Pilot Tone Investigation for Joint Channel Estimation, Equalization, and Demodulation Based on Neural Networks

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Abstract

Designing the optimum receiver for different channel conditions is a difficult task, because the required channel statistics are usually not known at the receiver. In this study, we propose a neural network (NN) based approach to demodulate the transmitted signal over fading channels. The novelty of the resulting scheme lies in the combination of channel estimation, equalization, and demodulation procedures in a single NN structure. We assess the performance of the proposed receiver for Rayleigh fading channels. It is demonstrated that the Rayleigh theoretical bound may be achieved by the proposed receiver if the frame structure has a sufficient pilot duration in the training mode. It is also shown that the proposed receiver is robust for low SNR cases.

1. Introduction

Neural network (NN) based solutions has emerged as a practical technique with successful applications in many fields such as control engineering, biomedical engineering, electronics engineering and recently for communication engineering [1]. Neural networks could be employed to derive meaning from complicated or imprecise data to solve different type of problems [2]. For instance, by using their universal approximation abilities, learning, and adaptation abilities they are generally used to approximate unknown nonlinear functions.

Recently, neural network structure is applied to detect signals in communication systems [3]. Moreover, it is also applied for demodulation of signals [4-6]. In [4], it was shown that NN based receivers are equivalent to the bank of matched filters and the Viterbi decoder. Authors utilized more complicated structures such as Elman Artificial Neural Network (EANN), and Time-Delay Neural Network (TDNN) and stated that relatively large number of hidden layer neurons are required in [5,6].

In [7], a channel estimator using neural network is presented for Long Term Evolution (LTE) uplink by considering multiuser SC-FDMA uplink transmissions with doubly selective channels. It is concluded that the obtained results are very promising to improve the service quality in the LTE Uplink System. In [8], different operation mode for Levenberg Marquardt algorithm powered back propagation feed forward neural networks are examined for channel estimation of OFDM receivers. A novel, semi-blind, optimized channel estimation technique is presented based on the outcomes of different experiments and the proposed operation mode offers more possibilities in this area.

In [9], channel estimation and equalization by using backpropagation neural networks (BPNNs) is proposed for OFDM systems while it has a huge computational complexity due to the training algorithm. For identifying the parameters of a nonlinear, multipath time varying, Ricean-fading down link satellite channel, NN based channel estimation method has been proposed in [10]. The channel is assumed to be varying over a reasonable range of Doppler frequencies. The proposed NN maximum likelihood sequence estimator (NN-MLSE) based receiver performs close to that of the ideal MLSE receiver in terms of symbol error rate (SER) for the addressed system. In [11], a new channel estimation algorithm based on adaptive neuro-fuzzy inference system (ANFIS) is proposed for MIMO-OFDM systems. The ANFIS algorithm is trained with correct channel state information by utilizing the learning capability of ANFIS, then the trained network is used as a channel estimator. According to the simulation results, the proposed channel estimator based on ANFIS performs better than classical algorithms based on pilot tones. In [12], channel estimation technique based on multi-layer perceptron (MLP) neural networks is proposed for space time coded MIMO-OFDM system. Their simulation results show that the performance of NN was better than least square (LS) and least mean square error (LMS) algorithms. Recently, channel impairments such as interference and phase offset are also investigated for additive white Gaussian noise (AWGN) channels [13]. In [13], it was shown that the proposed receiver has the same performance with the conventional correlation receiver for AWGN channel while it has clear advantage for interference and phase offset imperfections.

In this paper, we propose a simple NN based system for channel estimation, equalization, and demodulation for Rayleigh fading channels. Rayleigh fading effect caused by multipath reception needs to be estimated and equalized at the receiver. Therefore, a crucial part of the receiver structure is channel estimation, which is generally achieved by pilot symbols. Channel estimation is done for the pilot duration and the estimated channel is employed to equalize the received signal for data duration in practical systems. We show that the proposed receiver may be used for channel estimation, equalization and demodulation. The results show that the performance of the proposed system approaches to the Rayleigh theoretical bound provided that the pilot duration is sufficient.

2. Signal Model

We assume that the transmitter sends digital information by using binary phase-shift keying (BPSK) signal waveforms $\{s_0(t),\ s_1(t)\}$. Each waveform is transmitted within the symbol interval of duration T, $0 \leq t \leq T$ and the channel is assumed to corrupt the signal by introducing the AWGN and Rayleigh fading. Rayleigh fading is a specific type of signal fading when there are many objects in the environment that scatter the radio signal before it arrives at the receiver and there is no dominant propagation along a line of sight between the transmitter and receiver in a multipath environment. Signal model is given as following:

$$s_r(t) = h(t) * s_m(t) + \eta(t) \tag{1}$$

where the channel response $h(t)$ has a Rayleigh distribution and $s_r(t)$ is the received signal, $s_m(t)$ is the transmitted BPSK signal and $\eta(t)$ denotes a sample function of AWGN process with power spectral density $S_n(f) = N_0/2$. It is shown that $s_m(t)$ signals and corresponding basis function could be written as [14];

$$s_0(t) = \sqrt{\frac{2E_s}{T}}\sin(2\pi f_c t) \tag{2}$$

$$s_1(t) = -\sqrt{\frac{2E_s}{T}}\sin(2\pi f_c t) \tag{3}$$

Rayleigh theoretical bit error lower bound is given by [14];

$$P_b = \frac{1}{2}\left(1 - \sqrt{\frac{(E_b/N_0)}{(E_b/N_0)+1}}\right) \tag{4}$$

where E_b is the bit energy and N_0 is the noise spectral density.

3. Proposed Receiver

An artificial neural network (ANN) may consist of many input and output. The training and the operation are two modes of the network. In the training mode, the network is trained for a specific input data. In the operation mode, desired output is provided by the network when an expected input pattern is detected at the input.

There are two types of neural network architectures; Feedback ANNs and Feed-forward ANNs. Feed-forward ANNs are used in this paper as shown in Fig. 1. This structure allows signals to travel one way only; from input to output. In other words, feedback (loops) is not defined. Sampled and vector formed received signal in one symbol duration are given to the neural network demodulator (NND). By finding the maximum of the NND outputs, the transmitted data is obtained. It is necessary to generate input and target data sets to design and train the NN.
Feed forward multilayer neural network which is one of the simplest ANN's [15] is used to design the NN based system as shown in Fig. 1. Symbol period is choosen as $T = 0.01$ s and the carrier frequency is $f_c = 100$ Hz. Sample time is taken as $T_s = 1/1600$ s to generate $N_f = 16$ sample for each symbol period. Single hidden layer neuron is used, because a single correlation process is sufficient to detect BPSK symbols.

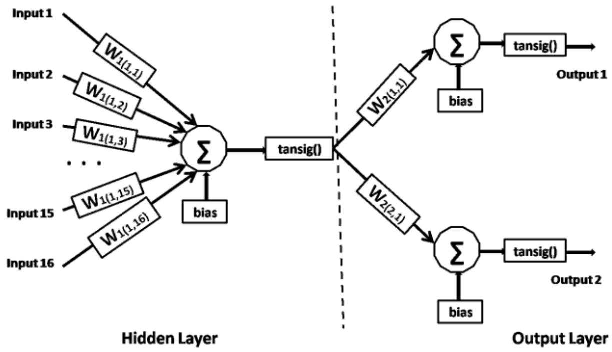

Fig. 1: Feed forward multilayer Neural Network structure

Many activation functions may be used to design an ANN. After extensive simulations, we observed that tangent sigmoid transfer function is the best for both layers. We also observed that Levenberg-Marquardt optimization yields best results [16] to train the designed networks.

Input training data set generation

Input training data set is generated by considering the transmitted symbol sequences as 0 and 1 periodically. Sequential and periodical transmission is preferred to guarantee and control presentation of each symbol equally in the input training data set. As s_r represents received and sampled signal, the received symbols in one symbol period are represented as,

$$s_r = \begin{bmatrix} s_r(0) \\ s_r(1) \\ \vdots \\ s_r(N_f-2) \\ s_r(N_f-1) \end{bmatrix}_{N_f \times 1} \quad r = 0,1 \tag{5}$$

N_f is the number of sample in one symbol period. Unity input training data matrix S_u is generated by combining these 2 column vectors for binary modulation level;

$$S_u = [s_0 \quad s_1]_{N_f \times 2} = \begin{bmatrix} s_0(0) & s_1(0) \\ s_0(1) & s_1(1) \\ \cdots & \cdots \\ s_0(N_f-2) & s_1(N_f-2) \\ s_0(N_f-1) & s_1(N_f-1) \end{bmatrix}_{N_f \times 2} \tag{6}$$

By repeating this unity set K times which means the number of pilot tones, the input training data set S_t is expressed as the following.

$$S_t = [S_{u,1} \quad S_{u,2} \quad \cdots \quad S_{u,K-1} \quad S_{u,K}]_{N_f \times [2\times K]} \tag{7}$$

Target data set generation

To generate target training data sets, 1 is used to represent expected output values and -1 for the other one. These numbers represent numerically the answer of question: "Is the transmitted data detected? ". The answer YES is represented by 1 where the answer NO is represented by -1. The target training data sets of NN having 2 output are given.

$$t_0 \quad = \quad \begin{bmatrix} 1 \\ -1 \end{bmatrix}_{2\times 1} \quad t_1 \quad = \quad \begin{bmatrix} -1 \\ 1 \end{bmatrix}_{2\times 1} \tag{8}$$

"Unity" target training data set T_u is generated by collecting/combining these 2 column vectors for binary modulation level.

$$T_u \quad = \quad [t_0 \quad t_1]_{2\times 2} \; = \; \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}_{2\times 2} \tag{9}$$

By repeating this unity set K times which means again the number of pilot tones, target training data set T is obtained as following:

$$T = [T_1 \quad T_2 \quad \cdots \quad T_{K-1} \quad T_K]_{2\times[2\times K]} \tag{10}$$

4. Simulation Results

This section presents computer simulation results of the proposed method for Rayleigh channel environments. By generating the real and imaginary parts of a complex number according to independent normal Gaussian variables, Rayleigh fading channel can be modelled. In Fig. 2, the proposed operational data frame structure is given. Pilot symbols are employed to train the NN based receiver.

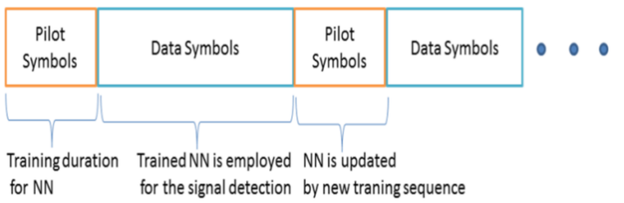

Fig. 2: The offered operational data frame structure

Therefore, NN is trained for joint channel estimation and equalization tasks. This means that NN receiver directly calculates necessary coefficients to equalize the received signals. For each channel condition, a new NND is designed and its performance is tested for the same channel condition. 2000 different channels are simulated in total to obtain the results. Pilots are inserted for channel estimation, equalization and coherent demodulation at the receiver end.

The number of pilot tones is directly related to the performance of the proposed receiver. To illustrate this effect simulations are carried out by selecting 256, 512, 1024, 2048 pilot tones at 0 dB training SNR level. The related performance results are shown at Figure 3-6 respectively. Results indicate that inserting small number of pilots yields in a poor training for NN receiver, causing the BER performance to degrade espicially for higher SNRs. However, it is shown in the simulations that the proposed NN receiver system is more robust in [0-20 dB] SNR range where the practical communication systems usually operate.

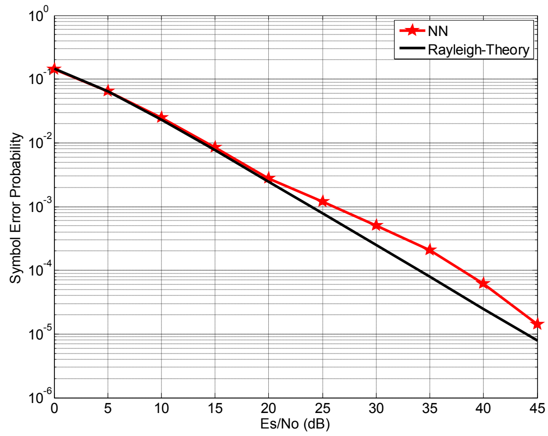

Fig. 3: SER performance of the proposed receiver (Training duration: 512 pilot tones)

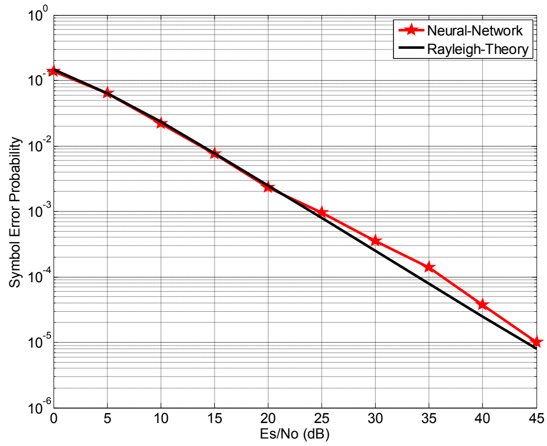

Fig. 4: SER performance of the proposed receiver (Training duration: 1024 pilot tones)

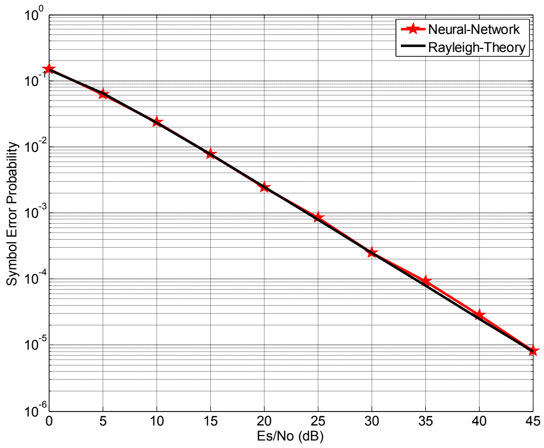

Fig. 5: SER performance of the proposed receiver (Training duration: 2048 pilot tones)

5. Conclusions

Neural network based receiver design has been proposed for channel estimation, equalization and demodulation tasks for pilot symbol assisted transmission over Rayleigh fading channels. It is shown that the Rayleigh theoretical bound could be achieved by the proposed structure.

These performance improvements are obtained at the expense of additional complexity caused by neural network structure in the receiver. However, by considering the provided advantages of using only one NN system for all channel estimation, equalization, and detection purposes, the additional complexity becomes acceptable for practical systems.

7. References

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