

Research Article

Multisegment Mapping Network for Massive MIMO Detection

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The massive multiple-input multiple-output (MIMO) technology is one of the core technologies of 5G, which can significantly improve spectral efficiency. Because of the large number of massive MIMO antennas, the computational complexity of detection has increased significantly, which poses a significant challenge to traditional detection algorithms. However, the use of deep learning for massive MIMO detection can achieve a high degree of computational parallelism, and deep learning constitutes an important technical approach for solving the signal detection problem. This paper proposes a deep neural network for massive MIMO detection, named Multisegment Mapping Network (MsNet). MsNet is obtained by optimizing the prior detection networks that are termed as DetNet and ScNet. MsNet further simplifies the sparse connection structure and reduces network complexity, which also changes the coefficients of the residual structure in the network into trainable variables. In addition, this paper designs an activation function to improve the performance of massive MIMO detection in high-order modulation scenarios. The simulation results show that MsNet has better symbol error rate (SER) performance and both computational complexity and the number of training parameters are significantly reduced.

1. Introduction

In recent years, as the number of mobile terminals has exploded, traditional small-scale MIMO systems cannot meet the requirements of various mobile services for communication rates. Therefore, the MIMO technology is gradually developing in the direction of large scale; compared with the traditional MIMO system, the massive MIMO system expands the number of device antennas to dozens or even hundreds, which further improves the performance of the communication system.

The communication system has obvious advantages using massive MIMO, but as the number of antennas increases, it will also bring detection problems, such as the more antennas, the higher the complexity of the detection algorithm [1].

Because of its powerful ability to solve complex tasks, deep learning has attracted worldwide attention, especially with the improvement of big data and hardware computing capabilities, which has been applied in various industries. Recently, some methods in deep learning have also been introduced into the communication field [2–5]. Samuel et al.

proposed a deep neural network, named Detection Network (DetNet) [6, 7]. The DetNet is a network structure that is specifically designed for massive MIMO detection; due to its low complexity and high detection performance, it has been widely studied. Furthermore, a related paper proposed Sparsely Connected Neural Network (ScNet) [8], which is an improvement of DetNet, because of its simpler network structure. However, the detection performance of these two networks is limited in high-order modulation scenarios. In addition, multilevel MIMO detection [9] is proposed to detect multilevel modulation symbols, but this is not suitable for massive MIMO scheme, and the complexity of multilevel MIMO detection is higher than DetNet. In [10], a new model-driven deep learning-based (DL-based) massive MIMO detector is proposed, which is designed by unfolding an iterative algorithm [11]. However, the complexity of this method is high in 16-QAM modulation.

In this paper, we designed a deep learning network for massive MIMO systems and named it MsNet, which is an improvement over DetNet and ScNet. Compared with DetNet and ScNet, MsNet reduces the complexity of the network and greatly improves the detection performance in

high-order modulation scheme. The main contributions of this paper are as follows: first, we simplify the sparse connection structure of ScNet and add two trainable variables to adjust the step size. Second, we design a special activation function for symbol detection to perform multisegment mapping of the input signal, which is suitable for high-order modulation communication scenarios. This activation function is more flexible than the activation function of DetNet and multilevel MIMO detection, which can further improve the detection performance of the network. Finally, in order to obtain appropriate residual coefficient values, we set the residual coefficients in the network as trainable variables.

The rest of the paper is organized as follows: Section 2 presents the system model. We come up with the MsNet architecture in Section 3. In Section 4, we verify the superiority of MsNet through simulation and discuss the complexity of the network. Finally, the conclusions are presented in Section 5.

2. System Model

We consider the multiuser MIMO system with M transmit antennas, and the total number of receiver antennas is N . The system model can be abbreviated as follows:

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

where $\bar{\mathbf{y}} \in R^N$ is the received signal vector and $\bar{\mathbf{x}} \in R^M$ is the transmitted signal vector. In addition, $\bar{H} \in R^{N \times M}$ is a time-varying and Rayleigh flat-fading channel, the elements of which are independent and identically distributed with complex Gaussian variables of zero mean and unit variance [12]. $\bar{\mathbf{n}} \in R^N$ is the additive white Gaussian noise (AWGN), which follows the distribution $CN(0, \sigma^2)$.

We can equivalently replace a complex expression with a real one, which is as follows:

$$\begin{bmatrix} \text{Re}(\bar{\mathbf{y}}) \\ \text{Im}(\bar{\mathbf{y}}) \end{bmatrix} = \begin{bmatrix} \text{Re}(\bar{H}) & -\text{Im}(\bar{H}) \\ \text{Im}(\bar{H}) & \text{Re}(\bar{H}) \end{bmatrix} \begin{bmatrix} \text{Re}(\bar{\mathbf{x}}) \\ \text{Im}(\bar{\mathbf{x}}) \end{bmatrix} + \begin{bmatrix} \text{Re}(\bar{\mathbf{n}}) \\ \text{Im}(\bar{\mathbf{n}}) \end{bmatrix}, \quad (2)$$

where $\text{Re}(\bullet)$ and $\text{Im}(\bullet)$ are the real and imaginary parts of (\bullet) , respectively. Equation (2) can be further abbreviated as follows:

$$\mathbf{y} = H\mathbf{x} + n, \quad (3)$$

where $\mathbf{y} \in R^{2N}$, $\mathbf{x} \in R^{2M}$, channel matrix $H \in R^{2N \times 2M}$, and noise $n \in R^{2N}$.

3. Massive MIMO Detection

Massive MIMO detection is an important part in communication; low-complexity and high-performance detection algorithms are still being explored. Many typical detection algorithms will bring many inspirations to new algorithms.

In this paper, we design a deep learning network for massive MIMO systems, which is named MsNet. MsNet is a further improvement of DetNet and ScNet, and we have

$$\hat{\mathbf{x}}_{\text{out}}^k = \text{sigS} \left(W_{1k} \left[\alpha_k \begin{bmatrix} \hat{\mathbf{x}}_{\text{in}}^k \\ H^T H \hat{\mathbf{x}}_{\text{in}}^k - \beta_k H^T \mathbf{y} \end{bmatrix} \right] \right), \quad (4)$$

where $\hat{\mathbf{x}}_{\text{in}}^k$ and $\hat{\mathbf{x}}_{\text{out}}^k$ are the input and the output of the estimate in the k th unit, respectively, $k = 1, \dots, K$, where K is the total number of layers in the network.

The structure of each unit in MsNet is shown in Figure 1.

As shown in Figure 1, we first linearly weight the known information $H^T H \hat{\mathbf{x}}_{\text{in}}^k$ and $H^T \mathbf{y}$ and the training variables α_k and β_k are added to MsNet for adjusting the step size. All the input vectors can be connected and transformed into a one-dimensional vector by Concat. In addition, sigS is an activation function, which can carry out multisegment mapping of input information. Since the activation function design of the DetNet network has poor performance for high-order modulation scene, it is extremely important to design a more flexible activation function to improve signal detection performance under different modulation methods. The design method of sigS is to construct a staircase function by the sum of multiple sigmoid functions, which performs multisegment mapping for the constellation point set of different modulation methods.

First of all, sigmoid is a well-known activation function in the field of deep learning, defined as

$$\text{sigmoid}(\mathbf{x}) = \frac{1}{1 + e^{-\mathbf{x}}}. \quad (5)$$

On the basis of the sigmoid function, we added parameter f .

Figure 2 shows the curves of sigmoid ($f\mathbf{x}$) with different values of f , where f can be interpreted as a slope. Second, to satisfy the multisegment mapping of the function curve, the activation function is designed as the sum of several sigmoid functions and a step function is constructed by combining the constellation point information of the different modulation modes.

The specific formula is as follows:

$$\text{sigSum}(\mathbf{x}) = L + E \sum_{t=1}^{2l-1} \text{sigmoid}(f\mathbf{x} + B_t), \quad (6)$$

$$B_t = 5 + (-1)^t (10t - 5). \quad (7)$$

In (6), L is the minimum value of the symbol set under different modulation modes and E is the minimum Euclidean distance between adjacent symbols. In addition, the total number of the constellation point sets is $2l$.

Figure 3 shows the curve of sigSum in different modulation methods, and the parameters of sigSum for different modulations are given in Table 1.

As shown in Table 1, sigSum can be written as $-0.707 + 1.414 \times \text{sigmoid}(10x)$ for QPSK and $-3 + 2 \times [\text{sigmoid}(10x) + \text{sigmoid}(10x + 20) + \text{sigmoid}(10x - 20)]$ for 16-QAM. Moreover, we can extend sigSum to 64-QAM, 256-QAM, etc.

Finally, in order to make the activation function learnable, we add a set of trainable variables $\{g_t, h_t\}_{t=1}^{2l-1}$ to (6), which is given by

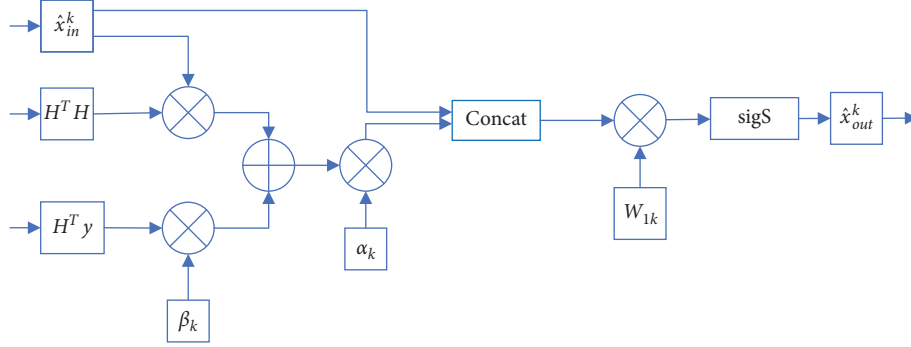


FIGURE 1: The structure of each unit in MsNet.

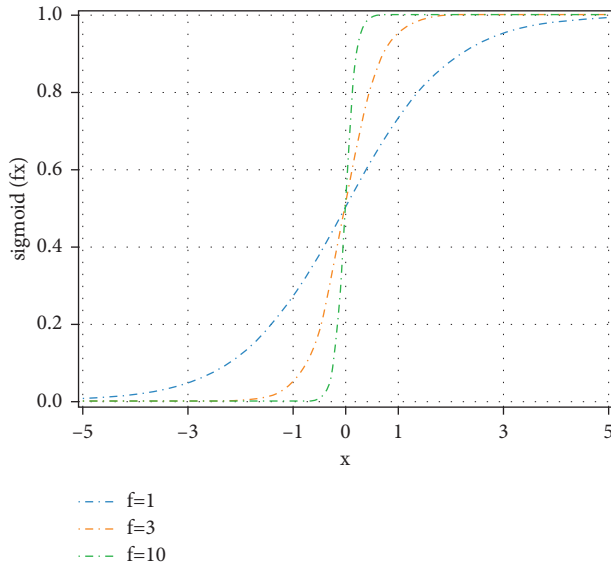
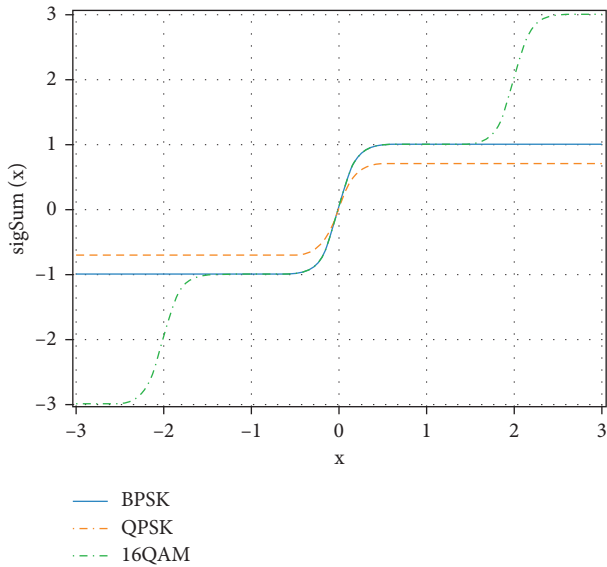

 FIGURE 2: Sigmoid function with different slope f .


FIGURE 3: sigSum function mapping curve under different modulation modes.

TABLE 1: sigSum parameters for different modulations.

Modulation: constellation point sets	f	L	E	B_t
BPSK: $\{-1, 1\}$	10	-1	2	$\{0\}$
QPSK: $\{-0.707, 0.707\}$	10	-0.707	1.414	$\{0\}$
16-QAM: $\{-3, -1, 1, 3\}$	10	-3	2	$\{0, 20, -20\}$

$$\text{sigS}(\mathbf{x}) = L + E \sum_{t=1}^{2l-1} \text{sigmoid}(g_t f \mathbf{x} + h_t B_t). \quad (8)$$

Equation (8) is the final activation function, and $g_1 = h_1 = 1$ to ensure that the initial structure of the activation function is not changed. g_t adjusts each stair corresponding to the mapping curve up and down, and each block of step size can be adjusted horizontally by h_t .

The overall structure of MsNet is illustrated in Figure 4.

In ScNet, the residual coefficient is a fixed value of 0.9. However, compared with a constant, the learnable residual coefficient can be adjusted adaptively to an appropriate number, thus improving the performance of detection. It can be expressed as

$$\mathbf{x}_{\text{in}}^k = \mu_k \mathbf{x}_{\text{out}}^{k-1} + (1 - \mu_k) \mathbf{x}_{\text{in}}^{k-1}, \quad (9)$$

where μ_k is the residual coefficient of the network at layer k and $\mu_1 = 1$. Furthermore, in order to improve the detection accuracy with the increasing number of network layers, our loss function is given as [8]

$$l(\mathbf{x}; \hat{\mathbf{x}}_k) = \sum_{k=1}^K \log(k) \|\mathbf{x} - \hat{\mathbf{x}}_k\|^2. \quad (10)$$

4. Numerical Results

The networks are implemented by using Python with the TensorFlow library [13]. We train the network for 50000 iterations, and batch sizes of 2000 samples are used. Furthermore, the Adam optimizer [14] is used with a decay learning rate of 0.97 and starting learning rates of 0.0001 are used.

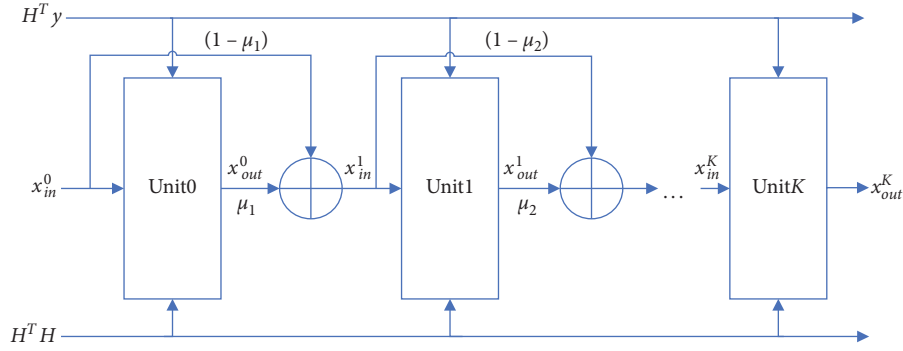


FIGURE 4: The overall structure of MsNet.

4.1. *Comparison of Different Activation Functions.* We compare the SER performance of different activation functions under QPSK, such as sigS(•), sigSum(•), ψ_t (•) [15], and σ_c (•) [9]. As shown in Figure 5, the SER performance of MsNet – sigSum(•) is better than MsNet – σ_c (•) and MsNet – ψ_t (•), and the performance gain of MsNet – sigS(•) over MsNet – sigSum(•) is about 0.5 dB at 5×10^{-5} . This is mainly due to the training variables in the sigS function, which make the network more flexible and allow it to achieve better SER performance.

4.2. *SER Comparison for Various Modulations.* We investigate the detection performance with multiple detection methods under different modulation modes. Specifically, we compare the SER performance of the proposed MsNet with various existing MIMO detectors, such as multilevel MIMO detection [9], DL-based detector [10], ScNet, and DetNet.

In Figure 6, we show the SER performance under BPSK, where $M=32$ and $N=64$. It can be seen that multilevel MIMO detection has poor detection performance in massive MIMO schemes and that the SER performance of DL-based method is limited under this antenna configuration. However, the DL-based method is still better than multilevel MIMO detection. Furthermore, DetNet, ScNet, and MsNet schemes outperform multilevel MIMO detection and DL-based detector, and it is clear that the proposed MsNet achieves the best performance. The reason for the performance improvement of MsNet is that a set of trainable variables $(\alpha_k, \beta_k, \{g_t, h_t\}_{t=1}^{2l-1}, \mu_k)$ were added to each layer, which makes the network more flexible by improving the stability and speed of convergence in the training process.

As shown in Figure 7, $M=32$ and $N=64$ for QPSK. The detection performance of DL-based and DetNet methods is similar. However, our MsNet still achieves the best performance among all of the detection methods. Specifically, when $SER = 5 \times 10^{-4}$, MsNet improves by about 1.3 dB and 3 dB as compared with ScNet and DetNet.

Finally, we compare the number of antennas associated with $M=32$ and $N=64$ and $M=32$ and $N=128$ for 16-QAM. From Figure 8, we can see that when the number of receiving antennas is increased to 128, the performance of the DL-based method is better than DetNet and ScNet because the detection performance of the DL-based method

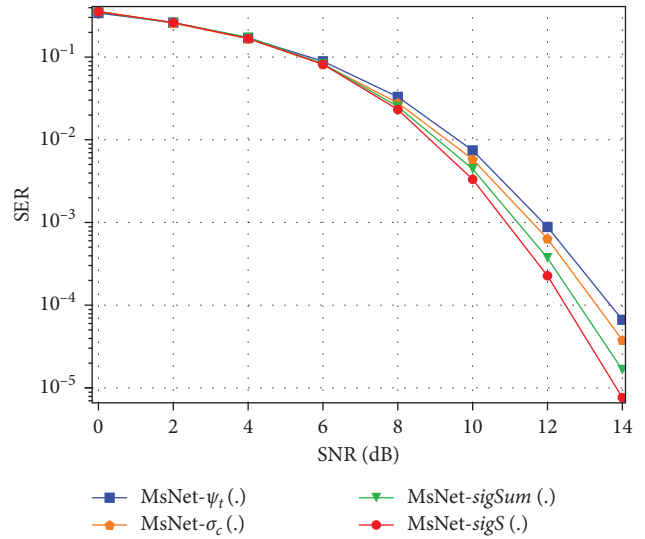


FIGURE 5: SER with different activation functions for MsNet: $M=32$ and $N=64$.

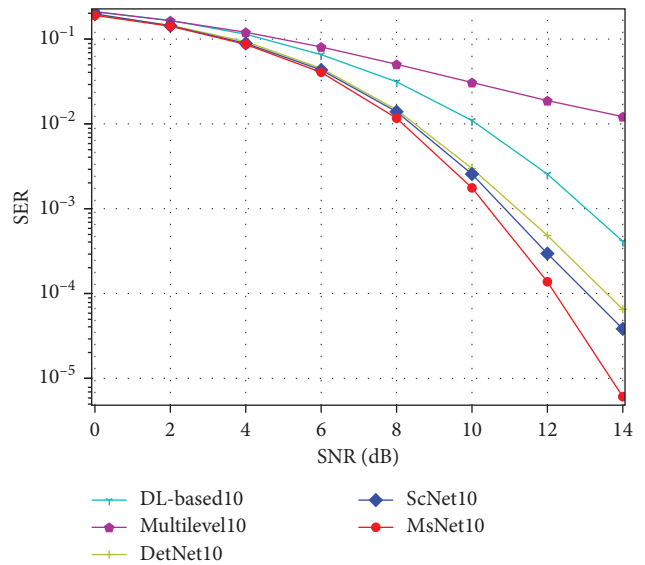


FIGURE 6: SER comparison of various detectors: $M=32$, $N=64$, and BPSK.

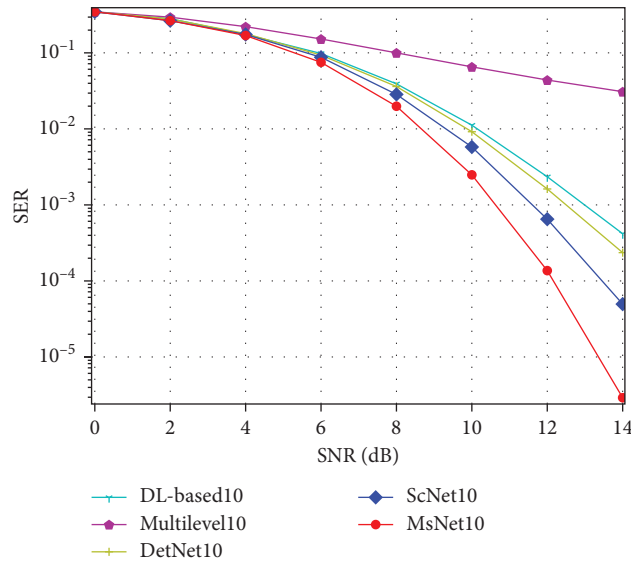


FIGURE 7: SER comparison of various detectors: $M=32$, $N=64$, and QPSK.

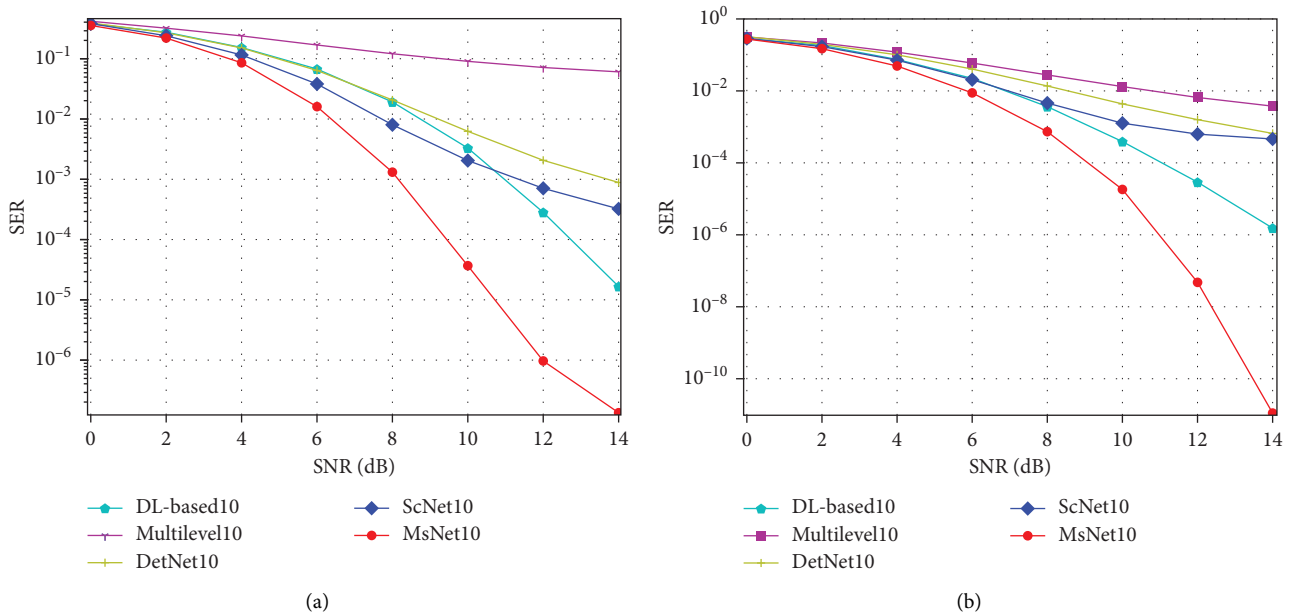


FIGURE 8: 16-QAM SER comparison of various detectors for (a) $M=32$ and $N=64$ and (b) $M=32$ and $N=128$.

with a great number of receiving antennas is improved. In addition, MsNet outperforms all the other detectors because its activation function is more suitable for high-order modulation scenarios. Because of the advantages of the channel-hardening phenomenon [16], SER of all of the considered detectors decreases as the number of receiving antennas increases.

4.3. Complexity Comparison. Table 2 shows the complexity of matrix multiplication operation for different networks.

In Table 2, in comparison with BPSK and QPSK, the complexity of DL-based detection is increased in 16-

QAM because the DL-based detection added two neural network layers to modify the residual error vector. In addition, the complexity of multilevel MIMO detection is higher than DetNet because its initial solution uses a twin-network neural structure. The MsNet requires $4LM^2$ fewer operations than the DetNet for BPSK, and that number for QPSK and 16-QAM is $16LM^2$. Compared to the ScNet, the complexity reduction of the MsNet is LM^2 operations for BPSK, and it is $4LM^2$ for QPSK and 16-QAM. The numerical results show that MsNet achieves a significant performance gain with lower complexity as compared to other reported works.

TABLE 2: Comparison of different network complexities.

$M \times N$ channel	BPSK	QPSK	16-QAM
DL-based	$MN + M^2N + M^2 + L(M^2 + 3M)$	$4MN + 8M^2N + 4M^2 + L(4M^2 + 6M)$	$4MN + 8M^2N + 4M^2 + L(12M^2 + 6M)$
Multilevel	$M^3 + 3MN + N^2M + M^2 + 6(L + 1)M^2$	$M^3 + 12MN + 8N^2M + 4M^2 + 24(L + 1)M^2$	
DetNet	$MN + N^2M + M^2 + 6LM^2$	$4MN + 8N^2M + 4M^2 + 24LM^2$	
ScNet	$MN + N^2M + M^2 + 3LM^2$	$4MN + 8N^2M + 4M^2 + 12LM^2$	
MsNet	$MN + N^2M + M^2 + 2LM^2$	$4MN + 8N^2M + 4M^2 + 8LM^2$	

TABLE 3: Comparison of trainable parameters.

32 × 64 channel	BPSK	QPSK	16-QAM
DL-based	20	20	8.322×10^4
Multilevel	6.864×10^4	2.724×10^5	2.724×10^5
DetNet	6.241×10^4	2.476×10^5	2.476×10^5
ScNet	3.105×10^4	1.235×10^5	1.235×10^5
MsNet	2.052×10^4	8.196×10^4	8.2×10^4

Finally, we compare the number of training parameters for different networks in Table 3. The chosen number of network layers is $K = 10$ for all detection methods.

In Table 3, we can see that multilevel MIMO detection has the highest number of trainable parameters for the same number of layers. In addition, for BPSK and QPSK modulations, trainable parameters of DL-based detection depend only on the number of layers. However, upon adding two neural network layers to the residual error vector in 16-QAM, the trainable parameters increased significantly. Furthermore, the simplification of the architecture can reduce the training parameters and complexity. Specifically, the trainable parameters of MsNet are reduced by 1.1×10^4 as compared with ScNet for BPSK and by 4.2×10^4 as compared with DetNet. In QPSK, the trainable parameters of MsNet are only 8.196×10^4 , which is much lower than the parameters of the other three networks. Therefore, MsNet has reduced the training time of the network.

5. Conclusion

In this paper, we propose an MsNet network structure for massive MIMO detection. Our simulation results show that, in comparison with other detection methods, MsNet can provide a low-complexity and high-performance solution for massive MIMO detection, especially in high-order modulation scenarios. In addition, the network structure of MsNet is more flexible than DetNet and ScNet.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest in the work.

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