Kalman Filter and Recurrent Neural Network based Hybrid Approach for Space Time Block Coded-MIMO Set-up with Rayleigh Fading

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Abstract: In this paper, an optimized channel estimation and symbol detection technique using a combination of Kalman Filter (KF) and Recurrent Neural Networks (RNN) is proposed. The hybrid estimator is used for Space Time Block Coded (STBC) Multiple Input Multiple Output (MIMO) set up over severely faded Rayleigh channels. Simulated results in terms of bit error rate (BER) values against signal to noise ratio (SNR) depict the effectiveness of the learning capability of RNNs aided by KF for the task of channel estimation and symbol detection over faded wireless channels.

Key-Words: STBC; Rayleigh Channel; Kalman filter; RNN; Estimation; BER; MIMO.

1 Introduction
Space Time Block Coded (STBC) Multiple Input Multiple Output (MIMO) set ups have emerged as likely options to meet the demands of ever expanding wireless networks. But the design of effective receiver mechanisms for the STBC-MIMO is still a challenging area. Of late, soft-computational approaches have received attention for application in these areas due to the ability of these tools to learn from the surrounding and use it subsequently. In this process incorporation of soft-computational tools like Artificial Neural Networks (ANN) based approaches as part of wireless communications have gained momentum [1]-[5]. Siu et. al. [2], reported one of the earliest applications of the ANNs in channel estimation task in digital communication. In [3], 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 estimation [4] [5]. In [4], an ANN channel estimation scheme has been proposed using levenburg- marquardt algorithm for systems over Rayleigh channels, whereas in [5], the use of feedforward ANN has been explored for use in MIMO channel estimation and compensation.

This work reports an optimized channel estimation and detection technique with Recurrent Neural Network (RNN) and Kalman filter (KF) for STBC-MIMO systems over channels with Rayleigh fading. The hybrid structure using KF-RNN is designed for two input and two output antenna systems, using BPSK modulation scheme. The performance of the STBC decoder is enhanced by the KF-RNN blocks which are used to estimate the channel with the aid of Walsh-Hadamard coded pilot symbols. KF generates the estimated channel response and the RNN block is then used to decode the degraded symbols from the impact of estimated channel. The learning property of RNNs is fully exploited in this work for decoding the degraded symbols over severely faded channels. Simulated results in terms of improved Bit Error Rate (BER) are observed over a SNR range of -10 to 10 dB which depicts the effectiveness of the proposed hybrid estimator for STBC MIMO systems compared to other existing ANN estimation techniques [4] [5].

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

2. Basic Considerations of ANN

ANNs are mathematical or computational models inspired by biological neural networks [6]. 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 RNN architecture used for the channel estimation problem has been described. In general, an ANN is formed by multiple layers of artificial neurons which are interconnected by certain connectionist weights. These are key in enabling the ANN to learn and use this knowledge subsequently. The artificial neurons act...
as processing blocks which provide the ANN the ability to execute processes concurrently. The weights on each connection can be dynamically adjusted until the desired output is generated for a given input. This is called training and it is repeated till the ANN generates the desired results. Generally, mean square error (MSE) is used to determine the level of training an ANN has undergone after which it becomes ready for testing [6].

In terms of network structures, there are fundamentally three different classes of networks [6]. Among the three, Recurrent Neural Networks (RNN)s, often generalized as IIR filter with feedback, have at least one feedback loop in it. The presence of feedback loop has a profound impact on the learning capability of the network and on its performance. Feedback loops involve the use of particular branches of delay elements, which result in a nonlinear dynamic behaviour. For example, a recurrent network may consist of a hidden layer of neurons, as shown in Figure 1. 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 [8]. RNNs are now finding applications in diverse fields as nonlinear prediction and modelling, adaptive equalization of communication channels etc. Recent research works have proved that RNN can be successfully applied to channel estimation problem with lesser neurons that outperforms the other feedforward ANN networks [7] [8].

### 3. Proposed Kalman Filter and RNN based Hybrid Approach for STBC-MIMO System

Wireless medium is constituted mainly by multipath fading channels, for which various problems like intersymbol interference (ISI) arise. It leads to degradation of the performance in realizing reliable high-speed communication links [9] [10]. The use of STBC with spatial diversity gains derived from MIMO set-up provides improved performance in highly faded wireless channels [11]-[13]. The overall performance in establishing wireless links can be further enhanced if the assistance of channel estimation is considered in the system. There are various techniques found in literatures for channel estimation in MIMO systems, which can be divided broadly into blind and non-blind methods [10]. 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.

Diversity scheme provides multiple statistically independent fading channels simultaneously doing data transmission such that fading effects are minimized. MIMO provides multiple antennas at the transmitter and receiver ends of a wireless link. 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 [10]. A MIMO system with M transmit antennas and N receive antennas has potentially full diversity (i.e. maximum diversity) gain equal to MN. 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. 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 [11].

In the present work, a channel estimation technique for STBC coded MIMO transmission is proposed for Rayleigh faded wireless channel with BPSK modulation using the high degree of adaptive behaviour of RNNs combined with KF.
Channel estimator block performs both joint detection and estimation operation using the hybrid RNN and KF, which works in an iterative manner to optimize the decoding scheme for STBC MIMO system. Figure 2 shows the transmitter and receiver structure of STBC MIMO system used in this work with KF-RNN channel estimator clusters. KF with the aid of pilot symbols has been reported to raise the BER performance in a wireless environment with an insignificant loss in the data transmission rate \[14\]-\[19\]. But in combination with RNN, this performance can be enhanced further. This aspect is explored here and described in the following sections. The state space equations for tracking the MIMO channel can be expressed as:

\[ h(t+1) = A(t)h(t) \] \hspace{1cm} (1)

\[ s(t) = C(t)h(t) + v(t) \] \hspace{1cm} (2)

where \( h \) is the channel tap, \( A \) is a time-varying transition matrix, \( C \) is the observation matrix and \( v \) is the measurement error vector. A first-order Auto-Regressive (AR) model provides a sufficient model for time varying channels. Therefore, \( A \) can be a diagonal matrix of autoregressive model factor \( \alpha \), where, \( \alpha = E[h_{ij}(t+1)\ast h_{ij}^{-1}(t)] \) \hspace{1cm} (3)

The KF equations for MIMO channel are divided into two parts. First part is the predictor:

\[ \tilde{h}(t + 1 | t) = A(t)\tilde{h}(t | t) \] \hspace{1cm} (4)

\[ P(t + 1 | t) = A(t)P(t | t)A^T(t) \] \hspace{1cm} (5)

\[ \epsilon(t) = s(t) - C(t)\tilde{h}(t + 1 | t) \] \hspace{1cm} (6)

\[ K(t) = P(t + 1 | t)C^T(t)[C(t)P(t + 1 | t)C^T(t) + R_v]^{-1} \] \hspace{1cm} (7)

And the second part is the update:

\[ \tilde{h}(t + 1 | t + 1) = \tilde{h}(t + 1 | t) + K(t)\epsilon(t) \] \hspace{1cm} (8)

where, \( R_v = \beta I \) and \( \beta \) is a covariance of the noise vector \( v \). The \( K \) matrix is called the Kalman gain and the \( P \) matrix is called the estimation error covariance. The first term in the state estimate in Eq. 8 is used to derive the state estimate at time \( t + 1 \). The second term in Eq. 8 is called the correction term and it represents the amount by which to correct the propagated state estimate due to the measurement. In figure 2, the KF first tries to estimate the random channel using Walsh-Hadamard coded pilot symbols, the channel will always degrade the received symbols at both RX1 and RX2 antennas in a destructive manner. These degraded symbols are then used to train the RNN, to give an accurate estimate of the transmitted symbols.

Figure 3 shows the diagram of the RNN block comprising of two independent networks NN1 and NN2 respectively. These two RNNs work independently on the received signals (\( y_1 \) and \( y_2 \)) affected by the randomly varying channel to recover transmitted bits (\( x_1 \) and \( x_2 \)) from TX1 and TX2. Transmitted signals from both the transmitters are partitioned into real and imaginary parts and are fed to the RNNs as training targets respectively. NN1 is used to recover transmitted bits from antenna TX1 and NN2 is used to recover transmitted bits from antenna TX2 while the RNN blocks are also trained to handle cross-correlated terms which provide significant information content to the system. These terms are provided as subordinate data samples to the system which constitute the training set. According to this scheme, channel is estimated in terms of weight and bias values of the RNN. Hence, the process of channel estimation is replaced with process of training the RNNs. No matrix computation is required in this technique as it is making full use of the learning property of the RNNs. An appropriate learning algorithm (Decoupled Extended Kalman Filter (DEKF)) is applied which adjusts the synaptic weights and bias values during training mode of the RNNs. During training, the complex received signals \( y_1 \) and \( y_2 \) at both the antennas are split into real and imaginary parts and are
Figure 3: KF-RNN based channel estimator block with two independent NNs, NN1 and NN2 respectively.

Figure 4: Architecture with independent ANN (NN1 and NN2) units in the proposed system fed to the input layer neurons of both NNs as shown in Figure 3. NN1 and NN2 possess the same architecture. Figure 4 shows the internal recurrent architecture of the NNs used in estimator block of the system. RNNs have appreciable capability to capture time-dependence of input signals due to the presence of at least one feedback loop in it. 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. This learning ability is then tested with unknown sets of input samples, which are passed through the network and

Table 1: Variation of Activation functions to achieve desired performance goal of MSE $10^{-3}$

<table>
<thead>
<tr>
<th>Activation Functions</th>
<th>Time in seconds</th>
<th>Epochs – NN1/NN2</th>
</tr>
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<tbody>
<tr>
<td>tansig-tansig-tansig</td>
<td>26.31</td>
<td>21/15</td>
</tr>
<tr>
<td>tansig-tansig-purelin</td>
<td>88.65</td>
<td>141/78</td>
</tr>
</tbody>
</table>

estimate of the transmitted signal $x_1$ and $x_2$ are calculated. Here, we clearly see that with the help of the Kalman filter, a RNN based approach to deal with the STBC-MIMO provides an option worth exploring for improved performance.

4. Experimental Details and Results

In a wireless setup, 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 [20]. The received signal $Y$ at any antenna 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 (AWGN) and $H$ is the channel matrix. If the RNN 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 RNN. The training part is completed initially and tested extensively over the range of SNR -10 to 10 dB.

The training and validation part of the RNN 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 RNN are utilized for training. The length of the hidden layers has been fixed by trial and error method. 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 1 gives knowledge about the behaviour of RNN with change in activation functions in three layers. Tan-sigmoid functions in all layers seem to give a better result than the other combination. The ANNs with specific configuration are shown in Table 2. In this work, it is assumed that the channel experienced by each transmit antenna is independent from the channel experienced by other transmit antennas. Channel fading condition is depicted in Figure 5.
Table 2: ANN specification

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
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<tbody>
<tr>
<td>ANN Type</td>
<td>RNN</td>
</tr>
<tr>
<td>Input Layer Size</td>
<td>4</td>
</tr>
<tr>
<td>No. of hidden layers</td>
<td>1</td>
</tr>
<tr>
<td>Activation Functions</td>
<td>tanSig-tanSig-tanSig</td>
</tr>
<tr>
<td>Maximum No. of Epochs</td>
<td>1000</td>
</tr>
<tr>
<td>MSE goal</td>
<td>$10^{-3}$</td>
</tr>
<tr>
<td>Training and testing data block size</td>
<td>8, 16 and 64 bits</td>
</tr>
<tr>
<td>Training samples</td>
<td>1000 sets in -3dB, to 3dB SNR in channel</td>
</tr>
<tr>
<td>Testing samples</td>
<td>1500 sets of 8, 16 and 64-bit blocks under moderate to severe fading</td>
</tr>
</tbody>
</table>

Error performances are measured as BER against the SNR values for both the cases. The performance of the system under extreme fading is depicted by the BER plot shown in Figure 6. The BER shows that under severe fading with simulated vehicular speed of around 120kmph, the proposed system tracks the signal variations properly and provides around 1.2 dB SNR gain improvement corresponding to the case when only the RNN-based approach is adopted. The system performs symbol recovery as well with consistent precision of around 92-95% over the range of SNR variations in the received signal and channel states. The proposed KF-RNN technique is compared with known channel condition and estimator with RNN block only. In the estimation done by RNN block, received signals at both the antennas are directly fed for training and corresponding estimate of the transmitted bits are obtained. Both these techniques are found to be efficient as in training the RNNs, no pilot bits are required, as compared to other pilot assisted methods [5]. This is an advantage that the system provides. The effectiveness of the proposed system for STBC-MIMO system is thus obvious.

5. Conclusion

Here, we proposed an optimized channel estimation and detection technique with Recurrent Neural Network (RNN) and Kalman filter (KF) for Space Time Block Coded (STBC) Multiple Input Multiple Output (MIMO) systems over Rayleigh fading channels. Experimental results show that under severe fading with simulated vehicular speed of around 120kmph, the proposed system tracks the signal variations properly and provides around 1.2 dB SNR gain improvement corresponding to the case when only the RNN-based approach is adopted.

The system performs symbol recovery as well, with consistent precision of around 92-95% over the range of SNR variations in the received signal and channel states. The RNN-based and the proposed hybrid KF-RNN approach additionally proves to be bandwidth efficient as these methods donot require training bits unlike certain reported techniques where pilot blocks are inserted to enable proper recovery of the symbols at the receiver end.
References:


