



Improvement of CL Algorithm in MIMO-OFDM System

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Abstract. The sphere detection algorithm is a low SNR algorithm in the MIMO-OFDM system with low complexity, but it still has a certain complexity. It is challenging to choose its initial radius and determine whether a point is in the ball. The improved algorithm is to find the CL algorithm's initial radius by the particle swarm algorithm's optimization ability. Then the convergence factor is given to speed up the shrinkage speed of the CL algorithm's radius. The improved algorithm is compared with the CL algorithm. The simulation results clear that when the SNR ratio is below 16 dB, the enhanced algorithm significantly affects algorithm complexity. The improvement of the algorithm is proved to be effective and reliable.

Keywords: MIMO-OFDM system · Spherical detection algorithm · Convergence factor

1 Introduction

MIMO-OFDM technology can remove the influence of inter-symbol interference and solve the problem of frequency selective fading to improve frequency band utilization. It can also increase the data transmission rate and increase channel capacity [1]. Compared with other technologies, it is more Advantage. The MIMO-OFDM system can use the multiple input multiple output system's signal detection algorithms on the narrowband orthogonal sub-channels of the orthogonal frequency division multiplexing system to complete the signal detection research of the system [2].

Among the signal detection algorithms, the ML algorithm is the best detection algorithm [3]. It is the best signal detection algorithm when the number of transmitting antennas and modulation order is low, and it is not applicable when the two are higher [4]. The proposed CL detection algorithm's performance tends to the implementation of the ML detection algorithm, and the complexity is lower [5]. Still, the CL algorithm's complexity will gradually increase with the decrease of SNR, so it is more difficult at low SNR Large, not suitable for use. In order to solve this phenomenon, the particle swarm algorithm is first used to obtain the optimal solution to find the CL algorithm's

initial radius. The MMSE detection algorithm is then combined with the CL detection algorithm to reduce the complexity of the CL detection algorithm at low SNR. There is still high complexity, so the convergence factor β is set to accelerate the shrinkage of the CL detection algorithm radius, reduce the number of search grid points required by the CL algorithm when the SNR is low, and improve the complexity of the CL algorithm [6].

2 MIMO-OFDM System Model

The MIMO-OFDM system model is shown in Fig. 1 below. The input signal is split after serial/parallel conversion to form an Nt layer data stream and $x = [x_1, x_2, x_3 \cdots x_{Nt}]$ represents its transmit signal. IFFT modulates the movement for OFDM, which means that low-speed multiple parallel data streams are simultaneously modulated onto Nt orthogonal sub-carriers. Then add a cyclic prefix CP before the output data stream to reduce the influence of channel delay spread.

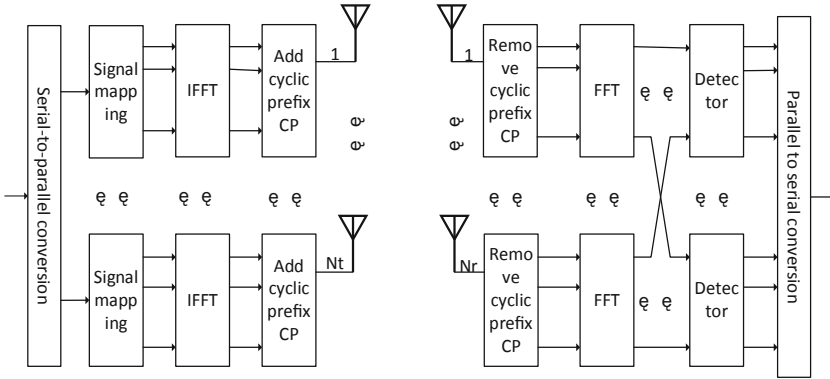


Fig. 1. MIMO-OFDM system model

The receiving end performs the reverse signal processing process of the transmitting end. First, the modulated signal is sent to Nr receiving antennas. The data streams received by different receiving antennas simultaneously are all linearly combined by Nr noisy data streams. The received signal of the system is represented by $y = [y_1, y_2, y_3 \cdots y_{Nr}]$, and the expression is:

$$y = Hx + n \tag{1}$$

The channel matrix is represented by H , and H can be represented as $H = [h_{ij}]_{Nt \times Nr}$; each element h_{ij} in the channel matrix is represented as the channel gain between antennas, i is the transmitting antenna, and j is the receiving antenna. n is expressed as Gaussian white noise with mean 0 and variance [7]. After the CP is removed, the remaining signal is demodulated by FFT; finally, the parallel data flow is detected by the detector. The data is recovered by the parallel/serial converter.

3 CL Algorithm Implementation

3.1 CL Algorithm Description

The sphere detection algorithm assumes an initial search radius d in a given search area, searches for grid points in a multi-dimensional sphere with the received signal vector r as the center of the globe, and finds the nearest grid point to the received signal [8]. The sphere decoding (SD) algorithm can be divided into depth-first strategy and breadth-first strategy. The sphere detection algorithm based on the depth-first approach restricts the search radius by the size of the Euclidean distance to obtain the maximum likelihood performance. The representative algorithms include the VB algorithm and the CL algorithm. The breadth-first strategy is to perform a one-way search by layer by limiting search grid points. Usual algorithms have the K-Best algorithm and the FSD algorithm [9].

The VB algorithm searches for the next signal grid point in the new search area after searching each time after a signal grid point is searched. Therefore, the search will be repeated many times, which increases the calculation amount of the algorithm and makes the algorithm difficult. Increased, and the key to the VB algorithm is the selection of the radius. Too small a radius will affect the experiment's accuracy, while too large a radius will result in too many search grid points and slower computing speed [10].

An improved CL algorithm of the VB algorithm appears in this case, and the CL algorithm proposed by A.M. Chan and I. Lee is an improvement of the VB algorithm [11]. The CL algorithm will update the candidate symbol set and its upper and lower bounds after searching for the signal grid point and then search from the breakpoint from the new reduced radius. So there is no repeated search, thereby reducing the investigation required time eases the CL algorithm's complexity [12].

3.2 CL Detection Algorithm Based on Particle Swarm Optimization

The particle swarm algorithm is a swarm optimization algorithm proposed by simulating a flock of birds' foraging behavior. Each particle represents a solution of the algorithm. They all have a speed expressing the direction and distance of the search path, and then the particle is at the optimal particle. Search in the solution space. Particle swarm can ensure the accuracy and sharing of information and find the best position through continuous improvement [13].

The optimization of particle swarm optimization is mainly accomplished through continuous iteration. First, the number of populations is initialized, and the system randomly generates the parameters, and each repeated loop mainly completes the optimization. The next iteration is to search by each particle's characteristics and their learning factors and keep the particles with better performance for the next search until the best position is obtained. At the end of each cycle, its particle in the particle swarm must update its speed and position until the end of the cycle. The update formula of the particle swarm algorithm is:

$$V_{id} = \omega V_{id} + C_1 \text{random}(0, 1)(P_{id} - X_{id}) + C_2 \text{random}(0, 1)(P_{gd} - X_{id}) \quad (2)$$

$$X_{id} = X_{id} + V_{id} \tag{3}$$

among them: ω — Inertia factor, indicating the influence of the inertial speed on the current speed update;

C_1, C_2 —The acceleration constant, usually a value of 2, is used to measure the degree of learning of the particle to the position with the best global performance and the best part of itself;

P_{id} —Represents the d-the dimension of the extreme individual value of the I-th variable;

P_{gd} —Represents the D-th dimension of the optimal global solution.

First, the optimal radius is obtained by the particle swarm algorithm. The channel matrix H is QR decomposed to receive $H = QR$, where Q is an orthogonal matrix, and R is a $Nt \times Nt$ dimensional upper triangular matrix. Using Q^T , the following formula can be obtained:

$$\|y - Hx\|^2 = \|y - QRx\|^2 = \|Q^T y - Q^T QRx\|^2 = \|Q^T y - Rx\|^2 = \|\bar{y} - Rx\|^2 \tag{4}$$

among them: $\bar{y} = Q^T y$.

Expand to:

$$\left\| \begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \\ \vdots \\ \bar{y}_{Nt-1} \\ \bar{y}_{Nt} \end{bmatrix} - \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1Nt} \\ 0 & R_{22} & \cdots & R_{2Nt} \\ \cdots & \cdots & \vdots & \cdots \\ 0 & \cdots & R_{Nr-1, Nr-1} & R_{Nr-1, Nr} \\ 0 & \cdots & \cdots & R_{Nr, Nr} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{Nt-1} \\ x_{Nt} \end{bmatrix} \right\|^2$$

It can be seen from the expansion that the optimization idea of the particle swarm algorithm is used to solve the optimal solution. Each particle’s path will produce a set of solutions. Under the modulation of P-QAM, each particle has P selection paths.

It can be inferred from solution $\hat{x}_{ML} = \arg \min_{X \in C_{Nt}} \|y - Hx\|^2$ of the ML algorithm,

$$\bar{x} = \arg \min_{X \in C_{Nt}} \sum_{j=1}^{Nr} \left\| \bar{y}_i - \sum_{j=i}^{Nr} R_{ij} X_j \right\|^2 \tag{5}$$

Suppose the distance from the I-th layer to the J-th node is

$$d_{ij} = \bar{y}_i - \sum_{j=i}^{Nr} R_{ij} X_j^2 \tag{6}$$

When the particle swarm completes the first search and performs the next examination, the particle swarm formula is updated. When the termination condition of the algorithm is reached, the particle swarm will produce an optimal solution. The distance between

the generated solution and the received signal is taken as The search radius of the sphere detection algorithm. The CL detection algorithm is searched according to the search radius determined by the particle swarm algorithm. The detection points of the sphere detection algorithm meet the following conditions:

$$\|y - Hx\|^2 \leq d^2 \quad (7)$$

After QR decomposition of the channel matrix H, Eq. 7 can be written as $\|\bar{y} - Hx\|^2 \leq d^2$, which is expanded as

$$d^2 \geq \sum_{j=1}^{Nr} \left\| \bar{y}_j - \sum_{i=1}^{Nr} R_{ij} X_j \right\|^2 \quad (8)$$

Further expand into

$$d^2 \geq \left\| \begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \\ \vdots \\ \bar{y}_{N_T-1} \\ \bar{y}_{N_T} \end{bmatrix} - \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1N_T} \\ 0 & R_{22} & \cdots & R_{2N_T} \\ \cdots & \cdots & \vdots & \cdots \\ 0 & \cdots & R_{N_T-1,N_T-1} & R_{N_T-1,N_T} \\ 0 & \cdots & \cdots & R_{N_T,N_T} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N_T-1} \\ x_{N_T} \end{bmatrix} \right\|^2$$

The analysis of the above formula expands to:

$$d^2 \geq \|\bar{y}_{N_T} - R_{N_T,N_T} x_{N_T}\|^2 + \|\bar{y}_{N_T-1} - R_{N_T-1,N_T} x_{N_T} - R_{N_T-1,N_T-1} x_{N_T-1}\|^2 + \cdots \quad (9)$$

The above formula is only related to $\|\bar{y}_{N_T} - R_{N_T,N_T} x_{N_T}\|^2$ and x_{N_T} , so

$$\left[\frac{-d + \bar{y}_{N_T}}{R_{N_T,N_T}} \right] \leq x_{N_T} \leq \left[\frac{d + \bar{y}_{N_T}}{R_{N_T,N_T}} \right] \quad (10)$$

Among them: $\lceil \quad \rceil$ —the upper bound is rounded, $\lfloor \quad \rfloor$ —the lower bound is rounded.

From Eq. (10), the value of x_{N_T} can be obtained, and the radius can be updated. Let $d_{N_T-1}^2 = d^2 - (\bar{y}_{N_T} - R_{N_T,N_T} x_{N_T})^2$ and $\bar{y}_{N_T-1} = (\bar{y}_{N_T} - R_{N_T-1,N_T} x_{N_T})^2$ be substituted into Eq. (10) to obtain

$$\left| \bar{y}_{N_T-1} - R_{N_T-1,N_T-1} x_{N_T-1} \right|^2 \leq d_{N_T-1}^2 \quad (11)$$

Expand to interval form as

$$\left[\frac{-d_{N_T-1} + \bar{y}_{N_T-1}}{R_{N_T-1,N_T-1}} \right] \leq x_{N_T-1} \leq \left[\frac{d_{N_T-1} + \bar{y}_{N_T-1}}{R_{N_T-1,N_T-1}} \right] \quad (12)$$

Obtain the value of x_{N_T-1} from Eq. (11), and then calculate other values of x in turn. In this process, each time a value of x is obtained in this process, the radius will be updated

once. Secondly, the MMSE detection algorithm is used to reduce the interference caused by noise. The linear operator G can ensure that there is at least one grid point in the search area when the search radius of CL is too small [14]. Then use the attenuation factor to accelerate the convergence speed of the spherical algorithm radius. The shrinkage factor β is used to accelerate the convergence speed of the radius. When a valid grid point is found, the radius is updated. To avoid the search area being empty, the updated radius is:

$$\bar{d}^2 = e^{-\beta \times n_{SNR}} d^2 + (1 - e^{-\beta \times n_{SNR}}) d^2 \tag{13}$$

Among them: d —initial radius; β —compression factor;

Also, the relationship between the algorithm performance loss p and the radius d :

$$p = 1 - \exp\left(-\frac{d^2}{\sigma^2}\right) \sum_{j=0}^{N_t} \frac{1}{j!} \left(\frac{d^2}{\sigma^2}\right)^j \tag{14}$$

4 Performance Simulation and Analysis of CL Algorithm

This simulation software uses Matlab for simulation, the modulation method used is 16QAM, the number of antennas is configured as 2×2 , and the noise type is Gaussian white noise.

Figure 2 below shows the comparison of the complexity of the VB and CL algorithms. It can be seen from Fig. 2 that the computational complexity of the CL algorithm is obviously lower than that of the VB algorithm under the same conditions, so this article chooses to improve and optimize the CL detection algorithm.

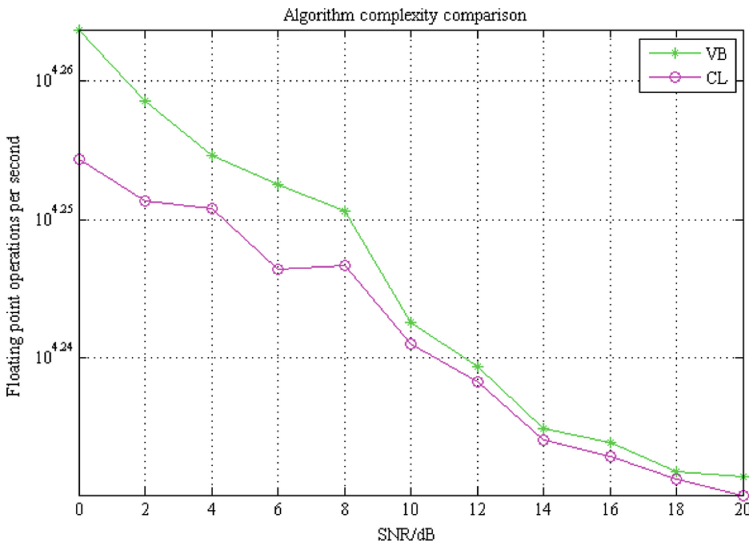


Fig. 2. Comparison of the complexity of VB and CL algorithms

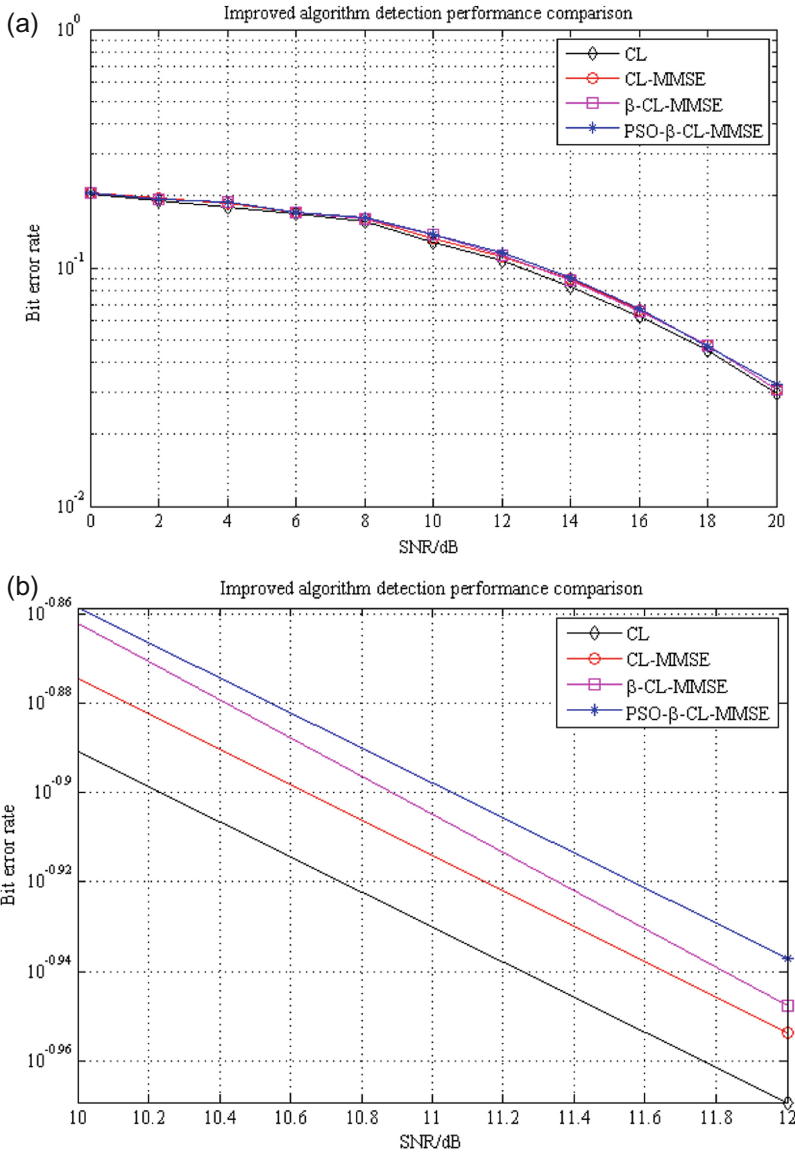


Fig. 3. (a) Comparison of detection algorithm detection performance. (b) Comparison of detection algorithm detection performance

The above Fig. 3(a, b) shows the performance simulation comparison chart of the four detection algorithms. It can be seen from the figure that the error rate difference between the improved algorithm and the traditional CL algorithm is not large. In other words, the improved algorithm can achieve the good detection performance of the CL algorithm, but the performance will be lost. The improved algorithm uses the optimization ability of particle swarms to search for the initial radius. Although the traditional CL detection algorithm does not have a good initial radius, it can still have good detection performance.

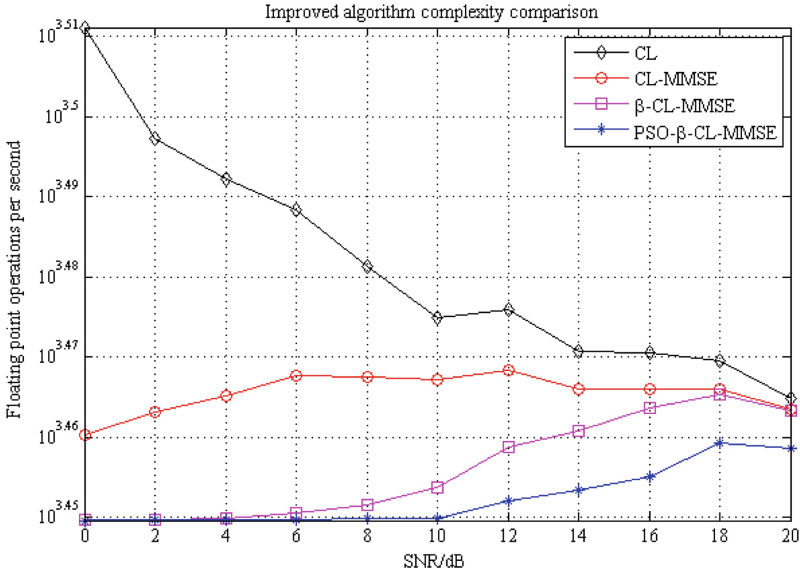


Fig. 4. Comparison of the complexity of three algorithms

Figure 4 above is a comparison of the complexity of the improved algorithm and the traditional CL algorithm. From the comparison of the model, when the signal-to-noise ratio is small, the $PSO - \beta - CL - MMSE$ algorithm's complexity is significantly lower than the other three algorithms, which means that the improved algorithm is effectively more inferior than the different two algorithms the complexity of the algorithm.

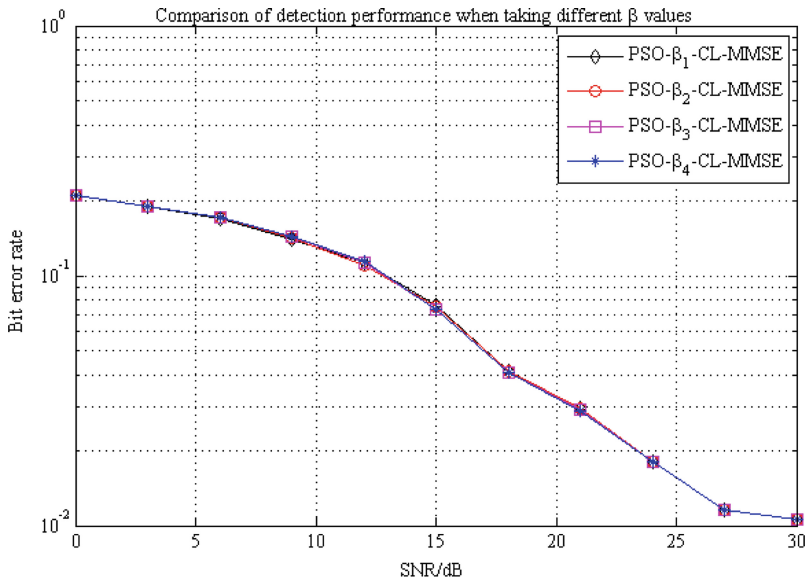


Fig. 5. Improved algorithm's detection performance under different β values

The above Fig. 5 is a simulation comparison of the bit error rate of the $PSO - \beta - CL - MMSE$ improved algorithm when different values of β are taken. Among them, the importance of $\beta_1, \beta_2, \beta_3, \beta_4$ are 0.5, 0.1, 0.04, 0.02, and the difference can be seen from the figure. The convergence factor of β is consistent in detection performance.

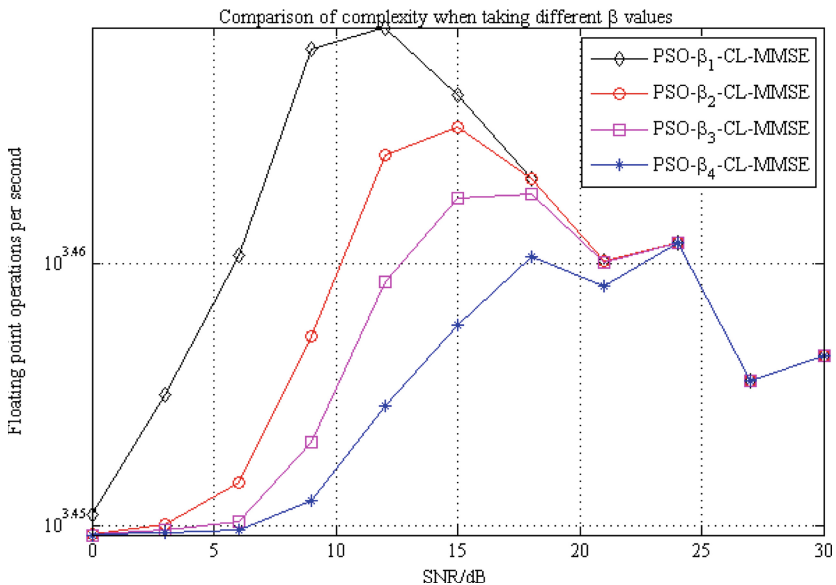


Fig. 6. Comparison of algorithms complexity at different β values

Figure 6 above shows the complexity of the $PSO - \beta - CL - MMSE$ algorithm when β takes different values. It can be seen from the figure that as the value of β decreases, the complexity of the algorithm gradually decreases, and as the signal-to-noise ratio gradually increases, The impact of the importance of β on the complexity of the algorithm is slowly falling.

5 Conclusion

The purpose of this paper is to find a low-complexity sphere detection algorithm based on the MIMO-OFDM system to improve the detection performance of the algorithm. Given the sphere detection algorithm's high complexity, the general solution is to improve the initial radius or speed up the shrinkage. The method used in this paper is a combination of the two, so the $PSO - \beta - CL - MMSE$ algorithms are proposed. The simulation results show that the improved algorithm dramatically reduces the algorithm's complexity when the signal-to-noise ratio is low while retaining better detection performance. The enhanced algorithm is a practical improvement in the CL algorithm.

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References

1. Jing, S.: Research on channel estimation and signal detection algorithms in MIMO_OFDM system Shen Jing. Beijing University of Posts and Telecommunications, Beijing (2012)
2. Jingpeng, G.: Research on joint method of channel estimation and signal detection in MIMO_OFDM system. Harbin Engineering University, Heilongjiang (2014)
3. Rui, W.: An improved ZF-OSIC signal detection algorithm in MIMO system. Inf. Technol. **34**(4), 165–168 (2017)
4. Men, H., Jin, M.: A low - complexity ML detection algorithm for spatial modulation systems with PSK constellation. IEEE Commun. Lett. **18**(8), 1375–1378 (2014)
5. Zhibin, X., Weichen, Z., Tongsi, X.: A low-complexity sphere detection algorithm for MIMO systems. Ship Sci. Technol. **35**(8), 28–33 (2013)
6. Dan, W., Chao, S.: Improved MIMO system ball decoding and detection algorithm. Sensors Microsyst. **35**(8), 123–126 (2016)
7. Jiejun, W.: Research on improved algorithm of SM system signal detection based on signal vector. Chongqing University, Chongqing (2016)
8. Nan, L., Qianzhu, W., Deling, H.: Research on low-complexity massive MIMO signal detection algorithm. Inf. Commun. **1**, 32–34 (2017)
9. Jianqing, C., Lijia, G., Hui, H., et al.: Performance simulation comparison of sphere decoding algorithm in MIMO system. Antenna Servo Technol. **38**(6), 38–41 (2012)
10. Nguyen, V.H., Berder, O., Scalart, P.: On the efficiency of sphere decoding for linearly precoded MIMO systems. In: Wireless Communications and Networking Conference (WCNC), pp. 4021–4025. IEEE, Shanghai (2013)
11. Ngo, H., Larsson, E., Marzetta, T.L.: Energy and spectral efficiency of very large multiuser MIMO systems. IEEE Trans. Wirel. Commun. **61**(4), 1436–1449 (2012)

12. Diyuan, G.: Improved research on sphere decoding and detection algorithm in MIMO system. Northeastern University, Liaoning (2014)
13. Chunmeng, G.: Research on spatial modulation signal detection algorithm based on particle swarm optimization. Harbin Institute of Technology, Heilongjiang (2015)
14. Rui, L., et al.: Research on the application of sphere decoding algorithm in signal space diversity system. *Comput. Appl. Res.* **34**(5) 1452–1454 (2017)