Neural Network Based Receiver Design for Software Defined Radio over Unknown Channels

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Abstract

In communication systems, the channel noise is assumed to be white and Gaussian distributed. Therefore, in general practical systems, optimum receiver structure designed for the additive white Gaussian noise (AWGN) channel is employed. However, in wireless communication systems, noise is often caused by a strong interferer, which is colored in nature. Color of the noise is defined as the variation in power spectral density in the frequency domain. Designing the optimum receiver for different channel models is difficult and not reasonable because channel model is not known at the receiver and channel statistics are needed. In this paper, we propose neural network (NN) based approach to demodulate the transmitted signal over unknown channels. Simulation results in various signal environments are presented to the performance of the proposed system. It is shown that the proposed approach has the same performance with the conventional demodulator structure for AWGN channels while it has clear advantage for unknown channel models.

1. Introduction

Software Defined Radio (SDR) is a very popular approach for improving performance of conventional radio systems without necessitating costly and time-consuming changes to physical hardware [1]. Therefore, the ideal SDR leads to a revolution in the design of the receiver with respect to the conventional receiver. In other words, The SDR approach is a radio fully programmable in baseband stage by employing digital signal processors (DSPs)[2]. Therefore, some new signal processing techniques such as "Neural Network" could be employed within these structures to improve the performance of the receivers.

Information processing paradigm inspired by biological nervous systems is called the Artificial Neural Network (ANN). It is applied to solve specific problems by using the interconnected processing elements (neurons) working together [3]. Neural networks can be used to solve different type of problems with their remarkable ability to derive meaning from complicated or imprecise data. Neural Networks (NNs) play important roles in many engineering areas such as control engineering, biomedical engineering, electronics engineering and recently for communication engineering [4]. For example, they are generally used to approximate unknown nonlinear functions by using their universal approximation abilities, learning, and adaptation abilities. Active research has been done in neural network for communication systems [6-7] and several NN approaches have been proposed to design receivers [8-12].

It is well known that reliable coherent data detection is not possible unless an accurate channel state information is available at the receiver. However, it is generally AWGN channel is considered to model the noise effects in wireless communications systems. However, in wireless communication systems, a strong interferer, which is colored in nature, dominates the noise model.

In order to deal with the demodulation problem of transmitted signals over unknown channels, we propose neural network based SDR receiver that uses existing pilot tones for the training procedure. Therefore, our goal is to develop a neural network based receiver that will account the unknown random effect due to the presence of unknown interference and enable statistically efficient demodulation using a small number of pilots (training).

2. Conventional Optimum Receiver for AWGN channels

We assume that the transmitter sends digital information by use of binary phase shift keying (BPSK) signals waveforms $\{s_1(t), s_2(t)\}$. Each waveform is transmitted within the symbol interval of duration T, $(0 \le t \le T)$ and the channel is assumed to corrupt the signal by the addition of white Gaussian noise.

$$r(t) = s_m(t) + n(t), \quad 0 \le t \le T \tag{1.1}$$

where r(t) is the received signal, $s_m(t)$ is the transmitted signal and n(t) denotes a sample function of AWGN process with power spectral density $S_{nn}(f) = N_0/2$. It shown that $s_m(t)$ signals and corresponding basis function could be written as

$$s_1(t) = \sqrt{\frac{2Es}{Ts}} \cos(2\pi f_c t) \tag{1.2}$$

$$s_2(t) = -\sqrt{\frac{2Es}{Ts}} \cos(2\pi f_c t) \tag{1.3}$$

$$\phi(t) = \sqrt{\frac{2}{Ts}} \cos(2\pi f_c t) \tag{1.4}$$

The main goal is to design a receiver that is optimum in the sense that it minimizes the probability of making an error for conventional receiver. Therefore, optimum receiver could be easily derived by using the Maximum a posteriori probability (MAP) decision rule [13]. In Fig.1, optimum receiver is given while assuming prior probabilities of transmitted symbols are equal.

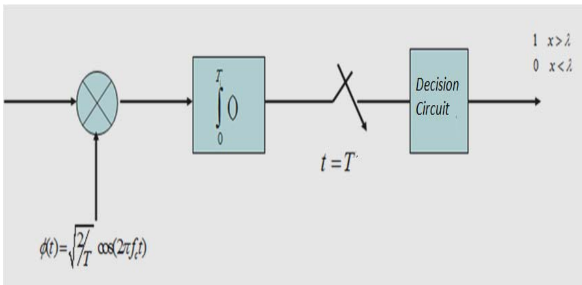

Fig. 1: Conventional Receiver for AWGN channel

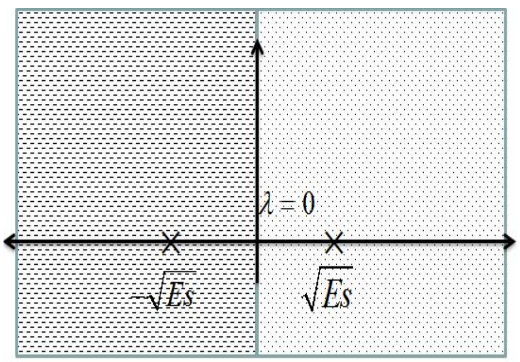

Fig. 2: Constellation Diagram of BPSK Signals

In this case, theoretical bound for BPSK signaling could be written as follows [14] by using the constellation diagram given in Fig. 2

$$P_b = Q\left(\sqrt{\frac{2E_b}{No}}\right) \tag{1.5}$$

where E_b is the bit energy and equals to symbol energy E_s and $Q(.)$ function is given as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-\frac{t^2}{2}} dt \tag{1.6}$$

4. Proposed Receiver

An artificial neuron has many inputs and one output. The training mode and the using mode are two modes of operation for the neuron. In the training mode, the neuron can be trained for specific input data. In the using mode, associated output of the neuron becomes the current output when a taught input pattern is detected at the input.

Feedback networks and Feed-forward ANNs are two kinds of architecture of neural networks. In this paper, we are using Feed-forward ANNs (Fig. 3) that allow signals to travel one way only; from input to output. In other words, the output of any layer does not affect that same layer that means feedback (loops) is not defined.

NND (Neural Network Demodulator) takes sampled and vector formed received signal in one symbol duration. The transmitted data is obtained by finding the maximum of the NND outputs. In this paper, one separate NN is designed for each symbol detection case. Therefore, totally M number of NN's are designed. To design and train NND, it is necessary to generate input and target data sets. For this purpose, input training data set generations are prepared naturally. The relative number "1" is used to represent expected output values while "-1" is emplyed for others. These numbers represent numerically the answer of question: "Is the transmitted data detected? ". The answer YES is represented by "1". And the answer NO is represented by "-1".

Feed forward multilayer neural networks are used to design NND (Fig. 3). Hidden layer neurons are selected by considering correlation receiver processing complexity. Clearly, M number of correlation process is needed to detect M number of symbols. In this case, it is clear that totally M number of hidden layer neurons will be used.

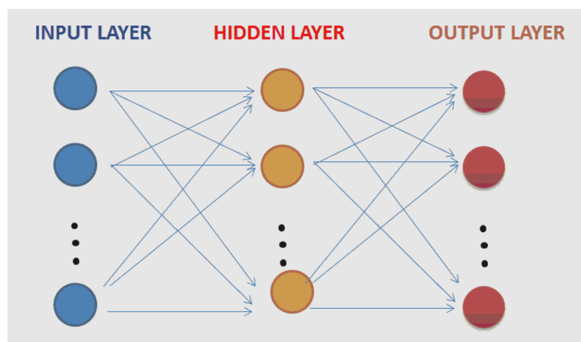

Fig. 3: Feed forward multilayer Neural Network structure

In other words, total M numbers of networks having 1 hidden 1 output layer neuron are designed. By considering this harmony it is aimed to provide reasonable complexity comparison between correlation receiver and NND. There are many activation function options in NND. In our simulations significant results are obtained by using tangent sigmoid transfer function and linear transfer function. Finally, it is decided that tangent sigmoid transfer function is the best for both layers (Fig. 4). We also concluded that Levenberg-Marquardt optimization yields best results to train the designed networks.

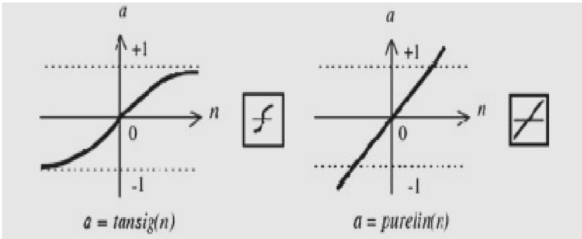

Fig. 4: Function characteristics of NN transfer functions

5. Simulation Results

First, we investigate the performance of the proposed scheme employing BPSK modulation over AWGN channel. Fig. 5 shows the bit error rate (BER) performance of the proposed receiver for AWGN channel. For this purpose, we also added the performance of optimum receiver and theoretical bound of BPSK modulation for AWGN channel. It is observed that proposed SDR receiver based on Neural Network has the same performance with the optimum receiver for AWGN channel.

For comparison purposes, the unknown interferences are added the transmitted signal and BER performance is evaluated. Signal model is revised as

$$r(t) = s_m(t) + n(t) + \alpha_1 I_1(t) + \alpha_2 I_2(t) \qquad (1.7)$$

and it is demonstrated in Fig. 6. It is shown that in Fig.7 proposed neural network based SDR receiver outperforms existing conventional receiver that do not account for the interference. It exhibits a gain of about 1.4 dB over conventional receiver at $BER = 10^{-5}$ when the training sequence has "14,000" symbols. It is also shown that the performance difference between the proposed and conventional increases for higher SNR values.

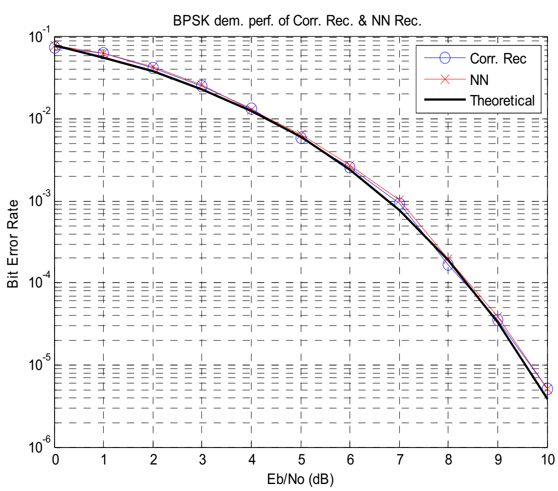

Fig. 5: BER comparison of proposed receiver and conventional receiver for AWGN

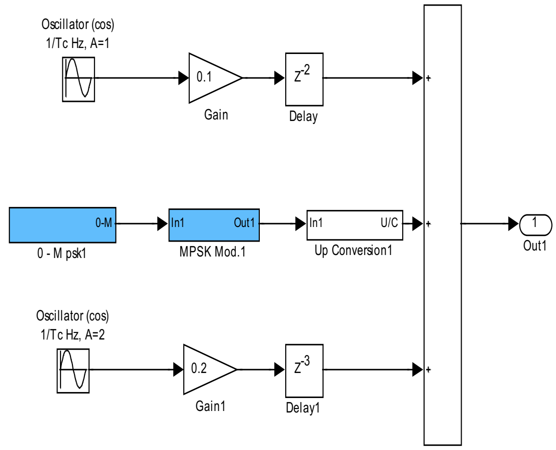

Fig. 6: Simulink Model for multi interference case

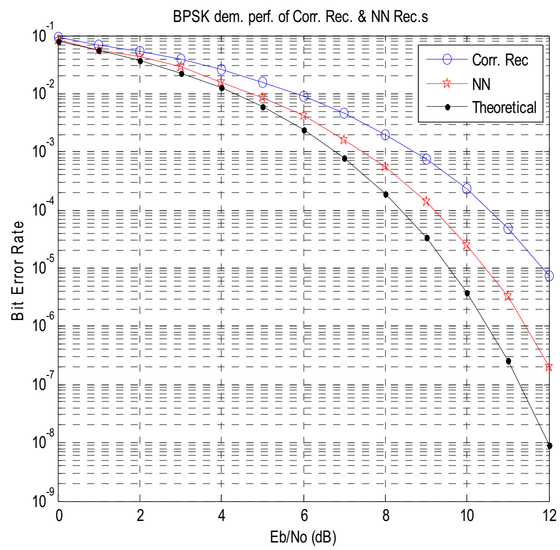

Fig. 7: BER comparison of proposed receiver and conventional receiver for Multiple Interferers.

6. Conclusions

The problem of signal demodulation in a practical wireless communication system where the receiver has only access to a noisy estimate of the channel provided by training symbols was investigated. We proposed the neural network based SDR receiver that takes into account the unknown channel model by training sequence. Our numerical results indicated that the proposed receiver has the same performance with the conventional receiver for AWGN channel while it has clear advantage for interference dominated channels. This performance improvement was obtained with requiring additional complexity caused by neural network structure in the receiver. However, it is shown that additional complexity is reasonable for practical systems.

7. References

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