time hence increases speed of convergence. In fact, PPN is a subset of the generalized FLANN structure.
Various applications of the FLANN, modified FLANN decision feedback architecture, and FLANN cascaded with Chebyshev orthogonal polynomial (FLANNCP-AE) have been reported for functional approximation, nonlinear system identification, and channel equalization by Zhao and Zhang (2008). It has been shown that BER and MSE performance of the FLANN-based equalizer is superior to other NN structures such as MLP and PPN under wide variation of Eigenvalue ratio (EVR) and signal-to-noise ratio (SNR) conditions for both linear and nonlinear channel models in the case of PAM or QAM. An adaptive equalizer is proposed by Zhao and Zhan (2009) in which combination of FLANN and FIR filter is used to compensate linear and nonlinear distortions in nonlinear communication channel. They proposed the adaptive equalizer for two level signals. The information rate through a channel can be increased by increasing the bandwidth and the associated symbol rate. And if the channel bandwidth is to remain fixed, then the only option to increase the information rate for limited bandwidth is to increase the amount of information encoded in a symbol, i.e. to increase the number of level of signal.

A data stream s(k) is transmitted from the transmitter and is corrupted due to the channel characteristics and also deformed by additive White Gaussian noise. The channel impulse response h(k) considered in this study is expressed as follows:

\[
h(i) = \begin{cases} 
\frac{1}{2} \left[ 1 + \cos \left( \frac{2\pi}{7} (i - 2) \right) \right], & i = 1, 2, 3 \\
0, & \text{otherwise} 
\end{cases}
\]  

(1)

The corrupted signal x(k) is feed to equalizer input to remove the distortion produced. If M is the number of distinct signal levels, then each symbol carries \(\log_2 M\) bits of information, and the overall information rate rises to 2B \(\log_2 M\). So, multilevel signals are used where high information transfer rate is required over low bandwidth channels. Therefore this paper proposed an adaptive equalizer capable of equalizing multilevel complex signal using CFFLANN. Results for the equalization process of 4-level complex signals are shown in this paper. The basic question which arises in mind quickly as soon someone talk about complex signal processing is that even all physical signals and waveforms are real valued so why bother to consider complex-valued signals and systems? Complex signal notions have two important viewpoints or implications: communication theory view radio implementation view:

A. Communication theoretic aspects

- Most spectrally efficient in phase and quadrature phase (I/Q) modulation techniques (complex modulation, radio waveforms) are based on complex signal processing.
- For modeling of the radio channel and receiver signal processing for equalization and detection.

B. Radio implementation aspects

- All advanced frequency translation techniques and thus the related receiver architectures (low-intermediate frequency, direct-conversion, etc.) utilize complex signals.

II. COMBINATION OF FIR AND FLANN (CFFFLANN)

It is a combination of FLANN and FIR. Both the parts are combined adaptively. This combined network is named as CFFFLANN. In this paper this network is used to equalize 4-level (randomly selected 1+i, 1-i, -1+i, -1-i) complex signal x(k). The input of the equalizer is m dimensional input. A data stream x (k) and its m-1 delayed are feed to the first block of the equalizer. This is a functional expansion block. This block expands the m dimensional input to \(1+3m+i^c_2\) output i.e. this expanded function block comprises a subset of orthogonal \(\sin\) and \(\cos\) functions, the original pattern and the outer product to model nonlinear channel. For example consider m=3, inputs are u1, u2, u3 the corresponding output of this block will be \(X(k)=[1 \ u1 \ \cos u1 \ \sin u1 \ u2 \ \cos u2 \ \sin u2 \ u3 \ \cos u3 \ \sin u3 \ u1 \times u2 \ u1 \times u3 \ u2 \times u3]\). It has lower complexity due to the absence of any hidden layer and the adaptive algorithm is more easily used to train this network. Consider a set of basis functions \(B=\{\psi_i(k)\}\), where \(i=1, 2, 3\) and \(k\) is time index. Let \(B_{N1}=\{\psi_i(k)\}_{i=1}^{N1}\), be a set of basis functions to be considered for the FLANN subsection of the proposed CFFLANN as shown in Fig.3.8, where FLANN subsection consist of \(N_{1}\) basis functions to form the vector X(k)=[\(\psi_1(k) \ \psi_2(k) \ \ldots \ \psi_{N1}(k)\)]'. The element of X(k) i.e. \(\psi_i(k)\) are the \(N_1\) outputs of the FLANN subsection at \(k\)th time index.
III. Modified Least Mean Square Algorithm (MLMS)

MLMS is similar to LMS algorithm except an additional momentum term is added in this modified algorithm for fast convergence. Let $E(k)=\frac{1}{2}(e(k))^2$, where $E(k)$ denotes an Instantaneous error, and error signal $e(k)$ is defined as the difference between desired signal $d(k)$ and the output signal $y(k)$.

\[ e(k)=d(k)-y(k) \]  

where  

\[ y(k)=\lambda(k)\gamma(k)S(W_1(k)^T X(k))+(1-\lambda(k))W_2(k)^T RX(k) \]  

According to LMS algorithm the update equations of $W_1(k)$ and $W_2(k)$ of CFFLANN are given by  

\[ W_1(k+1)=W_1(k)+\eta_1\delta_1(k) \]  

\[ W_2(k+1)=W_2(k)+\eta_2\delta_2(k) \]  

Where

\[ \delta_1(k)=e(k)\lambda(k)\gamma(k)S'(k)X(k) \]  

\[ \delta_2(k)=\frac{\partial E(k)}{\partial W_2(k)}=e(k)(1-\lambda(k))RX(k) \]

To increase the convergence speed of the system update equations are modified as follows

\[ W_1(k+1)=W_1(k)+\eta_1\delta_1(k)+u_1\delta_1(k-1) \]  

\[ W_2(k+1)=W_2(k)+\eta_2\delta_2(k)+u_2\delta_2(k-1) \]  

Where $u_1$ and $u_2$ are momentum factors used to speed up the convergence rate. For parameter $\lambda(k)$ and $\gamma(k)$ of CFFLANN, using the gradient algorithm, the partial derivative of $E(k)$ with respect to $\lambda(k)$ and $\gamma(k)$ are given by

\[ \frac{\partial E(k)}{\partial W_1(k)}=e(k)\frac{\partial e(k)}{\partial W_1(k)}=e(k)(z(k)-z_1(k)) \]  

\[ \frac{\partial E(k)}{\partial W_2(k)}=e(k)\lambda(k)\gamma(k)S(W_1(k)^T X(k)) \]

Correspondingly, the parameter update equations based on the gradient algorithms are derived below

\[ \gamma(k+1)=\gamma(k)+\eta_2e(k)\lambda(k)S(W_1(k)^T X(k)) \]  

\[ \lambda(k+1)=\lambda(k)+\eta_1e(k)\gamma(k)(z(k)-z_1(k)) \]

Where $\eta_i \ (i=1,2,3,4)$ are real positive step size values of the update equation and all are supposed to be small enough to correct reception of the desired signal.

IV. Channel Characteristics Of Three Different Channels

<table>
<thead>
<tr>
<th>Channel</th>
<th>Transfer function in Z-transform form</th>
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</thead>
<tbody>
<tr>
<td>Channel1</td>
<td>0.209+0.995z^{-1}+0.209z^{-2}</td>
</tr>
<tr>
<td>Channel2</td>
<td>0.260+0.930z^{-1}+0.260z^{-2}</td>
</tr>
<tr>
<td>Channel3</td>
<td>0.304+0.903z^{-1}+0.304z^{-2}</td>
</tr>
</tbody>
</table>
The above three channels are considered in this paper results are carried out for these three channels. The system could be used to remove the adverse effect of any other linear or nonlinear channels also results would be quite satisfactory in every case.

V. PERFORMANCE MEASURES

The performance of the equalizer is evaluated by two parameters

A. MSE for training the network. MSE should reduce as the training time increases and should stabilize after long. Since the complex signal is completely characterized by phase and magnitude thus two types of MSE is considered in this paper i.e. magnitude and phase MSE.

B. BER, it should also decrease as SNR increases.

VI. SIMULATION RESULTS

The process to find MSE is carried out for SNR 15, 19 and 25. And the BER is plotted from SNR 5 to 25. Simulation results for three different channels are shown below. MSE is reducing as the number of iterations increases and BER is also reducing as SNR increases, which is desired. The main advantage of the equalizer is that the BER tends to zero even at low SNR which indicates that recovery of complex signals is very easy by using this type of equalizer.
Fig. 7. MSE vs iterations for complex signal at SNR=15dB (channel 2)

Fig. 8. MSE vs iterations for complex signal at SNR=19dB (channel 2)

Fig. 9. MSE vs iterations for complex signal at SNR=25dB (channel 2)

Fig. 10. Variation of BER of complex signal with different SNR values (channel 2)
Fig. 11. MSE vs iterations for complex signal at SNR=15dB (channel 3)

Fig. 12. MSE vs iterations for complex signal at SNR=19dB (channel 3)

Fig. 13. MSE vs iterations for complex signal at SNR=25dB (channel 3)

Fig. 14. Variation of BER of complex signal with different SNR values (channel 3)
We have developed a proper artificial neural network (ANN) model for adaptive nonlinear channel equalization for multilevel signals. The prime advantages of using ANN models are their ability to learn which is based on optimization of an appropriate error function and their excellent performance for approximation of nonlinear functions. CFFLANN is used to equalize the signals. System is capable of equalizing real as well as complex signals. Since the FLANN conations only one hidden layer thus convergence speed is very high. In addition, weights are adapted according to MLMS algorithm resulting fast convergence. Nonlinear channels produce linear (L) as well as nonlinear (N) distortions. CFFLANN have two parts

A. FLANN: To cancel the nonlinear distortions produced by nonlinear channels.

B. FIR: To cancel the linear distortions produced by nonlinear channels.

The output of the equalizer $y(k)=\lambda(k)z(k)+(1-\lambda(k))z_i(k)$, where $\lambda(k)$ is convex combination parameter. $\lambda(k)$ is adaptively adjusted during the training between 0 and 1 to handle the linear and nonlinear distortions respectively. As the characteristic of the channel varies the step size varies accordingly hence adaptation in weighs depends on channel characteristics i.e., for different channels step size is different and time dependent also.

Multilevel signals are used where high information transfer rate is required over low bandwidth channels. So, this nonlinear equalizer is designed to equalize multilevel complex signals. Transmission bandwidth is one of the precious resources in digital communication systems. To achieve better use of this resource, signals are commonly transmitted through band-limited channels. So the received signals get affected by inter symbol interference (ISI). A channel equalizer is used to recover the transmitted data from the received signals. If the nonlinearity associated with the system or channel is very high the performance of the equalizer degrades. The performance of the equalizer can be improved by increasing the SNR.

REFERENCES


