Low complexity Massive MIMO detection algorithm based on improved LAS

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Abstract. Massive multiple-input multiple-output (M-MIMO) technology is a key technology for 5G communications and future mobile wireless networks. Although the likelihood ascent search (LAS) algorithm in the existing detection algorithms is relatively low in complexity, the algorithm is easy to fall into the local optimum, resulting in poor global performance. Therefore, based on this algorithm, this paper proposes an improved detection scheme based on the LAS algorithm in the reduced neighborhood. This algorithm combines the idea of a reduced neighborhood and iteratively improves the LAS algorithm. The algorithm is designed by reducing the size of the neighborhood and increasing the number of iterations. The algorithm compares the BER performance of different neighborhood parameters, and obtains a set of parameters to significantly reduce BER through simulation comparison.

1. Introduction
The current fifth-generation wireless communication system has introduced massive MIMO technology, which can significantly improve the capacity and spectrum efficiency of the communication system. Therefore, the communication system using M-MIMO technology has gradually become a research hotspot [1]. However, M-MIMO faces many challenges. The traditional Maximum Likelihood (ML) detection algorithm [2] can obtain the lowest bit error rate (BER), but the computational complexity increases as the number of antennas increases. Linear detection algorithms such as Zero Forcing (ZF) detection and Minimum Mean Squar (MMSE) detection algorithms are less complex, but compared with ML algorithms, their performance gap is large. In the nonlinear measurement method. [3] introduced the Sphere Decoding (SD) algorithm, which is an implementation method of ML detection. The algorithm tries to find the transmitted signal vector with the smallest ML metric. The disadvantage is that the complexity is depends on the signal-to-noise ratio. Although the average complexity can be significantly reduced, in the worst case, its computational complexity is still the same as that of ML detection. [4] proposed a serial interference cancellation (Successive Interfere Cancellation, SIC) algorithm, which selects a signal for detection each time, and then subtracts the interference caused by the detected signal from the received signal, which can eliminate the detected signal. The interference effect of the signal on the undetected signal improves the detection performance, but when an error occurs in the detection of one layer, it will affect the detection result of the next layer, that is, there is an error propagation phenomenon. [5] proposed a graph-based message passing (MP) algorithm, but in the
case of a loop graph, the detection effect of this algorithm is not good because the mean variance cannot converge. [6] proposed a likelihood ascent search (LAS) algorithm, which starts from an initial solution and searches for the best solution (including the initial solution) in the neighborhood until the ML overhead reaches saturation. The LAS algorithm only accepts solutions that are better than the current solution, causing the algorithm to easily fall into the local optimum, resulting in poor detection performance of the algorithm. [7] proposed two LAS algorithms, namely single symbol LAS (S-LAS) and multistage LAS (MLAS). The S-LAS algorithm only finds the best vector in a neighborhood where the symbol is different from the initial solution at one symbol, resulting in poor performance. However, M-LAS improves performance by exploring multiple symbols (i.e., two or three symbols) in the neighborhood that is different from the initial solution at more symbols, resulting in higher complexity. In [8], an unconstrained LAS (unconstrained LAS, ULAS) algorithm was proposed. The search allows to find the optimal vector without any constraints in the neighborhood, which can further reduce the bit error rate. The Reactive Tabu Search (RTS) algorithm proposed in [10] uses a feedback mechanism to actively adjust the neighborhood range. Although it improves the probability of jumping out of the local optimal solution, it is still far from the performance of the optimal ML algorithm. Gap and the algorithm complexity is increased.

Based on the above analysis, this paper proposes an improved likelihood-increasing search algorithm based on previous research. The algorithm is based on multiple iterations and reduces the size of the neighborhood, which not only solves the problem of neighborhood search algorithms that tend to fall into local optimality. At the same time, the computational complexity is reduced without sacrificing performance.

2. System model
Consider the uplink of a massive MIMO system. It is assumed that the base station has S antennas and the user has U antennas. Without loss of generality, assume that S is not less than U. Assuming that M modulation is used, the point set in the constellation is \( \Omega = \{ \mu_1, \mu_2, \cdots, \mu_M \} \), and the signal relationship is

\[
\hat{y} = \hat{H}x + z
\]

where \( \bar{x} = [x_1, x_2, \cdots, x_c]^T \) is the transmitted signal vector, \( \bar{y} = [y_1, y_2, \cdots, y_c] \) is the received signal vector, \( \hat{H} \) is the channel matrix of \( S \times U \) dimension, \( \bar{z} = [z_1, z_2, \cdots, z_c] \) represents independent and identically distributed additive white Gaussian noise, with variance \( \sigma_z^2 \). To facilitate discussion, transform the massive MIMO system into a real number form

\[
y = Hx + z
\]

Where \( y \) is a \( 2S \times 1 \) real equivalent received vector and \( x \) is is a \( 2U \times 1 \) real equivalent transmit vector, \( z \) is a \( 2S \times 1 \) equivalent noise vector, and \( H \) denotes the \( 2S \times 2U \) equivalent channel matrix given by

\[
H = \begin{bmatrix} R(\hat{H}) & -I(\hat{H}) \\ I(\hat{H}) & R(\hat{H}) \end{bmatrix}_{2S \times 2U}
\]

\( R(\bullet) \) and \( I(\bullet) \) represent the real and imaginary parts respectively.

3. Introduction to traditional LAS algorithm
The goal of MIMO detection is to estimate the transmission vector \( x \). For the model in (2), under the assumption of perfect CSI, the ML detection rule given

\[
\hat{x} = \arg \min \|y - Hx\|^2
\]

further simplified to

\[
\hat{x} = \arg \min \|x^H H^H H x - 2y^H H x\|
\]
LAS detection is an iterative algorithm. It starts from the initial estimation $\hat{x}^{(0)}$ and then searches for those vectors that can improve the likelihood cost function among its neighboring vectors. If at least one vector is found, the improved neighbor vector is used as the new candidate vector, and another iteration is performed, and set $\hat{x}^{(n)}$ to the estimated vector at the nth iteration, expressed as:

$$C(\hat{x}^{(n)}) = (x^{(n)})^T H^T H x^{(n)} - 2 y^T H x^{(n)}$$

\begin{equation}
\Delta x^{(n)} = x^{(n+1)} - x^{(n)} = \lambda_p^{(n)} e_p
\end{equation}

here $x^{(n+1)}$ and $x^{(0)}$ denote adjacent vectors, $\lambda_p^{(n)}$ represents the magnitude of the vector, $e_p$ expressed as a unit vector, the p-th element is 1. In order to simplify the complexity, only one bit sign change is considered, Combining (5)(6)(7) to get the cost function difference is

$$\Delta C(\hat{x}^{(n+1)}) = (\lambda_p^{(n)})^2 H^T H - 2 \lambda_p^{(n)} * (H^T (y - H x^{(0)}))$$

4. LASNEW algorithm

The LAS algorithm is easy to fall into the local optimum. By designing the LASNEW algorithm, the number of iterations can be increased to improve the BER performance. At the same time, the algorithm designs a reduced neighborhood, introduces alpha, beta, reduces the size of the neighborhood, and greatly reduces the neighborhood Algorithm complexity.

**Algorithm 2: LASNEW**

**Input:** y, H, Max$^{\text{nebo}}$

**Output:** $\hat{x}$

1. **Initialization** $x^{(0)}$, L, $C_{\text{prev}} \leftarrow \infty$, the next cost of ML is $C_{\text{next}} \leftarrow \|y - H x^{(0)}\|^2$;
2. **While** LAS$^{\text{times}}$ $\leq$ Max$^{\text{nebo}}$ do
3. **Determine the L symbol position index set that needs to be updated** $f_i = \frac{(e)^T h_i}{\|h_i\|}, \{i = 1, 2, \ldots, 2U\}$,
4. **Update the selected index, introduce alpha, beta parameters** $\eta_i = \frac{(H_i^T H_i)^{-1} H_i^T e}{d_{\text{min}}}$;
5. **Update the best available vector** $C_{\text{temp}} \leftarrow \|y - H \hat{x}\|^2$
6. **If** $C_{\text{temp}} < C_{\text{next}}$ **then** $x_{\text{temp}} \leftarrow \hat{x}, C_{\text{next}} = C_{\text{temp}}$;
7. **If** $C_{\text{next}} < C_{\text{prev}}$ **then** (Determine the number of iterations)
8. LAS$^{\text{times}}$ = 1;
9. **else**
13. LAS_times = LAS_times + 1;
14. end
15. $x^{(r+1)} = x_{\text{new}}$;
16. $r = r + 1$
17. end
18. return $\hat{x} = x^{r+1}$

5. Simulation analysis

In this section, in order to further verify the performance of the algorithm, compare it with the traditional LAS detection algorithm. The simulation environment is set as follows.

| TABLE I. SYSTEM SIMULATION PARAMETERS |
|---------------------------------------|
| **Simulation** | **Parameter** | **Parameter value** |
| LASNEW | $x^{(0)}$ | ZF |
| | $\text{Max}_{\text{daho}}$ | 10 |
| Massive MIMO communication system | Baseband modulation method | 16QAM |
| | Number of transmitting antennas ($S, U$) | 16x16 |
| | Channel type | Independent and identically distributed AWGN |

As shown in Figure 1, the 16x16 antenna scale and 16QAM modulation method are used. The BER performance of the LASNEW algorithm with the initial solution of ZF is compared when the neighborhood parameter beta values are 0.2, 0.4, 0.6, and 0.8 respectively. When the noise ratio is constant, the smaller the beta value, the better the BER performance.

As shown in Figure 2, a 16x16 antenna scale, 16QAM modulation method, and a constant alpha value are used. When the neighborhood parameter beta values are 0.2, 0.4, 0.6, and 0.8 respectively, the number of neighbors of the LASNEW algorithm with the initial solution of ZF are compared. It can be seen that as the beta increases, the search vector becomes less and less, and the complexity can be reduced by reducing the neighborhood vector.

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Fig.1 Comparison of BER performance of LASNEW algorithms with different beta value
Figure 3 shows the performance comparison of the LASNEW algorithm under different symbol numbers. When the antenna scale is 16x16, the initial value is generated by ZF, the modulation method is 16QAM, and the bit error rate is $10^{-3}$, the 3-LASNEW algorithm is compared with 2-LASNEW gains about 1dB. It can be seen that increasing the number of updated symbols can improve the performance of the LAS algorithm.

6. Conclusion
In this paper, in the independent and identically distributed Rayleigh fading channel environment, using different selection parameters, an improved LASNEW algorithm is proposed for the massive MIMO system. This algorithm not only solves the problem of traditional LAS detection algorithms that tend to fall into local optimality, but also greatly reduces the algorithm complexity. Simulation results show that this algorithm can be used as a massive MIMO signal detection scheme. Due to the relatively simple change of the independent and identically distributed Rayleigh fading channel, the spatial characteristics of massive MIMO cannot be well reflected. The detection of MIMO signals in 3D scenes needs further exploration. This will be our next research work.

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