MLP/BP-based DFEs for Distorted QPSK Signal Recovery in Severe ISI Channels

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Abstract

In this work, we base on multi-layered perceptron neural networks with backpropagation algorithm (MLP/BP) to construct decision feedback equalizers (DFEs). The proposal is used to recover distorted quadrature phase-shift keying (QPSK) signal in severe intersymbol interference (ISI) channels. The better bit-error-rate (BER) and packet-error-rate (PER) performance as compared to least-mean-square (LMS) DFEs is achieved in the severe ISI channel. From the simulations, we note that the proposed scheme can recover distorted QPSK signals as well as suppress ISI and background additive white Gaussian noise (AWGN). As compared with the LMS DFE, the presented MLP/BP-based DFE under the severe ISI channel with AWGN can improve about 1.8dB at PER=10^{-1} and about 2dB at BER=10^{-3}. For data communications, we focus on the PER performance, whereas the BER performance is the major concern for multi-media communications.

Keywords: MLP/BP Neural Network (Multi-Layered Perceptron Neural Network with Backpropagation Algorithm), ISI (Intersymbol Interference), DFE (Decision Feedback Equalizer), NRZ (Nonreturn-to-zero), QPSK (Quadrature Phase-shift Keying)

1. Introduction

In a digital communication system, the source signal is transmitted over an intersymbol interference (ISI) channel, corrupted by noise, and then received as a distorted nonreturn-to-zero (NRZ) signal without zero crossing. It is the noisy signal that degrades the system performance. In most cases, the additional white Gaussian noise (AWGN) can be used to model the background noise.

In this work, we send QPSK signals over severe ISI channels. In such channels, the tail of each pulse in the received signal will be elongated, resulting in severe disfigurement for the received signal. The received signal pulse is unable to complete its transition within a symbol interval. As a result, it is necessary to apply data equalizers to recover the original waveform from the distorted one in practical digital communications [1], [2].

Conventionally, the NRZ signal recovery is based on either linear equalizers (LEs) [1], [2], or decision feedback equalizers (DFEs) [1], [2], [3]. The LE can restore the original transmitted signal, but it also amplifies high-frequency noise and severely degrades the system performance.

The DFE employing previous decisions to remove the ISI on the current symbol has been extensively exploited to serve ISI rejection. The least mean squares (LMS) algorithm is used to estimate the coefficients of the equalizer [1], [2], [3], [4] whose accuracy determines the system performance.
An artificial neural network consists of a set of highly inter-connected neurons such that each neuron output is connected to other ones or/and to itself through weights with or without lag. Recently, there are many different artificial neural networks had been proposed, but the MLP/BP neural network model [5] is the most important and popular one. We base on this model to construct the proposal. Because the neural-based equalization scheme is a multi-input multi-output architecture, we can extend the input and output number for more complex system.

Therefore, various equalizer designs based on artificial neural networks have been applied to the severely distorting signal recoveries. Having the capability of classifying the sampling patterns and fault tolerance, neural-based solutions have more flexibility and better performance than conventional equalization techniques. Based on the MLP/BP neural networks [5], the feedforward equalizers [6], [7], and the decision feedback equalizers [8], [9] have been widely used to NRZ signal recovery in severe ISI channels. For high-speed data communications, it is familiar to use waveform equalization technique to improve the data rate or reduce the error rate.

In our previous works, an MLP/BP-based DFE are used to tolerate sampling clock skew and channel response variance [10], and an MLP/BP-based MIMO DFE to suppress ISI, ACI, and AWGN in wireline parallel band-limited channels [11]. Also, we use an MLP/BP-based MIMO DFE for suppressing ISI and ACI in non-minimum phase channels [12], [13]. These studies are applied to the distorted PAM signal recovery.

Based on above studies, we present an MLP/BP-based DFE for distorted QPSK signal recovery in severe ISI channels. The proposed scheme can recover distorted QPSK signals as well as suppress ISI and background white noise. In addition, a QPSK system can double the data rate compared to a PAM or a BPSK one while maintaining the bandwidth of the signal. It is very suitable for high data rate applications. From the simulations, the better performance as compared to LMS DFEs is achieved.

This paper is organized as follows. The system overview is given in section 2. The proposed scheme is presented in section 3, while section 4 shows the simulation results. Finally, section 5 concludes the proposal.

2. System Overview

The system diagram of data communication systems is shown in Fig. 1 [2]. The description of the equivalent channel model is shown in Fig. 2. In this model, a finite impulse response (FIR) filter is used to model the ISI channel response with the AWGN as the background noise.

The ISI channel response with AWGN can be written as follows:

\[ H(z) = f_0 + f_1 z^{-1} + f_2 z^{-2} + \ldots + f_L z^{-L}, \]

\[ y_i = \sum_{k=0}^{L} f_k x_{i-k}, \]

\[ \tilde{y}_i = y_i + n_i, \]

where \( H(z) \) is the transfer function of the ISI.
channel; \( L \) is the length of the channel response; \( x_k \) is the input sequence; \( y_k \) is the channel output which is warped by ISI only; \( n_k \) is the AWGN; \( \hat{y}_k \) is the received signal which is distorted by both ISI and AWGN.

In this work, the severe ISI channel whose the transfer functions is:

\[
H(z) = 0.147 + 0.295z^{-1} + 0.590z^{-2} + 0.295z^{-3} + 0.590z^{-4} + 0.295z^{-5} + 0.147z^{-6}
\]

is used to verify the proposed scheme. In this channel, a deep spectrum null that lie in lower frequency cause large distortions. Its frequency response is illustrated in Fig. 3. Such channel is practical in high-speed digital communication systems.

![Frequency Response](image)

**Fig. 3 Frequency responses of severe ISI channels**

### 3. Proposed Approach

The MLP/BP neural network [5] is the most popular neural network model in the applications of the severe distorted signal recovery. The assumptions and the recursive formulas are shown as follows.

\[
\text{Output} = A_j = f(\text{net}_j),
\]

\[
\text{net}_j = \text{Summation Function} = \sum W_{ji} A_{i-1} - \theta_j,
\]

\[
E = \text{Error Function} = \frac{1}{2} \sum (T_j - A_j)^2,
\]

\[
\Delta W_{ji} = -\eta \cdot \frac{\partial E}{\partial W_{ji}} = \eta \cdot \delta_j \cdot A_{i-1},
\]

\[
\Delta \theta_j = -\eta \cdot \delta_j,
\]

for output layer:

\[
\delta_j = (T_j - A_j) \cdot f'(\text{net}_j),
\]

for hidden layer:

\[
\delta_j = \left( \sum \delta_{i-1} \cdot W_{ji} \right) \cdot f'(\text{net}_j).
\]

Where \( A_{ij} \) is the output of the neuron \( j \) in the \( n \)-th layer; \( f(.) \) is the transfer function; \( \text{net} \) is the output of the summation function; \( W_{ji} \) represents the weight of the connection between the neuron \( j \) in the \( n \)-th layer and the neuron \( i \) in the \((n-1)\)-th layer; \( \theta_j \) is the threshold of the neuron \( j \); \( T_j \) is the desired output of the neuron \( j \) of the output layer; \( E \) is the error function; \( \Delta W_{ji} \) is the update quantity of \( W_{ji} \); \( \Delta \theta_j \) is the update quantity of \( \theta_j \); \( \eta \) is the learning rate, and \( \delta_{ij} \) is the error signal of the neuron \( j \) in the \( n \)-th layer.

For the different system specification, we can select different transfer function to meet the requirement or the constraint. In this work, the transfer function as shown below is the unipolar sigmoid function.

\[
f(\text{net}_j) = \frac{1}{1 + e^{-\text{net}_j}}.
\]

The training procedure of the MLP/BP neural network attains different performance by changing initial conditions, learning rates, or other network parameters. Moreover, designers could perform numerous independent training runs and select the most suitable outcome as the final solution.

The block diagram of the proposed MLP/BP-based DFEs is shown in Fig. 4. In this work, we use a single-hidden-layer MLP/BP neural network architecture, where the log-sigmoid function is used as the transfer function. There are four tapped delay line registers for I-channel input, I-channel feedback, Q-channel input, and Q-channel feedback, respectively. The MLP/BP neural network has two output neurons that correspond to I-channel output and Q-channel output.

### 4. Simulation Results

The overall performance of the MLP/BP-based
DFEs is evaluated through the simulations for the distorted QPSK signal recovery in the severe ISI channel under different AWGN power. The channel condition is illustrated in section 2. This neural-based equalizer has 17 symbols in the forward length and 8 symbols in the feedback length. Because the signal includes real part and imaginary part, we separate the input symbols to I-channel and Q-channel. Accordingly, the number of neurons in the input layer is equal to 50 (25×2). This neural-based equalizer uses the single hidden layer MLP architecture. The number of neurons in the hidden layer is equal to 25. Since this equalization scheme produces the detection of a QPSK symbol each time, the number of neurons in the output layer is equal to 2 (1×2), corresponding to the outputs of I-channel and Q-channel.

The length of the training symbols is equal to 10^4 and the total training epochs are 10^2. In the training phase, the best parameters are recorded to search the lowest mean square error of the training set. We perform ten independent runs with different initial conditions to search a better solution. In general, a neural-based scheme is regarded as a sub-optimal solution.

If the training set is not big enough, the system performance will be decreased. Because the neural-based equalization schemes imply statistics process, the training set must stand for the all-possible inputs. In this work, the training data is generated by random sequence. To improve the accurate of training procedure, we suggest that the training data is as long as possible.

When the training phase is complete, we apply the result to recover the distorted signal. Consider a packet-based communication system, the length of transmitted data within a packet is 10^3 bits. There are 10^4 packets tested in different equalization schemes. Both the PER performance and BER performance are evaluated. For data communications, we focus on the PER performance, whereas the BER performance is the major concern for multi-media communications.

The input and output configuration of the LMS DFE as comparison is the same as that of the neural-based one. The learning rate of the LMS DFE is equal to 2^{-5}. Although a small learning rate can improve the performance of LMS DFEs in computer simulations, it is not practical in actual hardware implementation.

For this proposed neural-based scheme, different learning rates, equal to 2^{-1}, 2^{-2}, 2^{-3}, 2^{-4}, and 2^{-5}, have been evaluated. The evaluation results are shown in Fig. 5. The most suitable learning rate of
the presented configuration is equal to $2^{-4}$. The PER and BER performance is shown in Fig. 6. As compared with the LMS DFE, the presented MLP/BP-based DFE under the severe ISI channel with AWGN can improve about 1.8dB at PER=$10^{-1}$ and about 2dB at BER=$10^{-3}$.

### Learning Rate Evaluation

![Learning Rate Evaluation](image1)

**Fig. 5 Learning Rate Evaluation**

![PER Performance](image2) ![BER Performance](image3)

**Fig. 6 PER and BER Performance**

### 5. Conclusion

The simulation results show that the proposed MLP/BP-based DFEs can provide a significant improvement over the LMS DFEs for distorted
QPSK signal recovery in the severe ISI channel. Because this neural-based equalization scheme is a multi-input multi-output architecture, we can extend the input and output number for more complex systems. For hardware implementations, the architecture of the proposed MLP/BP-based DFE is more complex than a LMS DFE. However, we think that the rapid progress of VLSI technology will afford more complex approaches for better performance.

References