Channel Estimation Based on Machine Learning Paradigm for Spatial Modulation OFDM

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Abstract—In this paper, deep neural network (DNN) is integrated with spatial modulation-orthogonal frequency division multiplexing (SM-OFDM) technique for end-to-end data detection over Rayleigh fading channel. This proposed system directly demodulates the received symbols, leaving the channel estimation done only implicitly. Furthermore, an ensemble network is also proposed for this system. Simulation results show that the proposed DNN detection scheme has a significant advantage over classical methods when the pilot overhead and cyclic prefix (CP) are reduced, owing to its ability to learn and adjust to complicated channel conditions. Finally, the ensemble network is shown to improve the generalization of the proposed scheme, while also showing a slight improvement in its performance.

Index Terms—Channel estimation, data detection, deep neural network (DNN), ensemble learning, spatial modulation-orthogonal frequency division multiplexing (SM-OFDM).

I. INTRODUCTION

Spatial modulation (SM) is a promising modulation scheme at the cutting edge of wireless communication, that can achieve high spectrum and energy efficiency while remaining at a relatively low complexity level [1]. This modulation scheme allows for the exploitation of the unique channel characteristics that the multiple transmit antennas will have, to essentially recognize the antenna’s index and utilize it as a part of the constellation diagram. On the other hand, orthogonal frequency division multiplexing (OFDM) has been considered as a well-established and a highly popular modulation scheme that enables efficient use of the available bandwidth, and to combat the inter-symbol interference (ISI) that is present in frequency selective channels. Combining the two schemes together is known as spatial modulation-orthogon frequency division multiplexing (SM-OFDM) technique that is proposed in [1], where extra information bits are conveyed by active antenna indices of subcarriers to achieve enhanced data rate and robustness against the inter-antenna interference (IAI) within the subcarriers.

In SM detection schemes, the channel needs to be estimated. This has typically been accomplished using conventional methods such as least square error (LSE) and minimum mean square error (MMSE). LSE requires no prior information regarding the channel, rendering it rather simple to implement. On the other hand, the MMSE method requires second order statistics of the channel, which makes it significantly more complex. The increased complexity in MMSE is not without reason, as it improves the performance by a significant margin.

Recently, deep neural networks (DNNs) have had major development in the field of wireless communications, finding their way into many applications. DNNs specifically, have been shown promising results in channel estimation, due to their ability to learn and adapt to much more complex systems than a regular artificial neural network. In [2], the authors proposed a DNN in an OFDM system for joint channel estimation and symbol detection. The results show that the proposed DNN performs comparably to the much more complex MMSE method, and far exceeds it in low overhead situations, such as reductions in the number of pilots and the length of the cyclic prefix (CP).

The emerging SM technique is not an exception, and has also had many advancements aided by DNNs for data detection [3], [4]. For dynamic wireless channels, the authors in [3] proposed recently, a pair of DNNs to perform joint channel estimation and data detection in the SM scheme. The reported results of this paper showed that the DNN pair was capable of outperforming the conventional methods over the considered time varying channel. The authors in [4] proposed an autoencoder complex valued convolutional neural network based detector for generalized spatial modulation (GSM) scheme, first introduced in [5], with new extracted features. It is shown in this paper that the computational complexity is significantly reduced without any noticeable performance loss as compared to the conventional maximum likelihood (ML) detector.

Ensemble learning is a popular machine learning technique, where multiple networks are merged together into a singular model, with the aspiration of improving the performance. This technique has recently been finding its way into the field of communication. For instance, in cognitive radios as in [6], where ensemble learning is used in modulation classification. It was concluded that utilizing the ensemble framework would achieve results superior to that achieved by a single classifier. Furthermore, although not explicitly stated in [2], an ensemble network was utilized, where the outputs of multiple DNNs were concatenated in order to fully detect the entire OFDM frame. This form of ensemble network allows the DNNs to be of reasonable size, such that training time does not become too egregious.

In this paper, a novel DNN scheme for joint channel estima-
The proposed DNN architecture, as depicted in Fig. 2, consists of six layers, where the number of neurons for these layers are 256, 1000, 500, 250, 120, and 6, respectively. The
DNN takes two SM-OFDM symbols as inputs, the pilot SM-OFDM symbol and the data carrying SM-OFDM symbol. These two symbols are further separated into their real and imaginary counterparts and input into the network, thus the number of input neurons can be derived to be 256 neurons, if 64 subcarriers are used. The four hidden layers of sizes 1000, 500, 250, and 120 are activated using the Relu activation function. The output layer serves to predict and recover the received data as bits, while the activation function for this layer is the Sigmoid activation function. In our proposed system, this layer only predicts six bits, which means that a separate DNN needs to be trained for each six bits that need to be recovered. The outputs of the DNNs thus need to be concatenated in order to form an entire frame. In this way, the required size of the single DNN can be reduced significantly, while still utilizing all the data received in a single frame.

C. Ensemble Network Classifier

Multiple unique DNNs with their outputs merged together create an ensemble network. The technique of merging these networks and their quality determines the ensemble’s performance and generalization. For the already proposed DNN architecture, multiple DNNs are needed to be concatenated in order to detect an entire frame, forming an ensemble network. This concatenating ensemble structure does not necessarily aim to improve the overall system’s generalization, only to reduce the size of the required DNN. Another ensemble network architecture is proposed alongside it, that aims to improve the overall system’s generalization. For this proposed ensemble, the yield of multiple unique DNNs are examined, and an output is chosen based on the most probable case, according to each DNN’s hypotheses. The maximum a posteriori (MAP) classifier is used, which in this particular case is equivalent to the naive Bayes optimal classifier, proposed in [7], due to the bit-stream being completely random. The output of the ensemble can be stated as

\[
d_{i}^{\text{MAP}} = \frac{1}{K} \sum_{k=0}^{K-1} d_{i}^{k}
\]  

where \(d_{i}^{k}\) is the \(i\)-th output of the \(k\)-th DNN, \(d_{i}^{\text{MAP}}\) is the ensemble’s classification for the \(i\)-th output, and \(K\) is the number of DNNs used in the ensemble.

As (2) suggests, the ensemble’s classification is determined by the average of the hypotheses made by the DNNs. This is performed online, on a frame-by-frame basis. Utilizing this method allows the merging of different DNNs trained in various situations, allowing the ensemble to inherit their traits and potentially improve the overall system performance. Choosing the appropriate networks is thus vital to the ensemble’s performance and will determine its generalization.

III. Results and Discussion

In this section, extensive simulation is conducted to compare the bit error rate (BER) performance versus the signal-to-noise ratio (SNR) between the proposed DNN based detector and the classical LSE and MMSE detection schemes in SM-OFDM systems. Throughout the simulation, SM-OFDM scheme with two transmit antennas and one receive antenna is considered, with 64 subcarriers, a CP length of 16 samples, and modulated using the 4-QAM scheme. The Rayleigh fading channel model is also considered with the assumption that a perfect channel knowledge is available at the receiver.

A. Effect of Pilots

In Fig. 3, the impact of the number of pilots on the performance of SM-OFDM scheme with the proposed DNN based detection is assessed. A Rayleigh fading channel with 3 channel paths which has a maximum delay of 3 sampling periods is considered. This figure shows that when 32 pilots per transmit antenna are used for the SM-OFDM scheme, the proposed DNN performs comparably to the conventional MMSE method and far exceeds the performance of the LSE method. Reducing the number of pilots to 4 per transmit antenna, however, significantly impacts the performance of the
conventional MMSE and LSE methods, showing no significant improvement beyond the SNR of 20 dB. Meanwhile, the DNN method only suffered a performance degradation of 2 dB, as compared to the same scheme with 32 pilots to achieve a particular SNR. This comparison shows that the DNN method maintains its performance despite the large reduction in the number of pilots, making it more resilient and robust to reductions in the pilot overhead.

B. Effect of Cyclic Prefix

The addition of CP in OFDM systems converts the linear convolution into a circular convolution, mitigating ISI. This, however, comes at the cost of wasted time and energy. In this section, the removal of the CP is evaluated. To effectively show the impact of removing the CP, a Rayleigh fading channel with 8 paths and a maximum delay of 8 sampling periods is considered. The number of pilots per transmit antenna used for all methods in this section is 32. Fig. 4 shows that with CP, the performance is very similar to that in the previous section, with the MMSE method showing the best performance, and the proposed DNN being very comparable to it. It can also be seen from Fig. 4 that with removing the CP, the DNN scheme outperforms the MMSE method significantly. This is due to the DNN learning and adapting to these specific conditions in ways the conventional methods cannot.

C. Ensemble

In order to examine the effectiveness of the ensemble method, comprised of 4 unique DNNs, it is measured up against the proposed DNN and the conventional MMSE schemes. A Rayleigh fading channel with 3 channel paths and a 3 sampling period maximum delay is considered. In Figs. 5 and 4, it can be observed that the proposed DNN appears to be reaching BER saturation, this can be attributed to the DNNs being trained on a single SNR, leading to the DNNs to bias toward the trained SNR. The ensemble method shown in Fig. 5 on the other hand, does not exhibit the same level of biasing, due to the ensemble being fashioned from 4 unique DNNs trained on different SNRs. Fig. 5 also shows that the ensemble is able to improve on the performance of the proposed DNN scheme. These results demonstrate the potential of utilizing ensembles to improve the performance of data detection based on DNNs.

IV. CONCLUSION AND FUTURE WORK

In this paper, a joint channel estimation and data detection architecture based on machine learning paradigm for SM-OFDM scheme is proposed. The DNN based detection scheme is evaluated and compared to the classical MMSE and LSE detection methods. Simulation results demonstrate that the DNN is able to adjust to reductions in pilot overhead and CP redundancies, while the conventional methods could not. This is due to the DNNs ability to learn and adapt to the characteristics of the wireless channel. Additionally, an ensemble network is introduced that improved the generalization of the proposed DNN architecture, while showing a slight improvement in performance. Future work will focus on further investigation of ensemble network techniques, expanding the deep learning framework into GSM, and increasing the number of transmit and receive antennas.

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