Perceptron Algorithm for Channel Shortening in OFDM System with Multipath Fading Channels

Mohammad Alizadeh
Department of Communications
College of Electrical Engineering, Yadegar-e-Imam Khomeini (RAH) shahre-rey Branch, Islamic Azad University
Tehran, Iran
e-mail: malizadeh202@gmail.com

Saeed Ghazi-Maghrebi
Department of Communications
College of Electrical Engineering, Yadegar-e-Imam Khomeini (RAH) shahre-rey Branch, Islamic Azad University
Tehran, Iran
e-mail: s_ghazi2002@yahoo.com

Amir Atashbar
Department of Communications
College of Electrical Engineering, Yadegar-e-Imam Khomeini (RAH) shahre-rey Branch, Islamic Azad University
Tehran, Iran
e-mail: amir.atashbar@yahoo.com

Abstract—Channel shortening methods, in multicarrier systems, are applied for decreasing and almost compensating for the inter-symbol and inter-carrier interferences due to the channel delay spread. In this paper, we propose a new channel shortening technique for orthogonal frequency division multiplexing (OFDM) systems based. The proposed method is based on the neural network equipped with the Perceptron learning rule. Also we have tested our method in the OFDM system with multipath fading channels. The simulation results and mathematical analysis show the better performance of the proposed method, with BER criterion, compared to the commonly used channel shortening methods such as MMSE, MSSNR and MERRY in multicarrier systems. Also the proposed method has almost the same computational complexity, as well as the mentioned methods.

Keywords—channel shortening; multipath fading; Neural Network; OFDM; Perceptron; TEQ

I. INTRODUCTION

Nowadays, multicarrier modulation techniques such as orthogonal frequency division multiplexing (OFDM) and discrete multi-tone (DMT) have been employed in digital applications such as IEEE 802.11a, digital audio and video broadcast (DAB/DVB), digital subscriber line (DSL) and satellite radio. One of the advantages of the multicarrier systems is their robustness against inter-symbol interference (ISI) and inter-carrier interference (ICI). It is obvious that the longer duration of the OFDM symbols provides a higher immunity against the channel delay spread. In a typical OFDM broadband wireless communication system, a guard interval, called the cyclic prefix (CP), is inserted at the beginning of each symbol to avoid the ISI and ICI. The length of this guard interval must be at least equal to the maximum channel delay spread or the length of the channel impulse response [1]. If the CP length is shorter than the channel delay spread, the orthogonality of the sub-carriers will be lost, and as a result the ISI and ICI impairments will occur [2].

The most common technique for mitigating the ICI/ISI caused by the inadequate CP length entails employing a time domain equalizer (TEQ) at the receiver side [3]. The TEQ is a finite impulse response (FIR) filter which causes delay spread of the effective length of the channel impulse response to be not longer than the CP length [3]. In this paper, a method for TEQ design, based on employing artificial neural network (ANN) with Perceptron learning rule (PLR), is proposed. The important property of these methods is their ability for training the input data with/without a supervisor [4], [5].

The paper is organized as follows. Section II describes the system model. Section III proposes a new channel shortening technique based on a neural network with PLR. Sections IV and V present the simulation results and conclusions respectively.

II. SYSTEM MODEL

In the multicarrier system which is shown in Fig. 1, the input data stream is divided into blocks of N samples, and each sample is then modulated as a QAM signal with a different carrier. The modulation is efficiently implemented in discrete time-domain via an IFFT transform. After transmission through a dispersive channel h, the receiver uses FFT transform to recover the data [3]. In this model we
have not applied coding and decoding.

If the received data is in the form of a circular convolution of the channel impulse response and the transmitted data, then the received frequency domain output is a point-wise multiplication of the transmitted frequency domain data and the discrete Fourier transform (DFT) of the channel. If the CP length is longer than the channel length, then the convolution appears in the circular form, and the signals in the symbols are equalized by a bank of complex gains [2], [3].

Since inserting the CP to each symbol of data stream decreases the system performance, the CP is usually set to a small value, and a TEQ is applied for shortening the channel impulse response to this length [3].

III. CHANNEL SHORTENING TECHNIQUE BASED ON NEURAL NETWORK WITH PRL

The purpose of the learning rule (i.e., the algorithm that is performed for implementing the learning process) is to train the weight matrix of the network for achieving a correct output (target). The neural network learning rules are fall into three broad categories: supervised learning, unsupervised learning and reinforcement learning [4], [5]. In the supervised learning, which is illustrated in Fig. 2, the learning rule is provided with a set of learning data (training set) which are \{x(t), t = 1, ..., L\}, where p(t) is the input of the network and \(t\) is the corresponding correct output. The learning rule is used for adjusting the parameters of the network in order to move the network outputs closer to the targets [4].

The PRL is a supervised learning category and is expressed by the following equation [4].

\[
w(k+1) = w(k) + \eta(t - a(k))p(k)
\]  

(1)

where \(w\) is the weight matrix, \(p\) is the network input and \(t\) is the desired output of the network for input \(p\). Also, \(\eta\) is called the learning rate which is a positive constant smaller than one and \(a(k)\) is the network output [4]. We used the notations \(h = [h(1), ... , h(m)]^T\), \(c = [c(1), ... , c(m+n-1)]^T\) and \(w = [w(1), ... , w(n)]^T\), for the channel impulse response, the effective channel impulse response and the TEQ weights respectively. It is obvious that \(c = h \ast w\), where \(\ast\) denotes the convolution operation. The effective channel impulse response will be defined as:

\[
H = \begin{bmatrix}
H(1) & \cdots & H(1,n) \\
\vdots & \ddots & \vdots \\
H(m+n-1) & \cdots & H(m+n-1,n)
\end{bmatrix}
\]

(2)

where \(H\) is the channel toeplitz matrix. Thus, convolution operation can be constructed as a matrix multiplication. Generally, the TEQ design method attempts to minimize the rate of the energy of the effective channel samples beyond the CP length. Ideally, the rate of these samples must be zero. Therefore, this work attempts to use a single-layer neural network with the PLR to achieve this goal. Each sample of the samples of the effective channel \(c(i)\) can be described as:

\[
\begin{bmatrix}
w(1) & \cdots & w(n)
\end{bmatrix}_{1 \times n} \begin{bmatrix}
H(i,1) \\
\vdots \\
H(i,n)
\end{bmatrix}_{n \times 1} = c(i), \ 1 < i < m+n-1
\]

(3)

Equation (3) is considered as a multi-input neuron, in which \([H(i,1), ..., H(i,n)]^T\), \([w(1), ..., w(n)]^T\) and \(c(i)\) are the input vector, the weight matrix, and the output of neural network respectively. Since the channel is described by the Rayleigh fading model [3], the elements of the input vector and as a result, the outputs of the neural network are complex. To overcome convergence of the complex inputs, we separate the calculations into real and imaginary parts. In other words, the PLR is separately employed for minimizing the amplitudes of the real and imaginary parts of each sample of the effective channel beyond the CP. Hence, (3) will be written as

\[
\begin{bmatrix}
r(1,i) + j\beta(1,i) & \cdots & r(n,i) + j\beta(n,i)
\end{bmatrix}_{1 \times n} = R(i) + j\beta(i), \ 1 < i < m+n-1
\]

(4)
where \( w(i)=a(i)+jb(i), \) \( H(i,1)=r(i,1)+jr(i,1), \) and \( c(i)=R(i)+jl(i). \) After simplifying (4) and separating the real and imaginary parts, we obtain

\[
(1) r(i,1) - b(1)s(i,1) + j(a(1)s(i,1) + b(1)r(i,1)) + \\
+ a(n)r(i,n) - b(n)s(i,n) + j(a(n)s(i,n) + b(n)r(i,n))
\]

\[= R(i) + jI(i) \quad \text{(5)}
\]

Finally, by separating these two parts, the \( R(i) \) i.e. the summation of all of the real parts and \( I(i) \) as the summation of all the imaginary parts, we obtain

\[
a(1)r(i,1) + ... + a(n)r(i,n) - [b(1)s(i,1) + ... + b(n)s(i,n)]
\]

\[= R(i) \quad 1 < i < m + n - 1 \quad \text{(6)}
\]

and

\[
a(1)s(i,1) + ... + a(n)s(i,n) + b(1)r(i,1) + ... + b(n)r(i,n)
\]

\[= I(i) \quad 1 < i < m + n - 1 \quad \text{(7)}
\]

where \( [r(i,1), ..., r(i,n), -s(i,1), ..., -s(i,n) ]^T_{1 \times 2n} \), \( R(i) \) and \( [a(1), ..., a(n), b(1), ..., b(n) ]_{1 \times 2n} \) are the input vector, the weight matrix and the output of the ANN for the real part, respectively. Also, \( [s(i,1), ..., s(i,n), r(i,1), ..., r(i,n) ]^T_{1 \times 2n} \), \( I(i) \) and \( [a(1), ..., a(n), b(1), ..., b(n) ]_{1 \times 2n} \) are the input vector, the output and the weight matrix of the ANN for imaginary part respectively. In order to limit the number of the algorithm iterations, following constraint is imposed

\[
|c(CP+1)|^2 + ... + |c(m+n-1)|^2 < \sigma \quad \text{(8)}
\]

where \( c(.) \) represents a sample of the effective channel (i.e. \( (c(i)=R(i) + jI(i)) \)). Also, \( c(CP+1) \) and \( c(m+n-1) \) are the first sample after the CP and the last sample in the effective channel impulse response, respectively. In practice, \( \sigma \) is a small positive constant of 0.7. In fact, (8) expresses the neural network modifying the weight matrix until the sum of the all-samples energies beyond the CP is smaller than \( \sigma \). Therefore, at the end of each run of the algorithm, the constraint in (8) will be checked.

\[\text{IV. SIMULATION RESULTS}\]

In this paper, we have applied various channel shortening methods to a Rayleigh fading channel, and evaluate the resulting bit error rates (BER) for the OFDM multicarrier system. We compare our new proposed method, i.e., the Perceptron TEQ, with some commonly used methods such as the Maximum Shortening SNR (MSSNR) [6], [7], the Minimum Mean Squared Error (MMSE) [6], [8] and the Multicarrier Equalization by Restoration of Redundancy (MERRY) [3]. The parameters for our simulation were chosen similar to the IEEE 802.11a wireless LAN standard [3] with an FFT size of \( N = 64 \), a CP length of \( \nu = 16 \), using the QPSK modulation for each tone and some 48 taps for TEQs.

The channel model consists of \( h_{\text{local,1}} \) scatters near the transmitter, \( h_{\text{mid}} \) remote scatterers, and \( h_{\text{local,2}} \) scatterers near the receiver [3] which is implemented as bellow

\[
h = h_{\text{local,1}} * h_{\text{mid}} * h_{\text{local,2}} \quad \text{(9)}
\]

where \( h_{\text{mid}} \) consists of 32 uncorrelated Rayleigh fading taps with an exponential delay profile, and \( h_{\text{local,1}} \) and \( h_{\text{local,2}} \) each consisting of 6 uncorrelated Rayleigh fading taps with a uniform delay profile. An example of such a channel is depicted in Fig. 3.

![Figure 3](image)

The results of our proposed channel shortening method are illustrated in Fig. 4. It is assumed that the original channel impulse response has 42 taps and the length of the CP is 16 samples. This implies that if TEQ is not included, the ISI/ICI will greatly degrade the system performance. Figure 4 shows that after applying the Perceptron TEQ, the effective channel impulse response is shortened to 16 major taps which falls in the range of the CP length. All samples beyond the CP length contribute to the ISI/ICI, but they have very small energy, i.e., producing insignificant error.

The performance maybe measured as the BER, the convergence rate and the residual ISI. In this paper, the performance is measured by BER criterion. We applied different equalization to the channel model which was described in (9). The simulation results for the system with four TEQ methods as well as a system without a TEQ, are demonstrated in Fig. 5. In our simulation, the data point for each SNR value was obtained by averaging over all carriers for 100 blocks, and then repeating for a total of 2000 channel realizations. Surprisingly, it is obvious that our proposed method has a lower BER, especially for higher SNRs, than the commonly used methods such as MERRY, MMSE, and MSSNR methods.

[450]
IV. CONCLUSIONS

In this paper, we proposed a new channel shortening method based on the neural network with PLR. We have compared our proposed method with the MMSE, MSSNR and MERRY algorithms. The simulation result showed that our proposed TEQ method has a superior BER performance. Considering this fact, our design could be considered as a better alternative to the existing channel shortening methods for the OFDM systems in wireless multipath channels.

![Image of channel responses and TEQ coefficients](image-url)

Figure 4. The effects of applying Perceptron TEQ to a random channel.

![Image of system performance](image-url)

Figure 5. System performance with different TEQs for the random channel in (9).

REFERENCES


