Deep CNN-Based Signal Precoding and Detection for Enhanced MIMO Performance

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Abstract

The signal precoding and detection in Multiple Input Multiple Output (MIMO) systems can be remarkably practical. The innovation presented in the following article is a technique for precoding and signal detection in 5th-generation telecommunication systems, which operates based on deep learning. A precoding network is designed using convolutional networks for signal preparation to be transmitted through the channel. Finally, the proposed model has been compared with other similar models for signal detection under different conditions. The simulation output results demonstrate that the improved model has outperformed the competing approaches.

Keywords: Deep learning, Convolutional Neural Network (CNN), Signal Detection, MIMO Detection, precoding

1 Introduction

The Multiple Input Multiple Output (MIMO) systems are remarkable due to their special capabilities, which include high capacity, high physical security, and better coverage [**? ?**].In the MIMO systems, signal detection is one of the essential tasks conducted in the receiver [**?**].The classic signal detection schemes such as Zero Forcing (ZF), Minimum Mean Square error (MMSE) [**? ?**] , and Maximum Likelihood (ML) [**?**] have been used extensively in various telecommunication systems [**? ?**].In the classic signal detection algorithms, the channel matrix is considered to be known beforehand which is achieved with the aid of a channel estimation [? ?]. In recent years, Deep learning, as well as image processing and signal processing has been used in the domain of MIMO signal detection. In the schematics of signal detection based on deep learning, the channel matrix can be assumed to be unknown and the channel can be estimated using some pilots at the same time as detecting the signal[?]. The simplest deep network structure used for signal detection in the literature is based on the fully connected (FC) layers [?].This structure performs well in low dimensions, but the run time and complexity of the network go up with the dimension increase. Another technique is the model-based signal detection method called MdNet [?] which has been suggested for time-varying channel tracking. The number of learnable parameters in this structure is small and independent of the network dimensions. Therefore, the training process is done faster and the error performance is better than the FC-based structures. BiLSTM-DetNet (BD-Net) is another deep-learning based scheme which estimates the signal based on the ML detector with lower complexity [?]. The parallel deep learning network has also been suggested in [?] which offers good performance for time-varying channels. Moreover, the Trainable Projected Gradient Network (TPGNet) [?] is a deep learning based data-driven method which has a fast training process. Another signal detection method is the Deep Convolutional Neural Network-Maximum Likelihood Detector (DCNN-MLD) exploits interference properties to enhance detection. In [?], the convolutional layers have been used in the data processing module, and the FC together with Long-Short-Term-Memory (LSTM) have been applied in the iteration processing module. [?], the Trainable Approximate Message Passing (TAMP) algorithm is used for preprocessing the received signal. Furthermore, the Minimum Mean Squared Error (MMSE) filter and the Generalized Approximate Message Passing (GAMP) algorithm are adopted to improve signal detection in MIMO systems. In this paper, a new method is proposed utilizing deep convolutional networks. In this method, a precoder network is utilized to enhance the fidelity of the transmitted signal and also at the receiver, under the assumption that the received signal and channel matrix are known, employed A detector network to estimate the transmitted signal, and finally, to be able to better control the reduction of the transmitted signal error, a reduction method is used for a certain number of iterations, to perform the reconstruction on the transmitted signal better. In the proposed method, under various conditions, including the utilization of different modulation schemes such as BPSK, we evaluated the bit error rate and compared the performance between Rayleigh channels with varying numbers of antennas. Finally, we presented error diagrams demonstrating the superiority of the improved algorithm in signal detection at the receiver. The rest of the article can be outlined as follows: In Section II, the system model is described; Section III presents the proposed method; Section IV contains the simulation results; and in Section V, the conclusion is expressed.

2 Representing the model's system

In this section, the system model is presented. A MIMO system with N antennas at the transmitter and M antennas at the receiver is considered. The received signal, denoted as $\mathbf{y} \in \mathbb{C}^{M\times 1}$, can be expressed as [**?**]:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \quad (1)$$

where the transmitted signal is $\mathbf{x} \in \mathbb{C}^{N\times 1}$ whose entries are randomly selected from the set $\{-1, 1\}$. $\mathbf{n} \in \mathbb{C}^{M\times 1} \sim \mathcal{CN}(0, \sigma^2\mathbf{I}_M)$ is the additive white Gaussian noise, and $\mathbf{H} \in \mathbb{C}^{N\times M}$ is the channel matrix. The ML detector to detect the signal in the receiver is expressed as follows:

$$\hat{\mathbf{x}}^{ML} = \arg \min_{\mathbf{x}\in\{-1,1\}^N} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2$$

(2)

However, with an increase in the number of transmit symbols, the complexity of the ML detector escalates in a non-linear manner [**?**], N, which are discrete points in the modulation alphabet, the optimization problem is difficult. Therefore, some other less complex schemes shall be developed for MIMO signal detection.

3 The Proposed Method

This section illustrates the proposed approach for MIMO signal detection. The schematic representation of the suggested method is presented in Figure 1. The modulated signal is passed through a precoder network before its delivery to the receiver. Then, the acquired signal is directed into a detector network. The two precoding and detecting networks consist of deep convolutional neural networks in the process of training. The precoder network is composed of four convolutional layers. The first layer is equipped with 128 filters of 3 × 3 dimensions, followed by a second layer with an identical configuration. The third layer comprises 64 filters, also of size 3 × 3, while the final layer holds 2 filters, each measuring 3 × 3. The output of the first to third layers undergoes activation using the ReLU function. Meanwhile, for the last layer, the Tanh activation function is applied, followed by a batch normalization layer. The arrangement of the precoder is illustrated in Figure 2.

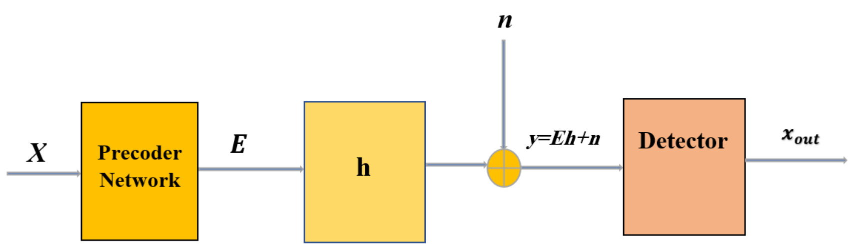

Fig. 1 The diagram of the proposed MIMO signal detection method

The detector network comprises nine convolutional layers. In the initial layer, there are 128 filters sized at 5×5. From the second to the sixth layers, 64 filters, each with dimensions of 5×5, are employed. Moving on to the seventh and eighth layers, 32 filters, sized at 3×3, are utilized. Finally, the last layer is equipped with a single filter measuring 3×3. At the output of the first to the eighth layers, the Relu activation function has been applied and the last layer contains Tanh as the activation function. The configuration of the detector network is displayed in Figure 3. The channel coefficients are generated from the Rayleigh distribution. Additionally, we assume that the channel noise is additive white Gaussian noise. The proposed algorithm employs the minimum mean squares loss function and utilizes the Adam optimizer for loss minimization purposes. The precoder and detector networks are trained jointly using various channel types. During the training phase, initially, the precoder network undergoes training for a specified number of iterations to update its weights. Subsequently, while maintaining the parameters of the precoder network constant, the training process proceeds to train the detector network. Moreover, the AdamOptimizer has been used to minimize the loss functions.

4 The Simulation Results

The results of the simulation have been documented in this section. The benchmark algorithms are as follows: DetNet (Detection Network), ZF (Zero Forcing) and MMSE (Minimum Mean Squared Error) [**?**]. In all simulations, both the transmitter and receiver antennas utilize the same numbers,

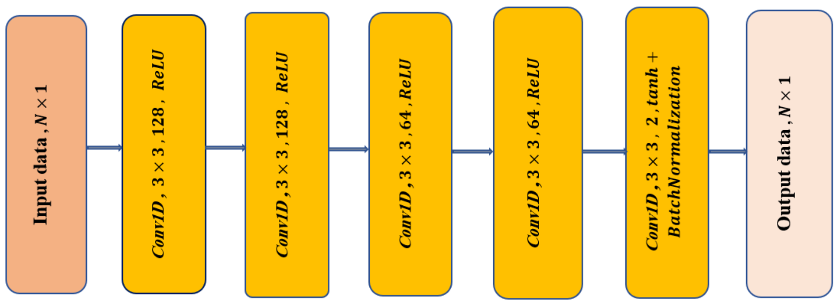

Fig. 2 The diagram the proposed precoder network

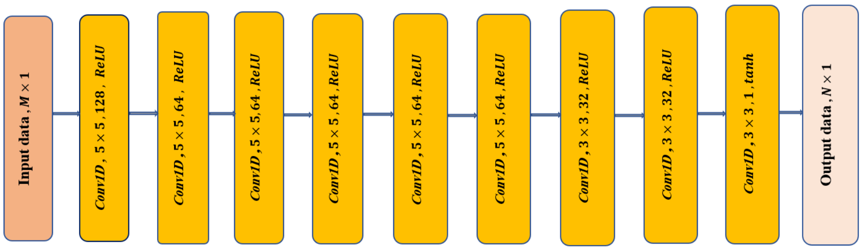

Fig. 3 The structure of the proposed detector network.

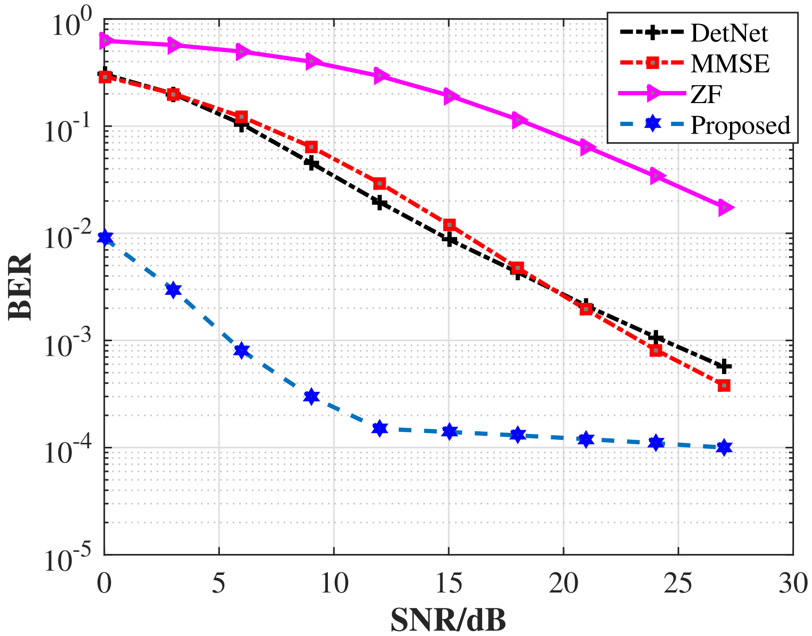

Fig. 4 The BER versus SNR curves of all the methods for M = N = 20.

and the modulation employed is BPSK. The simulations are conducted on a PC equipped with an Intel(R) Core i7-7500U CPU @ 2.70GHz 2.90 GHz within the TensorFlow framework. The batch size (B) is set to 750, with 100,000 training data and 20,000 test data. During training, the Signal-to-Noise Ratio (SNR) is maintained at 20dB, and the learning rate is set to 0.0001. The channel matrix is generated using the Rayleigh distribution with zero mean and unit variance. Figure 4 depicts the Bit Error Rate (BER) against SNR curves for ZF, DetNet, MMSE, and the Proposed method, all for M = N = 20.

From the figure, it's evident that the Proposed method outperforms the other techniques in terms of BER. Its superiority is particularly notable in low-SNR scenarios where signal transmission and detection pose greater challenges. The MMSE and DetNet curves largely coincide across SNR values.

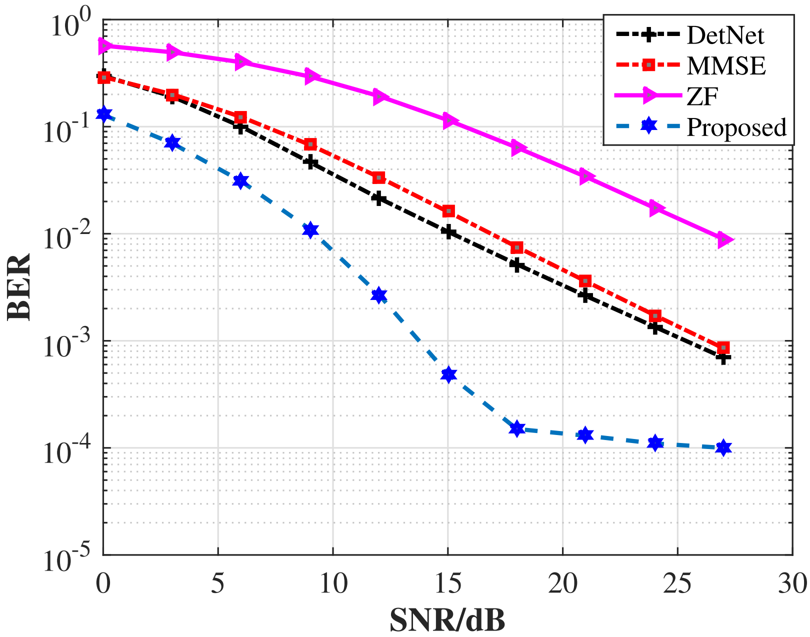

Fig. 5 The BER versus SNR curves of all the methods for M = N = 10.

In a corresponding examination, we assessed the performance of Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR) with reduced antenna dimensions. Figure 5 illustrates these curves for the scenario where M = N = 10. For DetNet and MMNet, the number of network layers has been fixed at 10.

Figure 6 presents a comparative analysis among DetNet, ZF, MMSE, and the proposed approach under varying antenna configurations at an SNR of 10 dB. It is observable that with an increase in the number of antennas, errors decrease across all algorithms except for ZF. Moreover, the error rate reduction is more pronounced in the proposed method. This underscores the superior performance of the proposed method, especially in scenarios with larger antenna arrays where the computational intricacies of the precoding and decoding processes are heightened. Figure 7 exhibits the error versus SNR curves for the proposed method across various antenna configurations of 10, 20, and 30. Notably, as the number of antennas in both transmitter and receiver increases, the performance of the proposed method improves significantly, marking a remarkable achievement. This trend persists even as the complexity of detection and estimation processes escalates with larger antenna arrays.

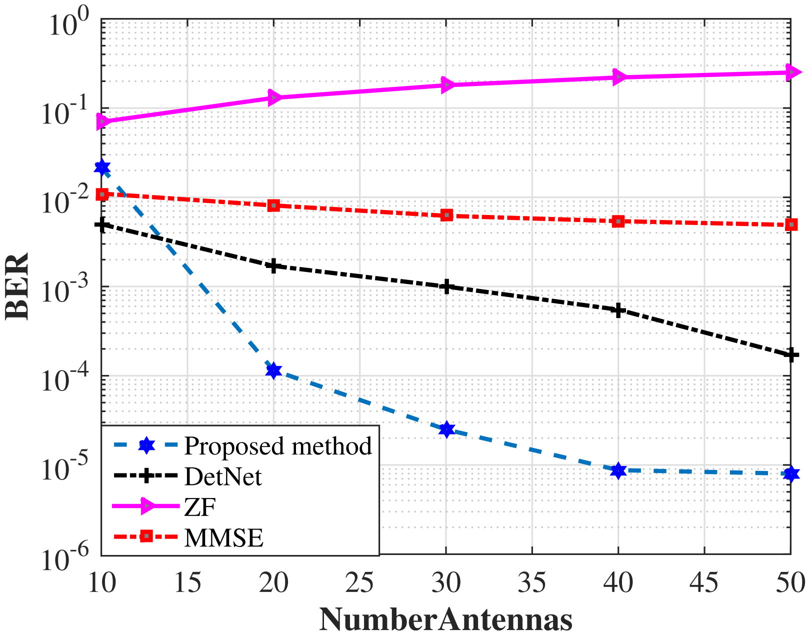

Fig. 6 The loss versus iteration curve for the proposed method

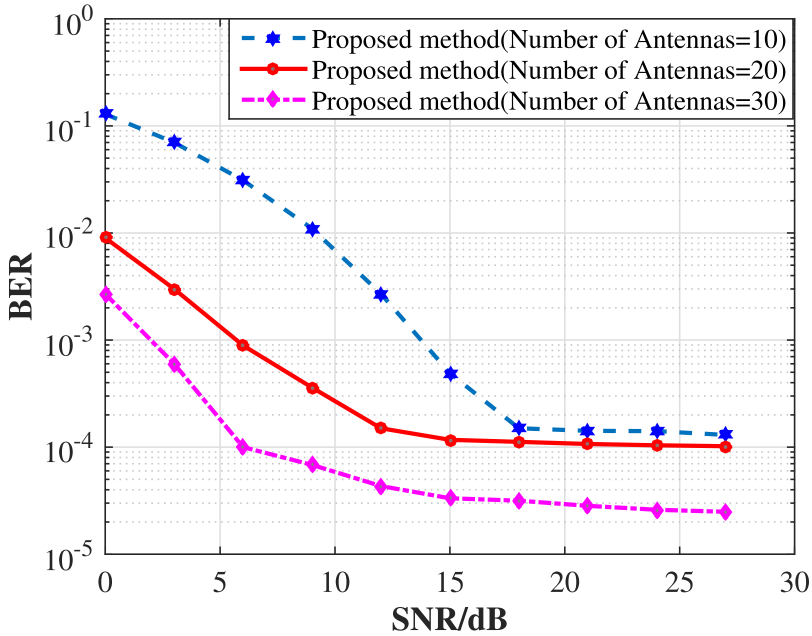

Fig. 7 The BER versus SNR curves of the proposed method for M = N = 10 and M = N = 20 and M = N = 30.

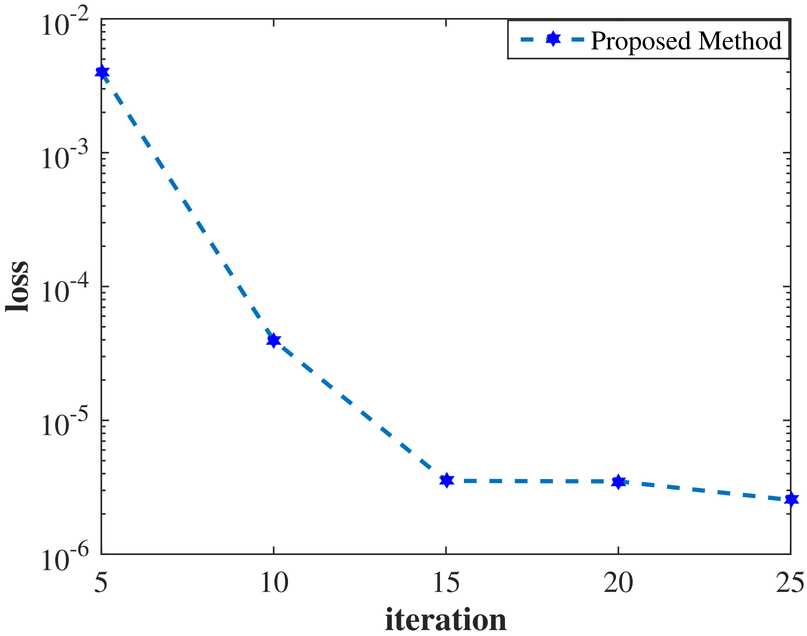

Fig. 8 The loss versus iteration curve for the proposed method

In Figure 8, the loss versus iteration curve of the proposed method is illustrated for iterations ranging from 5 to 25, with each iteration comprising 400 steps. In essence, the internal optimization involves 2000, 4000, 6000, 8000, and 10000 steps for iterations 5 to 25, respectively. It is evident that with an increase in the number of iterations during the learning process, the loss function converges to its minimum value, underscoring the favorable convergence behavior of the proposed method.

To assess computational complexity, the test time of the proposed method has been compared to that of its competitors in Table 1 for a scenario with 20 antennas. Results indicate that the proposed method significantly outperforms other schemes in terms of speed. Hence, the suggested technique not only achieves lower estimation error but also accomplishes this in considerably less test time compared to its counterparts.

Table 1 Test time comparison

Algorithm	**Test time (Seconds)**
Proposed Method	186.44
ZF	206.88
MMSE	232.92
DetNet	312.68

The test time of all of the methods.

5 Conclusion

In this paper, a new method for signal detection in MIMO systems based on deep convolutional neural networks has been presented. A deep convolutional neural network is used as the precoder in the transmitter side. Also, an other deep network has been exploited as the signal detector in the receiver. After training the two networks using some available pilot data, the whole system can provide a reliable signal transmission scheme. The simulation results confirm the efficiency of the developed structure in various scenarios.

6 References