Channel Estimation Technique for STBC Coded MIMO System with Multiple ANN Blocks

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ABSTRACT

In this work, a channel estimation technique based on Artificial Neural Networks (ANN) has been proposed as an alternative to pilot based channel estimation technique for Space-Time Block Coded Multiple-Input Multiple-Output (STBC- MIMO) systems over Rayleigh fading channels. ANNs, due to their high degree of adaptability, can be used for modelling the nonlinear phenomenon of channel estimation and for decoding the degraded symbols over severely faded channel. Two different ANN structures, namely Multilayer Perceptron (MLP) and Recurrent Neural Networks (RNN) have been trained and tested extensively for estimating the channel in STBC- MIMO systems with Binary Phase Shift Keying (BPSK) modulation scheme. Simulated results in terms of Bit Error Rates (BER) vs. Signal to Noise Ratio (SNR) have been used to compare the effectiveness of the learning capability of the two ANN structures over wireless fading channel. RNN structures are found to outperform the MLP, both in terms of training performance and BER results and thus proving its nonlinear dynamic adaptive behaviour.

General Terms

Design

Keywords

STBC; Rayleigh Channel; MLP; RNN; BER.

1. INTRODUCTION

Wireless channels are mainly multipath fading channels, which cause various problems like InterSymbol Interference (ISI) thereby degrading the performance in realizing reliable high-speed communication links [1] [2]. The use of Space-Time Block Coding (STBC) with spatial diversity gains derived from Multiple-Input Multiple-Output (MIMO) set-up seems to provide improved performance in highly faded wireless channels [3] [4] [5]. The overall performance in establishing links can be further enhanced if the assistance of channel estimation is considered in the system.

There are two common techniques found in literatures for channel estimation in MIMO systems, which can be divided into Blind and non-blind methods [2]. Blind estimation techniques are computationally intensive than the non-blind estimation, but the later causes wastage of available bandwidth by insertion of pilot symbols as training sequences along with actual data sequences.

In recent years, incorporation of Artificial Neural Networks (ANNs) for wireless communications has been gaining momentum, proving its effectiveness in tackling many difficulties of wireless transmissions [6]. ANNs can be successfully applied for modelling nonlinear phenomenon of channel estimation, as they can form arbitrarily shaped nonlinear decision boundary regions to take up complex classification problems. ANNs are known to perform complex mapping between its input and output space and hence, networks of different architecture have found successful application in channel estimation problem. In the Literature, it is found that Siu et. al. [7], reported one of the earliest applications of the ANNs in channel estimation task in digital communication. In [8], a three-layer ANN has been used to predict channel for MIMO systems. Similar research works in various times have been proving the importance of ANN to perform task of estimation [9] [10].

Recently, works have been reported in [11] to [13] where channel estimation technique is carried out using Recurrent Neural Network (RNN) for MIMO channels. These works have used RNN for MIMO channels but not for STBC coded MIMO channels. In this paper an effective channel estimation technique has been proposed with feedback RNN for STBC-MIMO systems over Rayleigh fading channels. This technique is an alternative to bandwidth-inefficient, pilot based channel estimation technique found in literatures. Learning property of RNNs is fully exploited here for decoding the degraded symbols over severely faded channels. Performance of the RNNs is further compared to Multilayer Perceptron (MLP) networks which are mainly feedforward network architecture. Simulated results in terms of BER are observed over a range of -10 to 10 dB which depicts the usefulness of the learning capability of RNNs for enhancing the task of channel estimation over wireless fading channels. This technique is thus found to be more efficient compared to pilot-based techniques both in terms of bandwidth requirement and Bit Error Rate (BER) curves [10].

This paper is organized into the following sections. Section 2 presents an insight into ANN networks considered for the proposed work. Section 3 describes the system model for channel estimation technique for STBC-MIMO channel using RNNs and MLPs. Experimental details and related results are included in Section 4. Finally Section 5 concludes the paper.

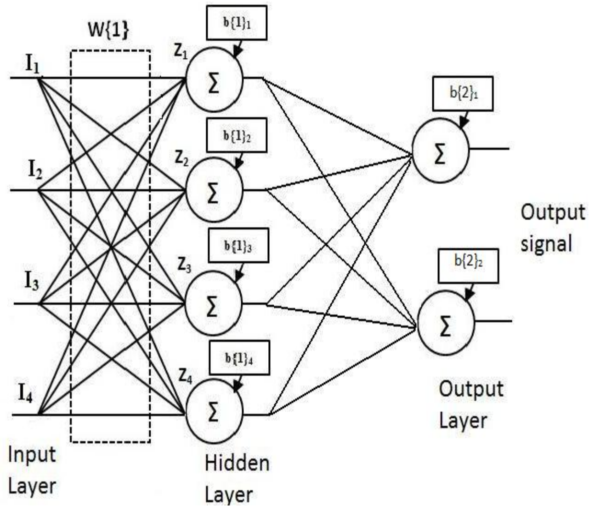

Figure 1: Feedforward architecture of MLP with hidden layer neurons

2. BASIC CONSIDERATIONS OF ARTIFICIAL NEURAL NETWORKS (ANN)S

ANNs are mathematical model or computational model based on biological neural networks [14]. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In this section, a brief description of the ANN architecture used for the channel estimation problem has been described.

In general, a Neural Network (NN) is a machine that is designed to model the way in which the human brain performs a particular task or function. It is a massively parallel distributed processor made up of simple processing units, called neurons, which possess learning ability and hence can generalize. Generalization refers to the NN's production of reasonable outputs for inputs not given during training. The nodes or artificial neurons are connected to each other by weighting. The weights on each connection can be dynamically adjusted until the desired output is generated for a given input. An activation function is used following the linear combination of neurons in NN model, for limiting the amplitude of the output of a neuron. In terms of network structures, there are fundamentally three different classes of networks [14].

A. *Single Layered Feedforward Networks*: In a layered neural network, the neurons are organized in the form of layers, where an input layer of source nodes projects directly onto an output layer of neurons, but not vice versa.

B. Multi Layered Feed forward Networks: There are one or more hidden layers, in this type, in which hidden neurons try to intervene between the external input and the network output in some useful manner. The ANN, in a feed forward form called Multi Layer Perceptron (MLP), is trained using (error) Back Propagation (BP) depending upon which the connecting weights between the layers are updated. This adaptive updating of the MLP is continued till the performance goal is met. Training the MLP is done in two broad passes -one a forward pass and the other a backward calculation with Mean Square Error (MSE) determination and connecting weight updating in between. Figure 1 shows the feedforward architecture of MLP with hidden layer neurons.

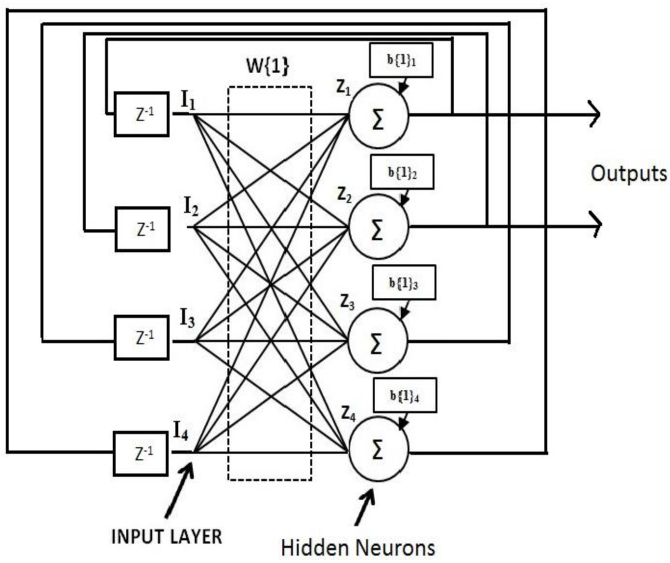

Figure 2: Feedback architecture of RNN with hidden layer neurons

Here, the feedback connections originate from hidden neurons as well as from the output neurons. The feedback loops involve the use of particular branches composed of unit-time delay elements (in terms of Z^{-1}) which provides a nonlinear dynamic behaviour to the network and helps to acquire state representations. Thus, RNNs are finding applications in diverse applications as nonlinear prediction and modelling, adaptive equalization of communication channels etc. [6].

There are two basic modes of training of RNN, a) epoch-wise training and b) Continuous training. In epoch wise training, an epoch involves a single string of temporally consecutive input-target response pairs that starts from an initial until it reaches a new state, whereas, in continuous training, the network learns while performing signal processing, which do not stop during learning.

3. SYSTEM MODEL FOR CHANNEL ESTIMATION TECHNIQUE USING ANNS

In this paper, a channel estimation technique for STBC coded MIMO transmission has been proposed over Rayleigh faded wireless channel with BPSK modulation, using high degree of adaptive behaviour of ANNs. The Transmitter and receiver structure of STBC- MIMO system with channel estimation is shown in Figure 3. Here the channel estimator block comprises of ANN networks which estimates the channel using their inherent dynamic behaviour. Diversity in data transmission is based on the idea that the probability that multiple statistically independent fading channels simultaneously experience deep fading is very low. MIMO is thus defined as the way of providing multiple antennas at the transmitter and at both link ends of a communication system respectively. The basic principle behind MIMO is that the transmit antennas and the receive antennas at both ends are "connected and combined" in such a manner that the quality in terms of BER, or the data rate for each user is improved. [2]. A MIMO system with M transmit antennas and N receive antennas has potentially full diversity (i.e. maximum diversity) gain equal to MN.

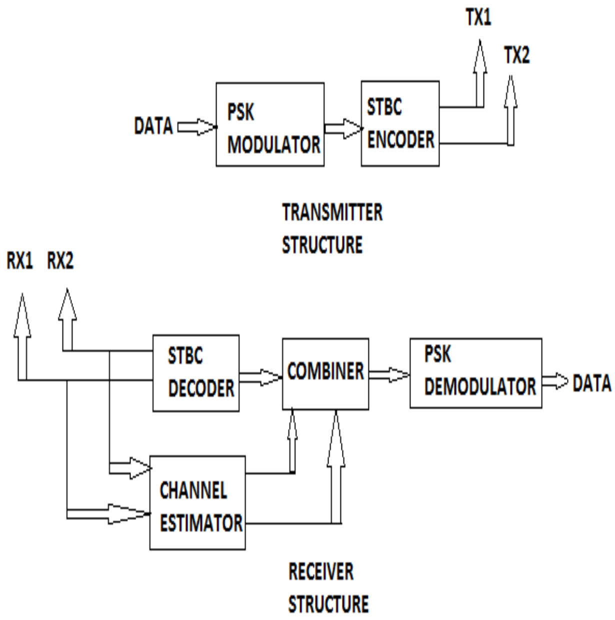

Figure 3: Transmitter and receiver structure of STBC system with channel estimation

STBC involves the use of spatial as well as time diversity for transmitting signal in wireless channels. In STBC, blocks of data are transmitted from different transmitter at different time instants for which a specific coding scheme is used [3]-[5]. There is a special version of STBC called Alamouti code which uses two transmit antennas and N receive antennas and can accomplish a maximum diversity order of 2N. It has the coding matrix $\begin{pmatrix} c_1 & c_2 \\ -c_2^* & c_1^* \end{pmatrix}$, where * denotes complex conjugate [3].

Channel estimation is regarded as a classification task in which ANNs can form decision regions in the space of received symbol sequences. Figure 4 shows the block diagram of the ANN assisted channel estimator block comprising of two independent neural networks NN1 and NN2 respectively. These two NNs work independently on the received signals (y1 and y2) to recover transmitted bits (x1 and x2) from TX1 and TX2. Transmitted signals from both the transmitters are partitioned into real and imaginary parts and are fed to the NNs respectively. NN1 is used to recover transmitted bits from antenna TX1 and NN2 is used to recover transmitted bits from antenna TX2.

According to this estimation scheme, channel is estimated in terms of weight and bias values of the ANN. Hence, the process of channel estimation is replaced with process of training the RNNs. A learning algorithm is applied which adjusts the synaptic weights and bias values during training mode of the RNNs. The complex received signals y1 and y2 at both the antennas are split into real and imaginary parts and are fed to the input layer neurons of both NNs as shown in Figure 4. NN1 and NN2 possess the same architecture. Both feedforward and feedback ANN architectures, namely MLP and RNN have been trained and tested to use in the channel estimator part and BER vs SNR curves have been evaluated as figure of merits over Rayleigh Faded channels.

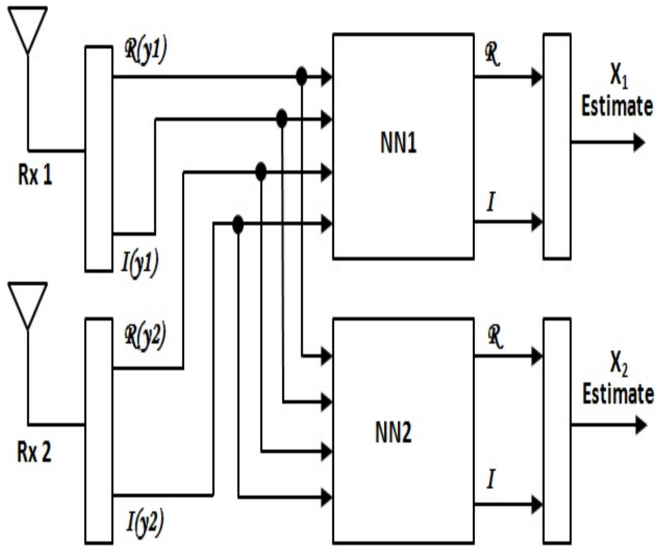

Figure 4: ANN based channel estimator block with two independent NNs, NN1 and NN2 respectively.

Table 1: ANN specification

ANN Type	MLP, RNN
Input Layer Size	4
No. of hidden layers	1
Activation Functions	tansig-tansig-tansig
Training Type	BFGS
Maximum No. of Epochs	1000
MSE goal	10^{-3}

Table 2: Variation of Training algorithm to achieve desired performance goal of MSE10^{-3}

Training Algorithm	Epochs for NN1 and NN2	
	MLP	RNN
Traingdx	123 and 140	127 and 146
Trainlm	18 and 49	14 and 49
Trainbfg	12 and 15	14 and 18

Table 3: Variation of Activation functions to achieve desired performance goal of MSE 10^{-3}

Activation Functions	Epochs for NN1 and NN2	
	MLP	RNN
tansig-tansig-tansig	16 and 26	8 and 17
tansig-tansig-purelin	20 and 158	21 and 78

4. EXPERIMENTAL DETAILS AND RESULTS

In wireless communications systems, each of the multipath components have different relative propagation delays and attenuations which results in filtering type of effect on the received signal. The mobile radio channel can be modelled as a linear time varying channel, where the channel changes with time and distance. The received signal Y can be expressed as a convolution of the transmitted signal X with channel impulse response h, as Y=X*H +N, where N is the Additive White Gaussian Noise and H is the channel matrix. If the

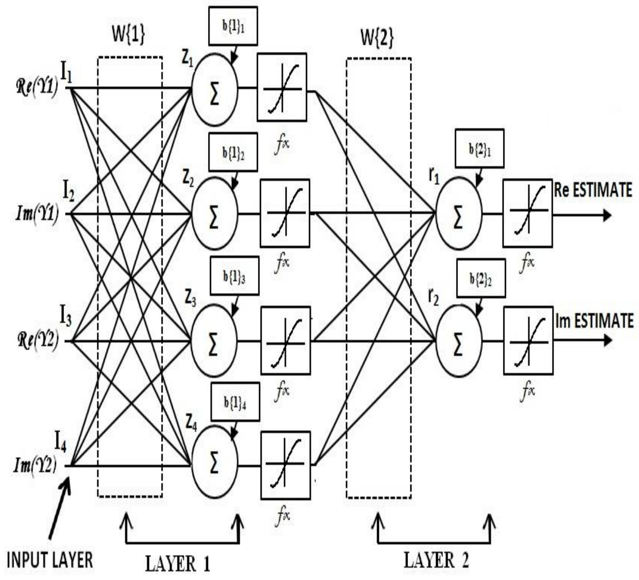

Figure 5: Architecture of one independent NN (NN1 and NN2) in the proposed MLP assisted channel estimator block.

ANN estimates the signal as X_E, an error matrix can be generated as, e= $X-X_E$, such that $X_E=X*H_E+N$ is the signal generated by the ANN [15]. The ANNs with specific configuration are shown in Table 1.

The training and validation part is a bit time consuming and requires tedious work to fix the configuration. Training is carried out till mean square error (MSE) approaches the desired goal of $10^{-3.}$ Several configurations for the MLP and RNN networks have been utilized for training. The length of the hidden layers has been fixed by trial and error method. The ANNs with specific configuration are shown in Table 1. Figure 5 and 6 show the architecture of the independent ANNs with the specified configuration. The size of the hidden layer has been fixed to be same with the input layer, as it gives an efficient result in terms of convergence time and number of epochs required to reach the goal.

Table 2 shows that Quasi-Newton training algorithm *trainbfg* outperforms the *traingdx* and *trainlm* algorithm, as both time and epochs required to meet the performance goal are less in the trainbfg algorithm. Table 3 gives knowledge about the behaviour of ANNs with change in activation functions in three layers. Tan-sigmoid functions in all layers seem to give a better result than the other combinations. Figure 5 and 6 show the internal recurrent architecture of the NNs used in estimator block of the system in MLP and RNN networks respectively.

In this work, it is assumed that the channel experienced by each transmit antenna is independent from the channel experienced by other transmit antennas. Error performances are measured as BER against the SNR values for both the cases. The systems are simulated over the range of SNR -10 to +10 dB. Figure 7 shows the corresponding BER curves which shows the RNN networks outperforming the MLP networks. RNNs have good capability to capture time-dependence of input signals due to the presence of at least one feedback loop in it, though it is essentially a feed forward structure. Feedback loop in delayed forms from the output to the hidden layer initiates dynamic updating of the weight and bias values connecting all three layers of RNN. During training, RNN

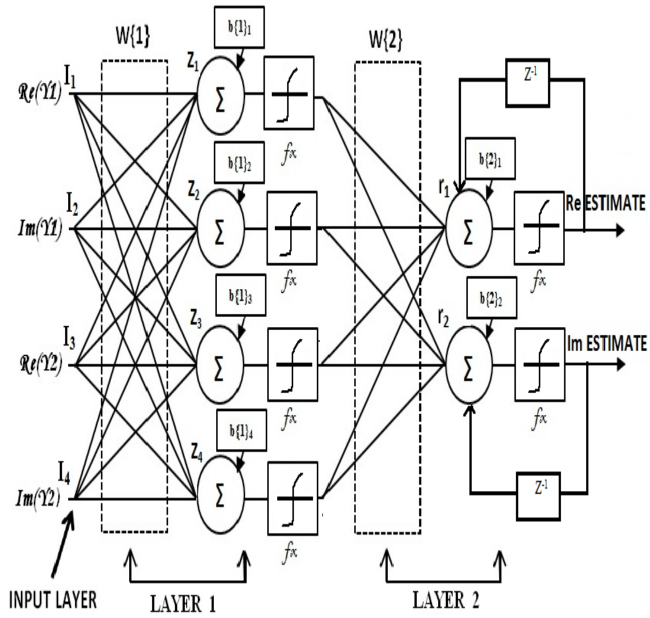

Figure 6: Architecture of one independent NN (NN1 and NN2) in the proposed RNN assisted channel estimator block.

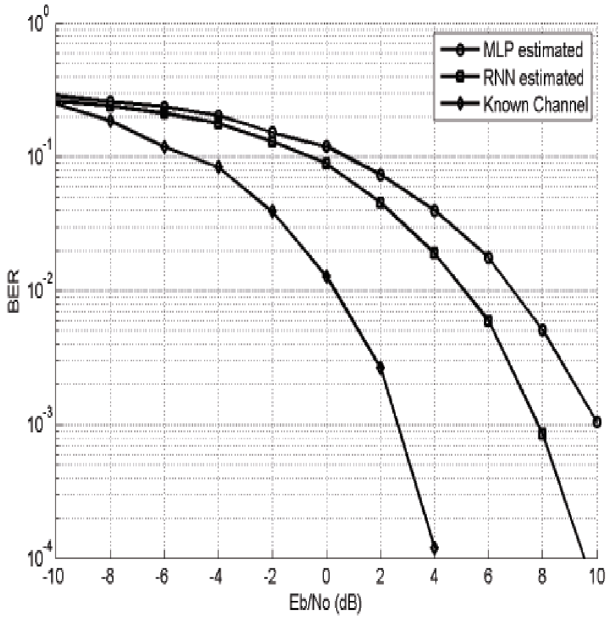

Figure 7: Performance of RNN assisted MIMO system with two training algorithms, namely, LM and Quasi Newton algorithm.

learns the temporal behaviour of input samples by relating transitions between layers with the help of state vector relationship among them. This learning ability is then tested with unknown sets of input samples, which are passed through the network and estimate of the transmitted signal x1 and x2 are calculated.

5. CONCLUSION

In this work, a channel estimation technique has been proposed based on two different Artificial Neural network (ANN) structures, namely MLP and RNNs for use in STBC

MIMO system in Rayleigh Faded channel. Estimate of the channel is calculated in terms of synaptic weights and bias values of the neural network. Different training algorithms have been used to analyze the calculation of weight and bias values. Learning property of ANN is fully exploited for decoding the degraded symbols over severely faded channel. This technique is found to be more bandwidth efficient compared to pilot-based channel estimation techniques. Simulated results in terms of Bit Error Rates (BER) vs. Signal to Noise (SNR) ratio depict the effectiveness of the learning capability of ANNs for the task of channel estimation over wireless fading channel. The work can be further extended to designing an optimized channel estimator using hybrid approach. The optimization may come in the form of a combination of adaptive filter and ANN, or the use of fuzzy neural approaches. This can be later exploited in multiuser MIMO schemes also.

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