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Generic Deep Learning-Based Linear Detectors for MIMO Systems Over Correlated Noise Environments

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ABSTRACT To support the and development and application of the fifth-generation (5G) communication and internet of things (IoT) networks, high data-rate wireless transmission is required. To meet the demand of high data-rate, multiple antennas are equipped at the transmitter and receiver, forming multiple-input multiple-output (MIMO) systems. A big challenge of MIMO is the detector design in correlated noise environments, which should achieve a fine performance with moderate computational complexity. To this end, we employ an iterative framework of a deep convolutional neural network (DCNN) and a linear detector for MIMO systems over correlated noise environments. In this framework, the linear detector can be zero-forcing (ZF), minimum mean square error (MMSE), ZF with successive interference cancellation (ZF-SIC), or MMSE-SIC, which produces an initial estimate of transmitted signals. The DCNN is used to capture the local correlation among noise, and it can produce a more accurate estimate of transmitted signals. Simulation results are finally provided to show that the proposed detector can outperform the conventional linear detectors substantially through capturing the local correlation characteristics among noise.

INDEX TERMS Deep learning, MIMO, correlated noise.

I. INTRODUCTION

With the deployment and development of the fifth-generation (5G) wireless communication systems [1]–[3], there is a explosively increasing progress in the data rate for wireless transmission [4]–[6]. To meet this requirement, many new techniques have been proposed to enhance the transmission quality and optimize the system resource management. Among these techniques, relaying technique is an effective one, which can help increase the coverage area and improve the transmission quality, without requiring additional transmit power [7]–[9]. There are two fundamental relying protocols, such as amplify-and-forward (AF) and decode-and-forward (DF). Besides these two relaying protocols, there are some other relaying protocols in the literature. The usage of relaying can help increase transmission security in the wireless networks, which also receives much attention from the academia and industry [10]–[12].

Besides the relaying technique, multiple antenna technique is an effective solution to meet demand, and it has been proven that the data rate can be linearly proportional to the number of antenna in multiple-input multiple-output (MIMO) systems [13]–[16]. A high challenge in MIMO systems is that how to effectively detect the transmitted signals at the receiver side [17]–[19]. In uncorrelated noise environments, the optimal MIMO detector is the maximum likelihood detector (MLD), which has the exponentially increasing computational complexity with respect to the number of transmit antenna and modulation size [20], [21]. To reduce the computational complexity, some linear detectors have been proposed for the MIMO systems, such as zero-forcing (ZF) and minimum mean square error (MMSE) detectors. The main drawbacks of the linear detectors is the noise enhancement, which can be relieved by the successive interference cancellation (SIC) technique to some extent.

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The above detectors can work for MIMO systems in uncorrelated noise environments. However, in practice, the noise in MIMO systems may be correlated, due to many practical reasons [22]–[24]. For example, the noise may be correlated in the time domain when it continues on two ore more time symbols; the noise may be correlated in the frequency domain when the channel estimation and synchronization are not ideal in the orthogonal frequency division multiplexing (OFDM) systems. In correlated noise environments, the correlation among different symbols can be exploited to improve the detection performance. In theory, the optimal detector in correlated noise environments is the maximum likelihood sequential detector (MLSD). There are two main limitations of MLSD in practice. The first limitation is the huge computational complexity, which exponentially increases with respect to the number of symbols in a transmission packet, number of transmit antenna, and the modulation size. Another limitation is that it requires the knowledge about the distributions of correlated noise among a packet, which is very difficult or even impossible to estimate in practice, especially when the correlation is time-varying.

Inspired by the recent progress on the intelligent data-driven networks applied in wireless communications [25]–[27], we turn to study the deep learning based detection for the MIMO systems under correlated noise environments. Deep learning is a data-driven method which can efficiently exploit the huge amount of wireless data for communication systems [28]–[30]. In particular, we apply an iterative framework of a deep convolutional neural network (DCNN) and a linear detector, where the DCNN is utilized to capture the local correlation among noise in different symbols [31]. The linear detector can be ZF, MMSE, Zf-SIC, or MMSE-SIC, which requires very limited computational complexity to implement. The linear detector produces an initial estimate of the transmitted signals, while the DCNN can produce a more accurate estimate of transmitted signals by exploiting the local correlation among noise. This iterative process continues, and it can help improve the detection performance for the linear detection. Finally, we provide some simulation results to validate the proposed studies.

The organization of this paper is given as follows. After the introduction in this section, we will discuss the system model of MIMO in Sec. II, and then introduce the linear detectors in Sec. III. After that, we will describe the iterative framework of DCNN and linear detectors in Sec. IV. Sec. V will present the simulation results and conclusions are finally made in Sec. VI.

II. SYSTEM MODEL

In this paper, we consider an $M \times M$ MIMO system, where there are M antennas at the transmitter and receiver. The MIMO channel follows time-varying Rayleigh fading, and it remains unchanged within the same transmission packet. For the n-th symbol ($1 \leq n \leq N$), the received signal at the m_1-th receiver is given by

$$y_{m_1}(n) = \sum_{m_2=1}^{M} h_{m_2,m_1} s_{m_2}(n) + w_{m_1}(n), \tag{1}$$

where $s_{m_2}(n)$ is the transmitted signal at the m_2-th transmit atenna, following some specific modulation scheme such as binary phase shift keying (BPSK) or quadrature phase shift keying (QPSK), and $w_{m_1}(n) \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN) at the receiver, where the details about the noise can be found in the literature [32], [33]. Notation $h_{m_2,m_1} \sim \mathcal{CN}(0, 1)$ represents the channel coefficient between the m_2-th transmit antenna and m_1-th receive antenna. By using the vector and matrix forms, we can rewrite (1) as

$$\mathbf{y}(n) = \mathbf{H}\mathbf{s}(n) + \mathbf{w}(n). \tag{2}$$

When the noise $\mathbf{w}(n)$ is independent among different symbols, the optimal detector for MIMO systems is the maximum likelihood detector (MLD), whose computational complexity exponentially increases with M and the modulation size. On the contrary, when the noise is correlated among different symbols, the optimal detector for MIMO systems is the maximum likelihood sequential detector (MLSD), whose computational complexity exponentially increases with M, N and the modulation size. This motivates us to study the linear detector for MIMO systems, which will be detailed in the next section.

III. LINEAR DETECTORS

In this section, we will describe four linear detectors, i.e., ZF, MMSE, ZF-SIC and MMSE-SIC, for the MIMO systems.

A. ZF DETECTOR

The ZF detector performs the detection by removing the spatial correlation among antennas in a forcing way, i.e.,

$$\mathbf{y}_{ZF}(n) = (\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H\mathbf{y}(n), \tag{3}$$

where the subscript ^{H} denotes the operation of conjugate transpose. Then, from each element in $\mathbf{y}_{ZF}(n)$, the component-wise detection is used. In this way, the ZF detector is completed. The ZF detection is quite simple to implement in practice, at the cost of severe noise enhancement in the detection. Specifically, the noise varies from $\mathbf{w}(n)$ to $(\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H\mathbf{w}(n)$, and the noise variance matrix changes from $\sigma^2\mathbf{I}$ to $(\mathbf{H}^H\mathbf{H})^{-1}\sigma^2$. When there exists a very small eigenvalue in $\mathbf{H}^H\mathbf{H}$, the noise will be severely enhanced in the detection, which limits the detection performance substantially.

B. MMSE DETECTOR

To implement the linear detector and meanwhile suppress the severe noise enhancement in ZF detector, the MMSE detection can be used, which is given by

$$\mathbf{y}_{MMSE}(n) = (\mathbf{H}^H\mathbf{H} + \sigma^2\mathbf{I})^{-1}\mathbf{H}^H\mathbf{y}(n). \tag{4}$$

Then, from each element in $\mathbf{y}_{MMSE}(n)$, the component-wise detection is used. In this way, the MMSE detection is completed. Note that the noise component in MMSE detector changes from $\mathbf{w}(n)$ to $(\mathbf{H}^H\mathbf{H}+\sigma^2\mathbf{I})^{-1}\mathbf{H}^H\mathbf{w}(n)$. Accordingly, the noise covariance matrix enlarges from $\sigma^2\mathbf{I}$ to $(\mathbf{H}^H\mathbf{H}+\sigma^2\mathbf{I})^{-1}\mathbf{H}^H\mathbf{H}(\mathbf{H}^H\mathbf{H}+\sigma^2\mathbf{I})^{-1}\sigma^2$. By comparing with the noise covariance in ZF detector, we can find that the MMSE detector can outperform the ZF detector through suppressing the noise enhancement to some extent.

C. ZF-SIC DETECTOR

Another way to suppress the effect of noise enhancement in ZF detector is to introduce the operation of SIC [34]–[36]. In ZF-SIC, the detection sequence of transmitted signals is firstly determined according to the diagonal element of matrix $(\mathbf{H}^H\mathbf{H})^{-1}$, given by

$$(\mathbf{H}^H\mathbf{H})^{-1}_{m,m}. \tag{5}$$

According to the minimum value of $(\mathbf{H}^H\mathbf{H})^{-1}_{m,m}$, the system chooses the first transmitted signal to be detected, whose index is denoted by m_1. Then, the m_1-th transmitted signal is firstly estimated from $\mathbf{y}_{ZF}(n)$, given by $\hat{s}_{m_1}(n)$. After that, the received signal $\mathbf{y}(n)$ is updated as

$$\mathbf{y}_1(n) = \mathbf{y}(n) - \mathbf{h}_{m_1}\hat{s}_{m_1}(n). \tag{6}$$

Accordingly, the channel matrix is updated from $\mathbf{H}$ to $\mathbf{H}_1$ by removing the m_1-th column. Then, the ZF detected signal is updated as

$$\mathbf{y}_{1,ZF}(n) = (\mathbf{H}_1^H\mathbf{H}_1)^{-1}\mathbf{H}_1^H\mathbf{y}_1(n). \tag{7}$$

From $\mathbf{y}_{1,ZF}(n)$, the m_2-th transmitted signal with the minimum value of $(\mathbf{H}_1^H\mathbf{H}_1)^{-1}_{m,m}$ is detected, and its estimate is given by $s_{m_2}(n)$. This process continues until the last transmitted signal $s_{m_M}(n)$ is detected. In this way, the ZF-SIC procedure is completed.

D. MMSE-SIC DETECTOR

Similar to ZF-SIC, the SIC can be also incorporated into MMSE to enhance its detection performance. In MMSE-SIC, the detection sequence of transmitted signals is firstly determined according to the diagonal element of matrix $(\mathbf{H}^H\mathbf{H}+\sigma^2\mathbf{I})^{-1}$, given by

$$(\mathbf{H}^H\mathbf{H}+\sigma^2\mathbf{I})^{-1}_{m,m}. \tag{8}$$

According to the minimum value of $(\mathbf{H}^H\mathbf{H}+\sigma^2\mathbf{I})^{-1}_{m,m}$, the system chooses the first transmitted signal to be detected, whose index is denoted by m_1. Then, the m_1-th transmitted signal is firstly estimated from $\mathbf{y}_{MMSE}(n)$, given by $\hat{s}_{m_1}(n)$. After that, the received signal $\mathbf{y}(n)$ is updated as

$$\mathbf{y}_1(n) = \mathbf{y}(n) - \mathbf{h}_{m_1}\hat{s}_{m_1}(n). \tag{9}$$

Accordingly, the channel matrix is updated from $\mathbf{H}$ to $\mathbf{H}_1$ by removing the m_1-th column. Then, the MMSE detected signal is updated as

$$\mathbf{y}_{1,MMSE}(n) = (\mathbf{H}_1^H\mathbf{H}_1+\sigma^2\mathbf{I})^{-1}\mathbf{H}_1^H\mathbf{y}_1(n). \tag{10}$$

From $\mathbf{y}_{1,MMSE}(n)$, the m_2-th transmitted signal associated with the minimum value of $(\mathbf{H}_1^H\mathbf{H}_1+\sigma^2\mathbf{I})^{-1}_{m,m}$ is detected, and its estimate is given by $s_{m_2}(n)$. This process continues until the last transmitted signal $s_{m_M}(n)$ is detected. In this way, the MMSE-SIC procedure is completed.

IV. PROPOSED GENERIC DEEP LEARNING BASED ITERATIVE DETECTION FRAMEWORK

Inspired by the recent advances in deep learning technologies and in order to improve the performance of the linear detectors in the presence of correlated noise, we propose a generic deep learning based iterative detection framework, which contains a linear detector and a deep convolutional neural network (DCNN) at the receiver. We will introduce the system structure as well as the DCNN in the next two subsections. Computational complexity analysis of the proposed iterative framework is presented at the last subsection.

A. A GENERIC ITERATIVE FRAMEWORK FOR LINEAR DETECTORS

As shown in Fig. 1, a linear detector and a DCNN are jointly used. The detector can be any kind of linear detectors, such as ZF, MMSE, ZF-SIC or MMSE-ISC. The detection workflow iteratively passes through the linear detector and DCNN in K iterations and the finally estimated signal is generated at the last iteration.

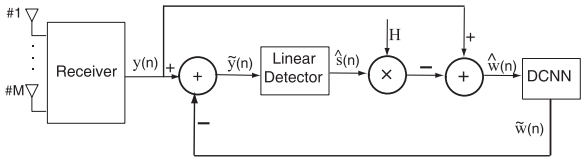

FIGURE 1. Structure of the generic deep learning based Iterative detection framework.

Basically, at each iteration, the linear detector firstly estimates the signal from the received signal and channel matrix, denoted by $\hat{\mathbf{s}}$. After that, we can estimate the noise as

$$\hat{\mathbf{w}}(n) = \mathbf{y}(n) - \mathbf{H}\hat{\mathbf{s}}(n). \tag{11}$$

Inspired by the successful application of residual learning for image denoising [37] and notice that if the detection result $\hat{\mathbf{s}}$ is not correct, the estimate of noise $\hat{\mathbf{w}}$ is not correct as well. We employ the DCNN to learn the latent correlation of $\hat{\mathbf{w}}$ and recover a more accurate estimation of the noise, which is given by

$$\tilde{\mathbf{w}}(n) = \mathbb{F}(\hat{\mathbf{w}}(n)), \tag{12}$$

where $\mathbb{F}(\cdot)$ represents an nonlinear transformation function parameterized by the DCNN. Thus, we can cancel the influence of correlated noises by

$$\tilde{\mathbf{y}}(n) = \mathbf{y}(n) - \tilde{\mathbf{s}}(n) \tag{13}$$

$$= \mathbf{H}\hat{\mathbf{s}}(n) + \mathbf{w}(n) - \tilde{\mathbf{w}}(n) \tag{14}$$

$$\triangleq \mathbf{H}\hat{\mathbf{s}}(n) + \mathbf{z}(n), \tag{15}$$

where $\mathbf{z}(n) = \mathbf{w}(n) - \tilde{\mathbf{w}}(n)$ represents the effective residual noise. Note that if the estimation of noise produced by the DCNN is more accurate compared with the prior linear detector, the effective SNR is increased for $\tilde{\mathbf{y}}(n)$. Hence, we can feed back the effective signal $\tilde{\mathbf{y}}(n)$ to the linear detector to improve the detection performance at the incoming iterations.

B. DEEP CONVOLUTIONAL NEURAL NETWORK

Fig. 2 shows the DCNN structure of the proposed generic iterative detection framework. Generally, the DCNN contains L convulutional layers and each layer contains F_l filters, where $l \in [1, 2, \ldots, L]$. For each filter denoted by $filter_{(l,j)}$ ($j \in [1, 2, \ldots, F_l]$) at the l-th layer, it will firstly perform zero-padding operation for the input data with the purpose of keeping the same length after convolution operation. After that, it will perform 1-D convolution on the padded data with kernel size of R_l to generate a corresponding feature map with rectified linear unit (ReLU) [38] activation function.

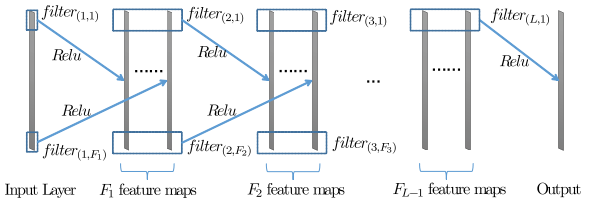

FIGURE 2. Structure of deep convolutional neural network.

Specifically, the first layer is the input layer and the last layer is the output layer. The rest layers are the hidden layers. For the first layer, it receives $\hat{\mathbf{w}}$ and produces F_1 feature maps for the second layer. For any hidden layer, it receives F_{l-1} feature maps from the prior layer and generates F_l feature maps for the posterior layer. For the last layer, it has only one filter, because we have to maintain the same spatial dimension as the input data. For convenience, we denote the DCNN structure as

$$\{L; R_1, R_2, \ldots, R_L; F_1, F_2, \ldots, F_L\}. \tag{16}$$

As we have discussed earlier, the training objective of DCNN is to generate a more accurate estimation of noise from $\hat{\mathbf{w}}$ as much as possible. This is equivalent to minimize the effective residual noise $\mathbf{z}$. In pursuing this objective, we employ the mini-batch stochastic gradient descending [39] and the L_2-norm loss function to train the learnable variables in the neural networks, so that we can obtain the loss value for every mini-batch size of N time slots as

$$Loss = \frac{1}{N}\sum_{n=1}^{N} ||\mathbf{w} - \tilde{\mathbf{w}}||^2 \tag{17}$$

$$= \frac{1}{N}\sum_{n=1}^{N} ||\mathbf{z}||^2. \tag{18}$$

C. COMPUTATIONAL COMPLEXITY ANALYSIS

For any detection algorithm, its computational complexity is always an issue we have to face. In this subsection, we analyze the required computational complexity caused by K iterations. The consumption of computation at each iteration in the proposed generic iterative detection framework is consisting of two parts: the computational complexities of the linear detector as well as the DCNN.

For linear detectors, we denoted the required computational complexity as $\mathcal{O}_{\mathcal{D}}$, where it is of $\mathcal{O}(M)$ for the linear detectors. For the DCNN, the computational complexity is given by [40]:

$$\mathcal{O}\left(\sum_{l=1}^{L}(F_{l-1}R_l M F_l)\right). \tag{19}$$

Therefore, the total computational complexity of the proposed framework is given by summing up these two parts for K iterations:

$$\mathcal{O}\left((K+1)\mathcal{O}_{\mathcal{D}} + K\sum_{l=1}^{L}(F_{l-1}R_l M F_l)\right). \tag{20}$$

From the above expression, we can see that the computational complexity of the generic iterative detection framework increases almost linearly with the number of iterations, which indicates that the extra computational complexity caused by the iterative framework is computationally tractable and acceptable.

V. SIMULATION RESULTS AND DISCUSSIONS

In this section, we present some simulation results in order to verify the effectiveness of the proposed generic iterative detection framework. The binary phase shift keying (BPSK) modulation is adopted at the transmitter, and both the transmitter and receiver contain $M = 4$ antennas. In addition, the channel matrix is time-varying and we apply a typical model, namely the Jakes model [41], to generate the channel matrix with the normalized Doppler frequency f_d setting to 0.1.

Specifically, we employ a typical temporal correlation model to generate the correlated noise [41], which is described by:

$$\mathbf{w}(n+1) = \sqrt{\rho}\mathbf{w}(n) + \sqrt{(1-\rho)}\mathbf{u}(n+1), \tag{21}$$

where $\mathbf{u}(n+1) \sim \mathcal{CN}(0, \sigma^2\mathbf{I})$ is an additive noisy term independent of $\mathbf{w}(n)$, and $0 \leq \rho \leq 1$ is the correlation coefficient. Specifically, $\rho = 0$ represents the uncorrelated scenario, while $\rho = 1$ represents the completely correlated scenario, respectively.

Moreover, with respect to the structure of DCNN, we use four convolutional layers, so that $L = 4$. The number of filters and filter sizes at each layer are set to $\{64, 32, 16, 1\}$ and $\{9, 3, 3, 15\}$, respectively. Therefore, we summarize the DCNN structure as $\{4; 9, 3, 3, 15; 64, 32, 16, 1\}$. The maximum number of iterations between the linear detector and the DCNN K is set to 3.

Regarding the data set, we set the mini-batch size to $N = 720$ time slots, so that it is only consisting of 720 time slots of the received signals $\mathbf{y}$, the channel matrix $\mathbf{H}$ and the correlated noises $\mathbf{w}$ suffered from the transmission for every data batch. To train the learnable variables inside the DCNN filters, we generate 10,000 batches for training set. To valid the generalization ability during the training process and test the performance after finishing the training, the valid set and test set both contain 1,000 batches. The simulation settings of important parameters are summarized in Table. 1 for convenience.

TABLE 1. summary of simulation settings.

Parameter	Value
K	3
L	4
$\{R_1, R_2, ..., R_L\}$	{36, 3, 3, 36}
$\{F_1, F_2, ..., F_L\}$	{32, 16, 8, 1}
M	4
f_d	0.1
ρ	From 0 to 0.9 (0.1 each step)
SNR	From 0 dB to 20 dB (2 dB each step)
N	720
Total Training batches	10,000
Total valid batches	1,000
Total test batches	1,000

Fig. 3 shows that the effect of correlation coefficient ρ on the BER performance for the ZF detector and the ZF based iterative detector (ZF-DCNN) detector, where the signal-to-noise ratio(SNR) is set to 30 dB. The correlation coefficient ρ varies from 0 to 0.9, where $\rho = 0$ and $\rho = 0.9$ correspond to uncorrelated scenario and highly correlated scenario, respectively. We can find from Fig. 3 that the BER performance of ZF-DCNN detector improves with the increasing of correlation level, which indicates that the DCNN can suppress the influence of correlated noise successfully when the correlation coefficient enlarges. Moreover, the BER performance of ZF-DCNN detector improves with the number of iterations between the ZF detector and the DCNN. Specifically, the ZF-DCNN with $K = 2$ can reduce the detection error of the conventional ZF detector to about 30% at the correlation level of $\rho = 0.8$, which verifies the effectiveness of the proposed generic iterative framework.

Fig. 4 demonstrates the BER performance of the ZF detector and the ZF-DCNN detector where the SNR various from 0 dB to 30 dB. The correlation coefficient ρ is set to 0.5, which represents a scenario that the noises are moderately correlated. We can find from Fig. 4 that the BER performance gap between the ZF detector and ZF-DCNN detector enlarges along with the SNR. Increasing the iteration between ZF and DCNN can also help improve the BER performance of ZF-DCNN in a wide range of SNR. In particular, the SNR gain of the ZF-DCNN detector over the standard ZF detector is 5 dB at the BER level of 10^{-2}. This indicates that the

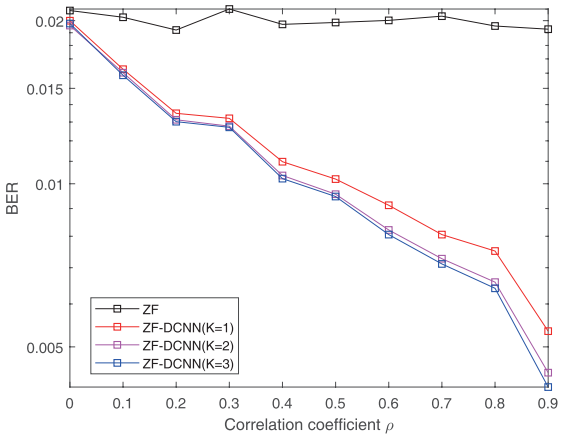

FIGURE 3. BER performance comparison versus correlation coefficient for the ZF detector and ZF-DCNN detector with SNR = 30dB.

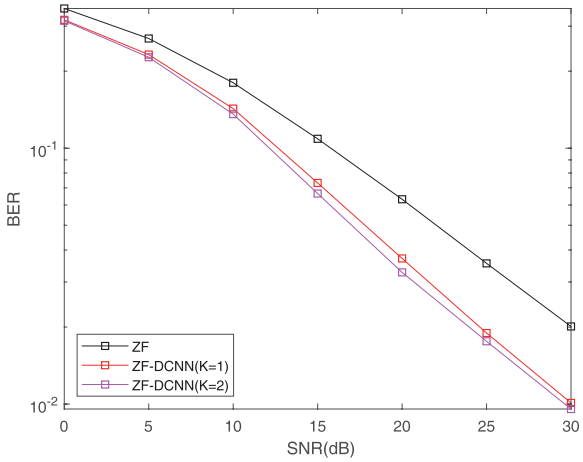

FIGURE 4. BER performance comparison versus SNR for the ZF detector and ZF-DCNN detector with $\rho = 0.5$.

proposed iterative framework outperforms the conventional ZF detector, which further verifies the effectiveness of the proposed generic iterative framework.

In order to validate the generalization of the proposed iterative framework, we also perform some simulations with various linear detectors such as the conventional MMSE, ZF-SIC and MMSE-SIC detectors. Similar to the Fig. 3, Figs. 5-7 demonstrate the BER perofrmance of MMSE and MMSE-DCNN, ZF-SIC and ZF-SIC-DCNN, MMSE-SIC and MMSE-SIC-DCNN in the presence of various correlation levels, respectively. As observed from these figures, all the iterative detectors outperform the corresponding conventional linear detectors in a wide range of correlation coefficient ρ from 0 to 0.9. More specifically, the iterative detectors with $K = 2$ can reduce detection error of the corresponding conventional linear detectors to about 60%, 26% and 30% at the correlation level of $\rho = 0.8$ with respect to MMSE, ZF-SIC and MMSE-SIC, respectively.

Furthermore, as similar with Fig. 4, Figs. 8-10 depict the BER performance of the standard linear detectors as well as

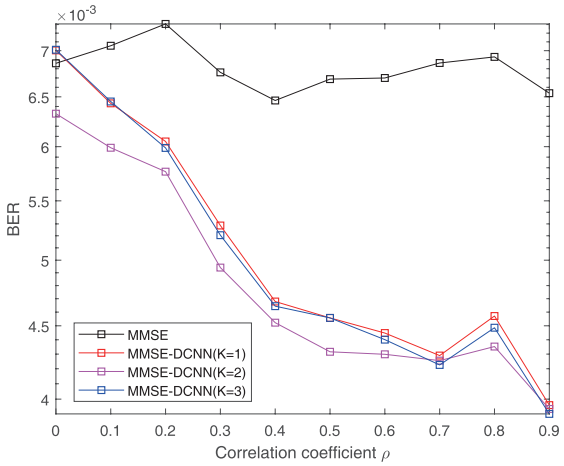

FIGURE 5. BER performance comparison versus correlation coefficient for the MMSE detector and MMSE-DCNN detector with SNR = 30dB.

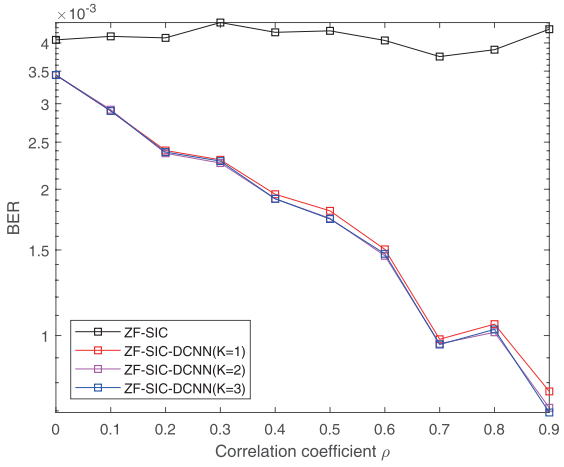

FIGURE 6. BER performance comparison versus correlation coefficient for the ZF-SIC detector and ZF-SIC-DCNN detector with SNR = 30dB.

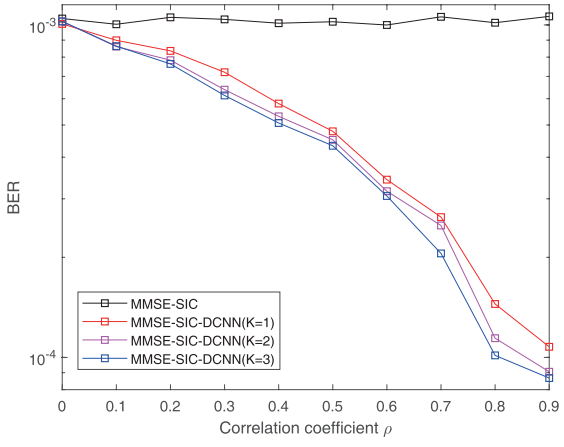

FIGURE 7. BER performance comparison versus correlation coefficient for the MMSE-SIC detector and MMSE-SIC-DCNN detector with SNR = 20dB.

the corresponding iterative detectors in the case that the SNR varies from 0 dB to 30 dB and correlation coefficient $\rho = 0.5$. We can find from these figures that the BER performance gap between the iterative detectors and the corresponding conventional linear detectors enlarges along with the increasing

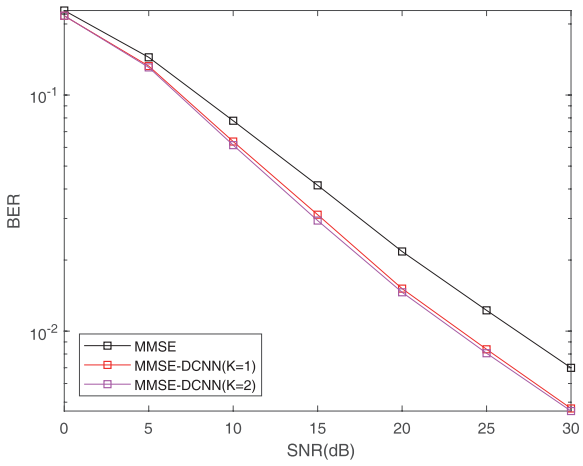

FIGURE 8. BER performance comparison versus SNR for the the MMSE detector and MMSE-DCNN detector with $\rho = 0.5$.

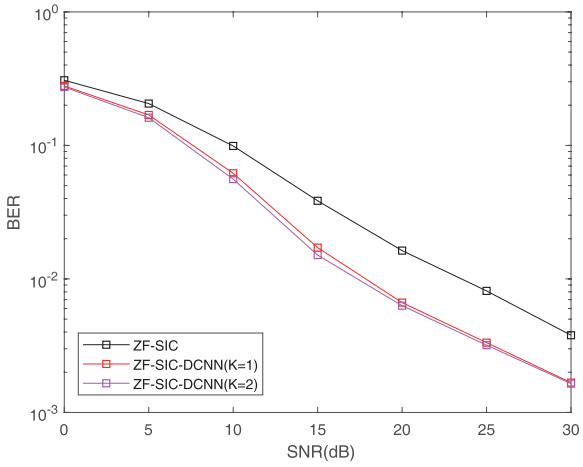

FIGURE 9. BER performance comparison versus SNR for the the ZF-SIC detector and ZF-SIC-DCNN detector with $\rho = 0.5$.

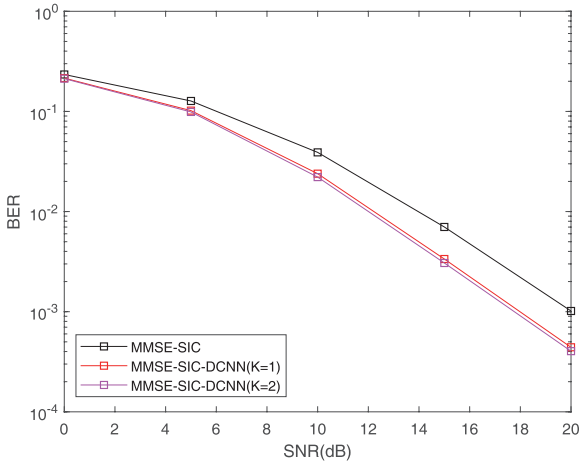

FIGURE 10. BER performance comparison versus SNR for the the MMSE-SIC detector and MMSE-SIC-DCNN detector with $\rho = 0.5$.

SNR. Specifically, the SNR gain of the iterative detectors over the corresponding standard linear detectors is about 5 dB in a wide range of SNRs. This further validates the generalization

of the proposed generic iterative framework in the presence of correlated noise.

VI. CONCLUSION

In this paper, we employed an iterative framework of DCNN and linear detectors to improve the detection performance for MIMO systems under correlated noise environments, which were effective to support the high data-rate transmission for the wireless communication systems. In this framework, the linear detector such as ZF, MMSE, ZF-SIC and MMSE-SIC produced an initial estimate of transmitted signals, while DCNN output a more accurate estimate of transmitted signals through exploiting the local correlation among noise. Simulation results were demonstrated to show that the proposed detector could outperform the conventional linear detectors substantially. In future works, we will apply this work to IoT applications, such as the urban environments detecting [42]–[46]. Moreover, we will investigate other intelligent algorithms [47]–[51], and apply to the MIMO systems in order to further enhance the detection performance. In further, we will apply the work in this paper into the mobile edge computing [52], [53], and try to enhance the system performance.

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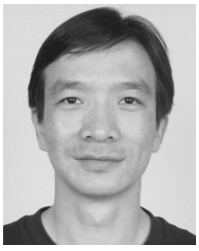

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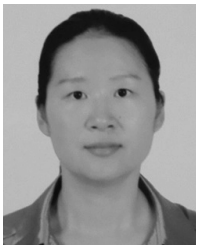

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