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Signal detection algorithms for massive MIMO system

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Abstract. As 5G communication networks are maturing, we have higher and higher requirements for the detection of communication signals. In this paper, for the Massive MIMO system signal detection problem, we mainly summarize the detection algorithms that can be used to replace the traditional ZF and MMSE, so as to avoid large-scale matrix inverse and reduce the computational complexity. It mainly includes the general iterative method, typically represented by SSOR, which makes the transmit signal matrix constantly close to the ideal value by iterating; the other is the level expansion class solution method, which takes the order expansion of the level as the initial value of the iteration to accelerate the convergence rate of the algorithm, typically represented by the MLI algorithm. However, today where the demand for communication is gradually increasing and the number of users is constantly getting larger, the performance of the above algorithms may degrade seriously, so the AI signal detection algorithm is a good alternative, which learns autonomously through deep neural networks, including model-driven and data-driven schemes.

Keywords: Massive MIMO, Signal Detection, Traditional Methods, Neural Network, Deep Learning.

1. Introduction

With the continuous development of social economy, transportation, science and technology, information “collection” shows a trend of explosive growth, the power communication transmission network has higher and higher requirements, so 5G technology came into being. Among some familiar communication standards, such as the 4G standard long-term evolution-advanced (LTE-A) [1], wireless local area network (LAN) standard IEEE 802.11n [2], multiple-input multiple-output (MIMO) technology has been very mature. MIMO) has been applied very maturely, and its configuration of a large number of antennas at the base station (BS) to serve a small number of users at the same time is regarded as a very effective technique that can be applied to 5G wireless communications. However, the traditional MIMO technique has some drawbacks, such as the inability to effectively utilize the space and the existence of limitations in the bibliography of antennas, in contrast to it, the Massive MIMO technique can be applied to scenarios in which the number of antennas is much larger than the number of users, and at the same time, it can be more efficiently proportional to the antennas of the BS segments and the sensing terminals [3].

In general, the algorithms we generally use for signal detection contain two kinds: nonlinear detection algorithms and linear detection algorithms. The nonlinear detection algorithm is generally the maximum likelihood (ML) detection algorithm [4], which has the advantage that it can realize the optimal performance, but for Massive MIMO systems with a large number of antennas, its complexity is also very high, and it is not suitable for being the final algorithm. In contrast, linear detection algorithms get good performance while processing the signal in a simpler way, including the forced zero (ZF) detection algorithm and the minimum mean square error (MMSE) algorithm, the former does not take the effect of noise into account and also has a poor BER performance when the signal-to-noise ratio is low, and the latter requires high-dimensional matrix inverse.

In this thesis we focus on algorithms that can be used instead of high-dimensional matrix inversion. For these algorithms that can be used as approximate substitutes, there are generally the level expansion class approximation method, the iterative class approximation solving method and the matrix gradient search based approximation solving method, for the iterative class approximation solving method, the typical algorithms are the symmetric successive overrelaxation method (SSOR) [5], the successive overrelaxation method (SOR) [6], Gauss-Seidel (GS) [7], which gradually approaches the optimal performance by gradually reducing the deviation of each unknown value, while avoiding the large-scale matrix inverse; for the level expansion class of approximation methods, the typical algorithm is the Neumann level approximation method [7-8], which utilizes the MMSE algorithm to solve the problem. It utilizes the second-order expansion of the Neumann series of the inverse matrix of the weighting matrix as the initial value of the iteration of the inverse of its chunked matrix to effectively improve the convergence speed of the algorithm while avoiding the high complexity.

Although the above alternatives avoid large-scale matrix inversion, the performance of these signal detection algorithms degrades as the number of users increases in large-scale MIMO systems. In recent years, Deep Learning (DL) techniques have gradually become popular as an emerging artificial intelligence technique. When DL techniques are used in the context of signal detection, it is usually categorized into two types: data-driven and model-driven. In the data-driven approach, the detector will be regarded as a black box and we only focus on the inputs and outputs [7,9]. Model-driven techniques can be seen as a deep unfolding of data-driven techniques, which iteratively unfolds itself by adding trainable parameters to the signal detection problem to form a trainable network structure [10-11].

The rest of the paper is organized as follows. Section II briefly introduces the uplink system model, Section III describes the traditional methods of signal detection, Section IV gives information about AI methods of signal detection. Finally, conclusions are drawn in Section V.

2. Uplink system model

In the uplink of a massive MIMO system, M antennas are configured at the BS, which transmit data with N single-antenna users (typically M $\gg$ N), and in this paper, we assume that the signals are transmitted over a Rayleigh fading channel. Let $\boldsymbol{S} = [\boldsymbol{s_{1,}} \boldsymbol{s_{2,}} \dots \boldsymbol{s_{N,}}]^{\boldsymbol{T}} \in \boldsymbol{C}^{\boldsymbol{N\times 1}}$ be the N×1 dimensional vector transmitted by all users, and $\boldsymbol{H} \in \boldsymbol{C}^{\boldsymbol{M\times N}}$ denote the Rayleigh fading channel matrix, which are independently and identically distributed (i.i.d.), and all have zero mean and unit variance [12]. In this way, the M × 1 received signal vector $\boldsymbol{y}$ at the BS can be expressed as

$$y = \mathrm{H}s + n \tag{1}$$

Here $\boldsymbol{n}$ is the M × 1 dimensional additive Gaussian white noise.

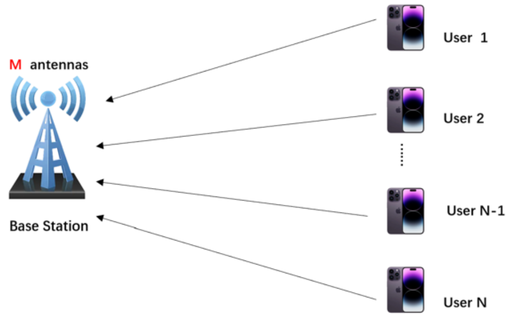


Figure 1. massive MIMO system in the uplink.

After obtaining the Rayleigh fading channel matrix $\boldsymbol{H}$ by performing the time-domain or frequency-domain frequency derivative [13-15] at BS, S of the ZF signal detector can be expressed as

$$\hat{\boldsymbol{s}} = (\boldsymbol{H}^H\boldsymbol{H})^{-1}\boldsymbol{H}^H\boldsymbol{y} = \boldsymbol{W}^{-1}\hat{\boldsymbol{y}} \tag{2}$$

where, $\boldsymbol{W} = \boldsymbol{H}^{\boldsymbol{H}}\boldsymbol{H}$, $\hat{\boldsymbol{y}} = \boldsymbol{H}^H\boldsymbol{y}$

Although the ZF method can approach the optimal performance, it requires large-scale matrix inversion, which is not very easy to realize in practical applications.On the other hand, the MMSE algorithm can also achieve near-optimal performance, in which the estimate of the user sending vector $\boldsymbol{s}$ can be expressed as [8]

$$\hat{\boldsymbol{s}} = (\boldsymbol{H}^H\boldsymbol{H} + \partial^2\boldsymbol{I}_{\boldsymbol{M}})^{-1}\boldsymbol{H}^H\boldsymbol{y} = \boldsymbol{W}^{-1}\hat{\boldsymbol{y}} \tag{3}$$

In this equation, $\hat{\mathbf{y}}$=$\mathbf{H}^{\mathrm{H}}\mathbf{H}$ and $\mathbf{W} = \mathbf{G} + \partial^2\mathbf{I}_{\mathbf{M}}$ are the weighting matrix of the MMSE signal detector, ∂^2 is the variance, $\boldsymbol{I}_{\boldsymbol{M}}$ is the unit matrix, and $\boldsymbol{G}$=$\boldsymbol{H}^H\boldsymbol{H}$ is the Gram matrix. However, it is similar to the ZF signal detection, which also involves the matrix inverse of $\boldsymbol{W}$. The algorithm has high complexity and is not easy to implement.

3. Traditional methods of signal detection

3.1. SSOR

It has been mentioned above that for massive MIMO systems, the number of users N is usually very large, which makes the complexity (K^3) in Eq. (2) of the ZF algorithm can be high. However, it is known from the literature [16] that the channel matrix $\boldsymbol{H}$ is progressively orthogonal in massive MIMO systems and $\boldsymbol{W}$ is a Hermitian positive definite matrix with probability 1. Therefore, we can avoid high algorithmic complexity by replacing the large-scale matrix inverse $\boldsymbol{W}^{-1}$ with a step-by-step iterative method. The traditional iterative method SOR [6] can be used to solve the M-dimensional system of linear equations $\boldsymbol{As} = \boldsymbol{b}$ ($\boldsymbol{A}$ is a positive definite matrix of dimension M × M, $\boldsymbol{s}$ is the solution vector in M × 1 dimensions, and $\boldsymbol{b}$ is the measurement vector in M × 1 dimensions)

$$\left(\boldsymbol{L} + \frac{1}{p}\boldsymbol{D}\right)\boldsymbol{s}^{(k+1)} = \left[\left(\left(\frac{1}{p} - \boldsymbol{1}\right)\boldsymbol{D} - \boldsymbol{L}^{\boldsymbol{H}}\right)\boldsymbol{s}^{(k)} + \boldsymbol{b}\right] \tag{4}$$

Here, k denotes the number of iterations, p denotes the relaxation parameter (determines the rate of convergence of the algorithm and the speed of convergence, the SOR algorithm becomes the GS algorithm when p=1 [7]), and $\boldsymbol{W} = \boldsymbol{D} + \boldsymbol{L} + \boldsymbol{L}^{\boldsymbol{H}}$($\boldsymbol{D}$,$\boldsymbol{L}$,$\boldsymbol{L}^{\boldsymbol{H}}$ are the diagonal components of the matrix $\boldsymbol{W}$, the strictly lower triangular component, and the strictly upper triangular component)

However, the SOR algorithm iterates asymmetrically, iterates slowly, and it is sensitive to the relaxation parameter p, which is prone to significant performance loss. According to [5], SSOR can well avoid the above problems

First,

$$(\boldsymbol{D} + p\boldsymbol{L})\hat{\boldsymbol{s}}^{(i+1/2)} = (\mathbf{1} - p)\boldsymbol{D}\hat{\boldsymbol{s}}^{(i)} - p\boldsymbol{L}^{\boldsymbol{H}}\hat{\boldsymbol{s}}^{(i)} + p\hat{\boldsymbol{y}} \tag{5}$$

Second,

$$(\boldsymbol{D} + p\boldsymbol{L}^{\boldsymbol{H}})\hat{\boldsymbol{s}}^{(i+1)} = (\mathbf{1} - p)\boldsymbol{D}\hat{\boldsymbol{s}}^{(i+1/2)} - p\boldsymbol{L}\hat{\boldsymbol{s}}^{(i+1/2)} + p\hat{\boldsymbol{y}} \tag{6}$$

where $i = 0, 1,$ is the number of iterations, $\hat{\boldsymbol{s}}^{(\mathbf{0})}$ is the initial solution, which is generally treated as a zero vector in SSOR, and the SSOR algorithm converges for any initial solution at $0 < p < 2$. From [5], $\bar{p} = \frac{2}{1+\sqrt{2(1-x)}}, x = \left(1 + \sqrt{\frac{N}{M}}\right)^2 - 1$. Therefore, for p, its value is determined by M and N only, and the value of p is fixed for a signal detection system with fixed M and N. Thus, the effect of the relaxation parameter on the performance is avoided.

From the simulation results in the literature [5], it can be seen that

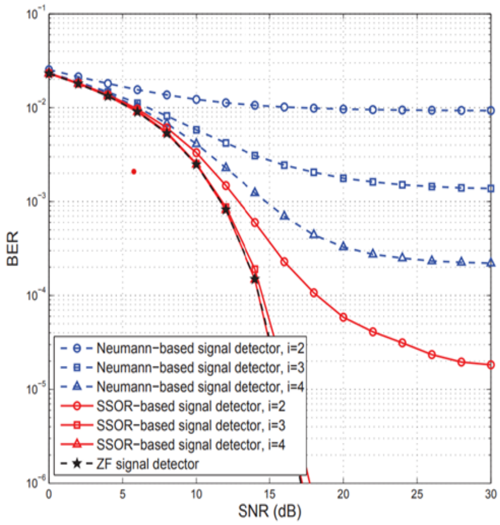


Figure. 2. BER performance comparison between Neumann-based and SSOR-based signal detectors (i equals k in this paper).

A massive MIMO system with M × N = 256 × 32 is assumed in the figure.2, and the Neumann-based signal detector and the SSOR-based signal detector are compared in terms of BER. From Figure. 2, it is known that to achieve the same BER performance, the signal-to-noise ratio (SNR) of the SSOR algorithm is lower than that of the Neumann algorithm, and only a small number of iterations are required for the SOR to approach the optimal performance.

3.2. Neumann

In addition to using iterative methods as an approximate alternative to large-scale matrix inversion, we generally use another method-Mixed Linear Iterative Detection (MLI) algorithm based on Neumann series to reduce the computational complexity.

To minimize the error, we replace $\boldsymbol{W}$ and $\boldsymbol{s}$ with $\boldsymbol{D}$+$\boldsymbol{E}$ and $\boldsymbol{D}$, respectively.

$$\boldsymbol{W}^{-1} = \sum_{t=0}^{\infty}\left(-\boldsymbol{D}^{-1}\boldsymbol{E}\right)^{\boldsymbol{t}}\boldsymbol{D}^{-1} \tag{7}$$

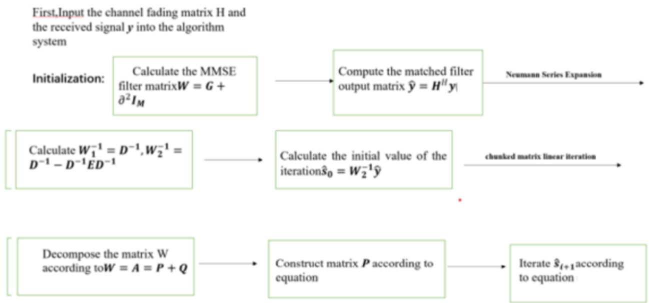
(converges when $\lim_{t\to\infty}\left(-\boldsymbol{D}^{-1}\boldsymbol{E}\right)^{\boldsymbol{t}} = \mathbf{0}$)

In the case of expanding only the first i terms, this can be varied as

$$\boldsymbol{W}^{-1} = \sum_{t=0}^{i-1} \left(-\boldsymbol{D}^{-1}\boldsymbol{E}\right)^{t} \boldsymbol{D}^{-1} \tag{8}$$

It can be seen from the simulation results that the computational complexity is O(N^3) when i<2, but after *i*>2, the computational complexity gradually increases and even reaches O(N^3).

The above is the process of Neumann series expansion. Here we introduce the specific steps of MLI algorithm [8]:



$$\boldsymbol{P}_{i,\ j} = \begin{cases} \boldsymbol{a}_{i,\ j}, & \boldsymbol{j-1 \le i \le j},\ \boldsymbol{i\,mod\,2 = 1} \\ \boldsymbol{a}_{i,\ j}, & \boldsymbol{j \le i \le j+1},\ \boldsymbol{i\,mod\,2 = 0} \\ & \boldsymbol{0},\ \boldsymbol{other} \end{cases}$$

$$\hat{\boldsymbol{s}}_{i+1} = -\boldsymbol{P}^{-1}\boldsymbol{Q}\hat{\boldsymbol{s}}_{k} + \boldsymbol{P}^{-1}\boldsymbol{b}$$

Figure 3.MLI algorithm.

In contrast to the SSOR linear iterative class of algorithms, this algorithm often has to set an initial vector value $\boldsymbol{s_0}$ to be substituted into the iterative equations for solving, and this initial value $\boldsymbol{s_0}$ is usually set to be a zero vector, which will affect the convergence rate of the algorithm. Based on the fact that the Neumann series can approximate the inverse result of the MMSE weighting matrix $\boldsymbol{W}$ with low complexity operation in the case of small expansion order, the MLI algorithm can accelerate the convergence rate of the algorithm and approximate the performance of the MMSE detection algorithm with fewer iterations.

Finally, from the simulation results, it can be seen that

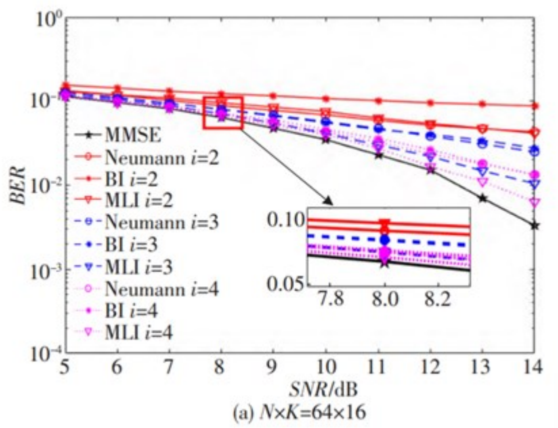


Figure 4. BER performance comparison among some algorithms (N is equivalent to M in this paper and K is equivalent to N in this paper) [8].

From figure.4, it can be seen that the MLI algorithm performs better for the same number of iterations.

3.3. GS

For the SSOR method, its relaxation parameter p is determined by the number of users and the number of antennas when in large-scale MIMO systems, and when its relaxation parameter is forced to be set to 1, it is not a bad iterative algorithm although the system performance may be degraded, we call it the GS algorithm, and its iterative formula according to [7] is

$$\boldsymbol{s}^{(i)} = (\boldsymbol{D} + \boldsymbol{L})^{-1}\left(\boldsymbol{y} - \boldsymbol{L}^{H}\boldsymbol{s}^{(i-1)}\right), i = 1,2 \ldots. \tag{9}$$

Here, i is the number of iterations.

According to the simulation results, it has better performance in terms of BER compared to Neumann's algorithm and is closer to Cholesky decomposition method

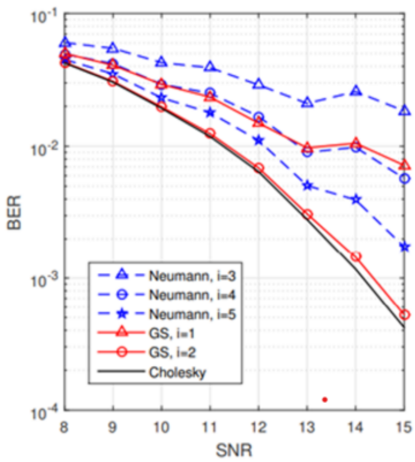


Figure 5. BER performance comparison among some algorithms (M=128, N=16) [7].

3.4. Analysis

By analyzing some of the above methods, here we summarize the advantages and disadvantages of each method. For the SSOR method, it only needs a small number of iterations to approach the optimal BER performance of the ZF signal detector, so its implementation of matrix inversion with low complexity can be applied to some common wireless communication problems, but it usually sets the value of $\boldsymbol{s_0}$ to 0, which tends to affect the convergence speed of the algorithm; the GS algorithm directly sets the relaxation parameter p to 1, which leads to some errors but The GS algorithm directly sets the relaxation parameter p to 1, which leads to some errors, but shows good performance in the simulation results; for the Neumann-based MLI algorithm, it can approach the performance of the MMSE with fewer iterations when the M/N is larger, and it converts the Neumann series expansion of the MMSE weighting matrix $\boldsymbol{W}$ with the expansion order of 2 to the initial value of the iterative equation $\boldsymbol{s_0}$, which speeds up the convergence speed of the algorithm; however, when the Neumann series unfolds above order 2, its algorithmic complexity gradually increases and even approaches O(N^3).

4. AI methods of signal detection

4.1. Model-driven of signal detection

All the above algorithms can be used to reduce the computational complexity of linear detection algorithms, however, the performance of all these algorithms is severely impaired as N in Massive MIMO systems continues to grow.

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As the field of Artificial Intelligence has evolved in recent years, Deep Learning (DL) techniques belonging to it have begun to be applied to the field of signal detection. Examples include the SAMP-Net DL algorithm based on Simplified Approximate Message Passing (SAMP) [17] and Det-Net [18], and DL algorithms dealing with channel estimation and signal detection for Orthogonal frequency-division multiplexing (OFDM) systems [19]. Inspired by the above literature, a more efficient and Richardson (Steepest Descent and Non-Stationary Richardson SDSR) based DL algorithm [11] has emerged, which adds trainable parameters to the traditional methods without adding redundant complexity and improves the algorithm performance. Its signal detector is a model-driven DL network (SDNSR-Net).

In SDNSR-Net, there are L+1 cascading layers. The very first layer, i.e., layer 0, which preprocesses the receiver signal $\boldsymbol{y}$ and the Rayleigh fading channel matrix $\boldsymbol{H}$, is passed backward sequentially to generate the initial values of each cascade layer one by one. The residual vectors $\boldsymbol{r}_0$ and $\boldsymbol{p}_0$, $\hat{\boldsymbol{s}}_0$ are set to 0 for making simplification.

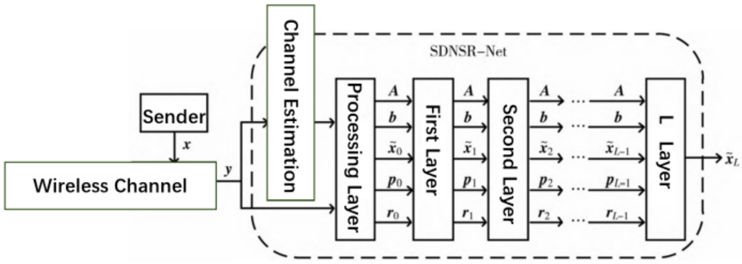

Figure 6. The entire frame of SDNSR-Net [11].

Except for layer 0, which is a preprocessing layer, all the other L-layers have the same standard structure, which are constructed based on the SDNSR-Net neural network, and their specific structure is shown in figure.7.

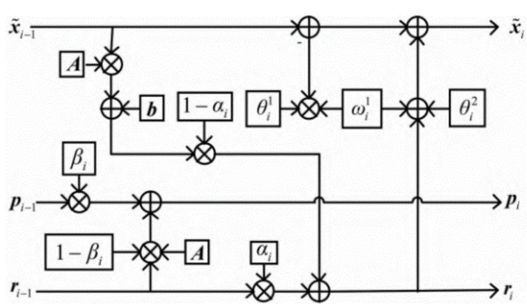

Figure 7. The standard frame of SDNSR-Net($A = \boldsymbol{H}^T\boldsymbol{H} + \partial^2\mathbf{I_M}$, $\boldsymbol{b} = \boldsymbol{H}^T\boldsymbol{y}$) [11].

The inputs of each layer are $\hat{\boldsymbol{s}}_{i-1}$, $\boldsymbol{r}_{i-1}$,$\boldsymbol{p}_{i-1}$,and the outputs are $\hat{\boldsymbol{s}}_i$,$\boldsymbol{r}_i$,$\boldsymbol{p}_i$,and the last layer outputs the estimated value of the sending signal $\hat{\boldsymbol{s}}$, $\hat{\boldsymbol{s}}_L$. It has been shown that $\hat{\boldsymbol{s}}_i$is not only related to the residual vectors of the current layer, but also the residual vectors of the previous layers in the iterative process, and thus they need to be put into consideration. Secondly, in order to simplify the neural network, only the effects of neighboring layers are considered and a damping mechanism [20] is added to speed up the convergence performance of the network, and the simplified formula is as follows [11]

$$\boldsymbol{r}_i = (1 - a_i)(b - \boldsymbol{A}\hat{\boldsymbol{s}}_{i-1}) + a_i\boldsymbol{r}_{i-1} \tag{10}$$

$$\boldsymbol{p}_i = (1 - \beta_i)\boldsymbol{A}\boldsymbol{r}_i + \beta_i \tag{11}$$

Here, a_i and β_i are trainable parameters, which are set to 0.5 in order to avoid the effect of residual errors in the previous and current layers.

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Through the continuous optimization of the initial SDNSR algorithm formula, we arrive at the initial update formula for $\hat{\boldsymbol{s}}_i$ applicable to SDNSR-Net [11]:

$$\hat{\boldsymbol{s}}_i = \hat{\boldsymbol{s}}_{i-1} + \omega_i \boldsymbol{r}_{i-1} = \hat{\boldsymbol{s}}_{i-1} + \omega_i (\boldsymbol{b} - \boldsymbol{A}\hat{\boldsymbol{s}}_{i-1}) \tag{12}$$

ω_i is the relaxation parameter, and the algorithm converges if and only $0<\omega<2/\theta_{max}$. θ_{max} is the maximum eigenvalue of $\boldsymbol{A}$.

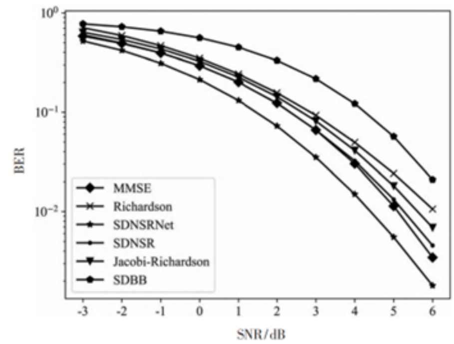

Figure 8. Detected BER Comparison for 128×32, 16QAM Modulation [11].

Simulation results show that SDNSR-Net outperforms various comparison algorithms in terms of BER.

4.2. Data-driven of signal detection

The above is an example of model-driven, but it was used more in the old days based on mathematical disciplines, when people couldn't process large amounts of data, so they had to rely on existing mathematical models to process the data and make the data fit the existing models. Nowadays, data-driven is becoming popular, which means that after getting a set of data, the data will be fed into a signal detector, so that the neural network can create its own model based on the data, so that the model can fit the data.

For data-driven, the principle is to input the original data into the receiver through Fast Fourier Transform (FFT), and then use the symbols modulated by Quadrature Phase Shift Keying (OPSK) at the transmitter as the ideal output to train the neural network, and then make the network output gradually approximate the ideal OPSK modulated symbols. A typical example of data-driven signal detection is a signal detection method applied to OFDM satellite communication systems. Its neural network consists of an input layer, three hidden layers and five output layers. Each layer of the neural network consists of multiple neurons connected in a -fully connected layer fashion (i.e., a single neuron in each layer is connected to a single neuron in an adjacent neural network) [21].

We assume that if the input layer data are $s_1, s_2, \dots, s_N$ for the ith neuron of the first neuron of each hidden layer, the output is represented as [21]

$$\boldsymbol{y}_i = f\left(\sum_{k=1}^{N} w_k \boldsymbol{s}_k + b\right) \tag{13}$$

Here, w_k denotes the weights, b denotes the bias, and f denotes the activation function.

The activation function can introduce nonlinearity into the neural network so that the neural network can converge more quickly, generally there are ReLu function and Tanh function. In simulation experiments, least squares (LS) channel estimation [22], Discrete Fourier Transform (DFT) based channel estimation and the above algorithms are compared. In terms of BER, the above algorithm has a significant advantage.

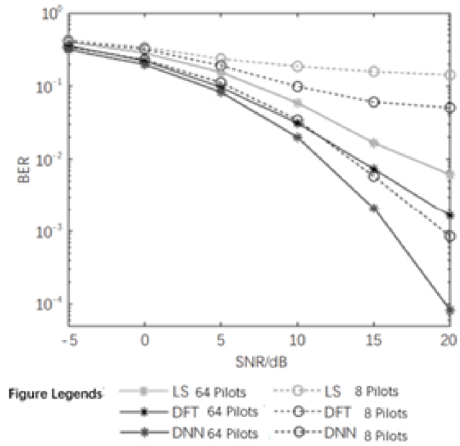

Figure 9. BER comparison for 128 subcarriers (DNN refers to the above data-driven algorithm) [21].

4.3. Analysis

Data-driven has some advantages and disadvantages compared to model-driven. If the original data is more complex and discrete, then data-driven is a better choice, which can process the data more quickly, of course, this also puts forward higher requirements for deep neural network design. If the amount of raw data is small, showing a certain pattern, and some mathematical models roughly match, then the existing mathematical model can be used to cash, which can save some technology development costs, but for large-scale data, model-driven may lead to a large error.

5. Conclusion

In this paper, for the Massive MIMO system signal detection problem, we mainly summarize the detection algorithms that can be used to replace the traditional ZF and MMSE, so as to avoid large-scale matrix inverse and reduce the computational complexity. It mainly includes the general iterative method, typically represented by SSOR, which makes the transmit signal matrix constantly close to the ideal value by iterating; the other is the level expansion class solution method, which takes the order expansion of the level as the initial value of the iteration to accelerate the convergence rate of the algorithm, typically represented by the MLI algorithm. However, in today's society where the demand for communication is gradually increasing and the number of users is getting bigger, the performance of the above algorithms may be degraded seriously, so the AI signal detection algorithm is a good alternative, which learns autonomously through deep neural networks, including model-driven and data-driven schemes, the former makes the data close to the existing mathematical model, typically represented by SDNSR-Net, and the latter makes the model close to the existing data. data. With the maturity of 5G networks and the imminent introduction of 6G networks, the traditional Massive MIMO signal detection technology may no longer be applicable, and a more stable, faster, and smaller error DL signal detection algorithm is the solution we need.

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