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Research article

An improved signal detection algorithm for a mining-purposed MIMO-OFDM IoT-based system

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Abstract: The coal mine internet of things (IoT) communication system is used for real-time monitoring of mining production to ensure the safety and reliability of personnel and equipment in the mine. To eliminate multipath fading in the process of wireless communication in mines, multiple-output multiplexing (MIMO) and orthogonal frequency division multiplexing (OFDM) technologies are introduced. In this paper, a wireless communication system architecture of IoT in mining based on MIMO-OFDM is constructed. Aiming to solve the problems of intersymbol interference and frequency selective fading at the receiver, an improved minimum mean square error ordered successive interferences cancellation (MMSE-OSIC) signal detection algorithm is proposed. First, the signal-to-interference plus noise ratio of the received signal is calculated and the calculation results are sorted. The lowest signal-to-noise ratio is selected as the weakest signal layer. Then, the MMSE-OSIC algorithm is used to extract all of the signals, except the weakest layer. Finally, a maximum likelihood (ML) algorithm is used to traverse the whole signal domain; the signal symbol with the smallest distance from the weakest signal layer is found as the original signal of the weakest signal layer, and it is combined with the signal detected by MMSE-OSIC; then, the final signal detection result is obtained. The simulation results show that, compared with three benchmark algorithms, the proposed MMSE-OSIC algorithm has better signal detection performance under the conditions of different modulation methods and different channel numbers.

Keywords: coal mine; IoT; MIMO-OFDM; signal detection; MMSE; ML

1. Introduction

At present, the common problems in underground coal mine communication systems in China are poor anti-interference performance, excessive background noise, low reliability and a harsh underground environment, which makes intelligent 5G communication equipment unable to achieve optimal performance in underground mobile communication systems. Therefore, improving the communication quality, anti-interference and noise resistance of existing underground mobile communication systems in coal mines, improving spectrum utilization and ensuring communication reliability, effectiveness and real-time performance are of great significance for the improvement of underground communication technology, safe production in coal mines and the modernization of the coal industry [1]. By applying the IoT technology to a coal mine environment, the mining-purposed IoT communication system is built, which can provide a new way to solve mine-related safety problems. The special working environment in coal mines makes mining production extremely dangerous. The use of a mining-purposed IoT system can enable the real-time detection of mining production safety conditions, which can effectively improve the reliability of underground personnel safety. Therefore, the effectiveness and reliability of the mining-purposed IoT communication system is an important guarantee for the safe production in coal mines. Currently, mining wireless communication systems include cellular communication (4G/5G), Wi-Fi, wireless sensor networks (WSN), ultra-wideband (UWB), visible light communication (VLC), etc. Mining-purposed wireless communication technology is mature, and there are many wireless communication methods available in mines, but there is a serious multipath fading problem in the actual mining-purposed IoT wireless communication system. Multipath fading can destroy the transmission characteristics of signals and generate intersymbol interference [2], which degrades the quality of wireless communication systems and reduces the reliability of underground communication systems. Therefore, the multipath fading problem of signal transmission has become a key factor restricting the communication reliability of the mining-purposed IoT system.

In a mine tunnel, signals affected by the channel environment in the transmission process will reach the receiver through multiple paths, resulting in mutual influence of signals, known as intersymbol interference. Therefore, eliminating inter-code interference is an important problem faced by mining communication systems. Because the traditional anti-multipath fading scheme is difficult to effectively implement in underground coal mines, the combination of orthogonal frequency division multiplexing (OFDM) technology and multiple-input multiple-output multiplexing (MIMO) technology can not only remove the influence of intersymbol interference and solve the problem of frequency-selective fading, but it can also increase the channel capacity [3]. MIMO technology makes full use of the spatial selectivity by dividing the channel into several sub-channels, causing the system capacity to significantly increase and the system spectrum utilization rate to correspondingly improve. OFDM can effectively suppress the frequency-selective fading caused by multipath propagation [4]. The combination of MIMO technology and OFDM technology allows for full exploitation of their respective advantages, which affords more advantages than other technologies. However, in a MIMO-OFDM system, the multiple receiving antennas at the receiving end receive mostly mixed noise and interference signals, so the signal detection technology becomes particularly important and plays a crucial role in improving the performance of the MIMO-OFDM communication system.

Signal detection is a technique that processes the baseband signal at the receiver to restore the transmission and signal. The purpose of MIMO signal detection is to use accurate channel state information to remove the influence of noise and interference in the received signal, and thereby recover the transmitted symbols. There have been many literature reviews on MIMO signal detection methods [5,6]. First, the best signal detection algorithm represented by the maximum likelihood (ML) algorithm can globally traverse the entire vector space of the transmitted signal, and this algorithm can yield the optimal solution. However, the complexity of this algorithm is high, especially when the number of antennas introduce high dimensionality, making the implementation of the algorithm extremely difficult. Second, typical linear detection algorithms use a weighted matrix to eliminate interference and perform linear filtering on the received signal. For example, zero forcing (ZF) detection and minimum mean square error (MMSE), where the ZF detection can remove interference between different antennas, but it also amplifies the noise in the process, resulting in higher detection errors when the signal-to-noise ratio (SNR) is low. The MMSE detection algorithm is improved on the basis of the ZF detection, which can be seen as a matching filter to further balance the effect of noise, resulting in better bit error rate (BER) performance. Finally, the most common nonlinear detection algorithm is the sequential interference cancellation (SIC) algorithm, which adds a decision feedback step to the linear algorithm and can be seen as an improvement of the linear algorithm; examples include ZF-SIC detection and MMSE-SIC detection algorithms. However, all of the above three signal detection methods have their own advantages and disadvantages and cannot be directly applied to coal mine scenarios. Therefore, it is necessary to design a new signal detection algorithm for actual coal mine wireless communication systems.

At present, the research on MIMO-OFDM systems for mines mainly focuses on channel modeling. Sun and Chen [7] analyzed the propagation characteristics of signals in a mine and obtained the optimal transmission frequency of electromagnetic waves through the use of the actual measurement data in the mine. He proposed 5G with large-scale MIMO antennas to be the key technology that will become the wireless communication technology for mining in the future. Wang et al. [8] presented a statistical model of broadband channels in mine tunnels and established a MIMO-OFDM system for mines. On this basis, the transmission performance of MIMO-OFDM technology in multipath fading was analyzed. Yao and Wu [9] established the mining-purposed MIMO correlation channel model by considering that the channel capacity of underground MIMO would be affected by the scattering parameters and antenna array correlation. In [10], a stochastic MIMO channel model was first proposed based on the wireless propagation conditions in mine tunnels, and then two spatial correlation channel models were established through the use of correcting channel matrices based on an abundant scattering environment. Zhang et al. [11] proposed a modeling method for MIMO correlation channels in coal mine tunnels. This method utilizes the impact response of electromagnetic waves propagating in the tunnel to obtain the frequency response of a single-input single-output system. Liu et al. [12] established a MIMO channel model of a coal mine and deduced the spatial correlation function of the channel model. Zhang et al. [13] studied the multiple factors affecting the MIMO information channel volume in an underground mine and conducted simulation analysis based on the application problems of MIMO in the special communication environment of a restricted non-free space in an underground mine. In [14], a novel fast recursive successive interference cancellation multi-user detection algorithm with inverse detection order is presented to reduce the computational complexity and improve the system capacity. A comparison of MIMO-OFDM systems for mines is presented in Table 1. However, most of these existing research methods focus on the analysis of the usability of MIMO-OFDM technology in underground mines, and there is relatively little research on signal detection methods for resisting multipath fading in underground coal mines. Therefore, it is necessary to investigate a signal detection algorithm for MIMO-OFDM systems for mines.

Table 1. Research comparison of MIMO-OFDM methods for use in mines.

Reference	Key method	Feature
[9]	Layered space-time codes and space-time trellis codes.	Overcome the impact of strong spatial correlation
[10]	A stochastic MIMO channel model and two spatial correlation channel models.	The error rate performance of the complex correlation channel model is closer to the measured data.
[11]	A model of MIMO correlation channels.	The existence of correlation reduces the capacity of the channel. Increasing the number and spacing of antennas can reduce the correlation coefficient and increase the channel capacity.
[12]	The space-time correlation of MIMO channels in mines.	The higher the spatial correlation of MIMO channels in coal mines, the higher the error rate of the system.
[13]	The MIMO information channel and particle swarm algorithm.	The MIMO applied to the mine passageway has certain feasibility and practices.
[8]	A modified time-varying multipath channel.	Improve the capacity of the system and overcome the multipath fading.
[14]	MIMO-OFDM system and MMSE filter.	Reduces the computational complexity and yields better detection performance.
[7]	Mine-purposed 5G mobile communication.	Improves the stability and reliability of wireless communication systems in mines.

Traditional signal detection algorithms can be divided into three categories, namely, linear detection algorithms, nonlinear detection algorithms and optimal detection algorithms; detailed research on these methods can be found in [15–20]. Wang et al. [21] made use of a traversal search technique in an ML detection algorithm to selectively modify the detection results of a zero forcing-ordered successive interference cancellation (ZF-OSIC) algorithm, so as to improve the detection performance with minimal increase in algorithm complexity; however, the detection performance of this algorithm is poor. In order to reduce the error probability, a V-BLAST algorithm has been proposed [22]. The principle of the V-BLAST algorithm is to preferentially detect the signal with a high SNR each time, so as to improve the quality of each judgment and minimize error propagation. But, the total computational complexity of this algorithm is too high. Elgabli et al. [23] proposed a signal detection algorithm based on the alternating minimization technique. When the number of sender antennas is close to the number of receiver antennas, the complexity of the algorithm is lower. Wu and Fu [24] proposed a large-scale MIMO signal detection algorithm based on a deep neural network; it has the advantages of low complexity, a fast convergence speed and good detection performance. Li et al. [25] proposed an end-to-end MIMO system signal detection scheme based on deep learning, which has better detection performance than MMSE algorithms in terms of time complexity. Jin and Kim [26] proposed a parallel detection network, which is composed of multiple detection networks based on deep learning in parallel. By designing a specific loss function, the similarity between detection networks is reduced and the system performance is improved. Liao et al. [27] introduced the cyclic structure into the neural network and proposed a low-complexity MIMO system detection network. The detection scheme can be trained from scratch, it has a cyclic network structure and it can be converted from other deep neural network models. At present, signal detection algorithms based on ML are considered to be the most popular type of scheme. To overcome the problem of high computational complexity of the ML detection algorithm for the generalized space shift keying (GSSK) systems, a low-complexity detection algorithm based on compressed sensing theory was proposed [28]. Focusing on the high complexity of the maximal ratio combining (MRC) signal detection in a MIMO orthogonal time frequency space (OTFS) system, a low-complexity MRC estimation algorithm was proposed [29]. In [30], an improved Richardson signal detection method is proposed; it uses the steepest descent and the whole-correction methods to improve the performance of the Richardson algorithm. In [31], a method that combines deep learning and successive interference cancellation algorithms for uplink signal detection in a massive MIMO system was proposed. Shen et al. [32] proposed a new signal detection algorithm for the uplink of MIMO systems that combines the orthogonal approximate message passing algorithm with a sparsely connected neural network to form a trainable network structure. Based on the structure and sparsity of multi-user generalized spatial modulation signals, the detection problem is transformed into a block sparse recovery problem, and a block-sparsity adaptive matching pursuit algorithm was proposed [33]. In practical applications, the availability of an algorithm depends on its detection performance and computational complexity. Unlike surface applications, the environmental parameters for mines are more complex and the equipment power is limited.

Based on the above analysis, this paper mainly focuses on the performance of traditional signal detection algorithms in a MIMO-OFDM system under the conditions of a coal mine environment and presents an improved MMSE-OSIC signal detection algorithm suitable for the coal mine-purposed IoT system. The main contributions of this article are summarized as follows.

- A MIMO-OFDM signal detection system with mining-purposed IoT is proposed. In this system, the capacity of the IoT in mining system is increased by dividing the channel into several subchannels by using MIMO technology, and the OFDM technology is used to effectively suppress multipath fading.
- An improved MMSE-OSIC signal detection algorithm is proposed. First, the signal-to-interference plus noise ratio of the received signal is calculated and the calculated results are sorted. The lowest SNR is selected as the weakest signal layer. Then, MMSE-OSIC algorithm is used to extract all of the signals except the weakest layer. Finally, an ML algorithm is used to traverse the whole signal domain; the signal symbol with the shortest distance from the weakest signal layer is found as the original signal of the weakest signal layer and combined with the signal detected by MMSE-OSIC; then, the final signal detection result is obtained.
- The effectiveness of the proposed algorithm is verified through extensive simulations. By comparison with ZF, ZF-OSIC and MMSE null criteria algorithms, the effectiveness of the MMSE-OSIC algorithm is verified. Compared to the classical MMSE-OSIC and ML detection algorithms, the proposed algorithm has better performance under the conditions of different modulation methods and different channel multipath numbers.

2. MIMO-OFDM signal detection system for mining-purposed IoT

This paper focuses on a MIMO-OFDM signal detection system for mining-purposed IoT, as shown in Figure 1. MIMO technology can achieve better multiplexing gain by using multiple antennas, thus improving the capacity and reliability of the wireless communication system [34]. The signal is encoded into the OFDM system through MIMO, and an OFDM symbol is formed by quadrature subcarrier modulation. It is transmitted to the mine by the transmitter, and the spatial information-related channel is subject to interference by noise in the transmission process; the receiver receives the signal into the OFDM system for demodulation. The signal is detected by via a fast Fourier transform, and the original signal is finally recovered by MIMO decoding.

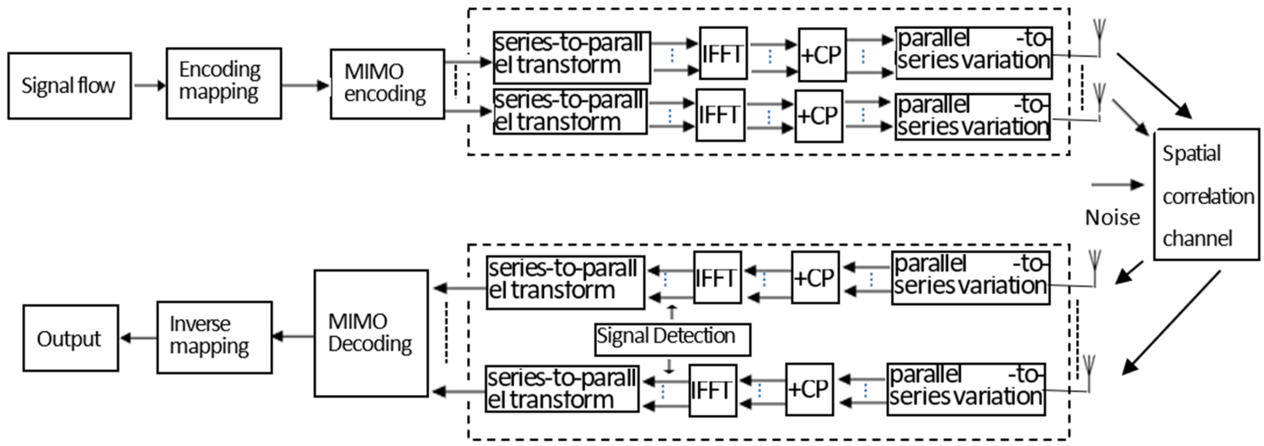

Figure 1. MIMO-OFDM signal detection system for mining-purposed IoT.

Therefore, the signal detection process of a MIMO-OFDM system for mines is described as follows:

1) The signal is encoded by MIMO and then entered into the OFDM system for modulation. Through the series parallel conversion, the signal is expressed as $\{X_i\}_{i=1,2,\ldots,m}$;

2) The signal changes from the frequency domain to the time domain signal through the fast Fourier inversion transformation, and with the cyclic prefix, the signal can be expressed as $\{X(t)_i\}_{i=1,2,\ldots,m}$;

3) The signal enters the mine's spatial correlation channel through the transmitting antenna, and it is received by the receiving antenna under the influence of channel noise. The received signal can be expressed as $\{Y(t)\}_{i=1,2,\ldots,m}$;

4) The received signal is demodulated into the OFDM system at the receiving end. After removing the cyclic prefix and performing the fast Fourier transform, the signal changes from the time domain to the frequency domain, which can be expressed as the fast Fourier transform. The signal changes from the time domain to the frequency domain, which can be expressed as $\{Y_j\}_{j=1,2,\ldots,n}$. The subcarrier of the signal is detected by the signal detection technology, and the detected signal can be expressed as $\{K_i\}_{i=1,2,\ldots,m}$.

The number of antennas at the transmitting end and the receiving end are respectively set as N_T and N_R, and the matrix of the mine correlation channel is H_{corr}. Assuming that the channel is only affected by additive white Gaussian noise, the mean value of the noise vector N is 0 and the variance is σ^2; then,

$$Y = H_{corr}X + N \tag{1}$$

For the MIMO-OFDM signal detection system in the mine, when the signal is detected, the subcarrier on the orthogonal subchannel is actually detected [35]. When there are K subcarriers, it is equivalent to the sum of signal detection for the matrix $N_T \times N_R$ of K channels. The notations in this paper are listed in Table 2.

Table 2. List of symbols.

Symbol	Meaning
N_T	Number of antennas at the transmitter
N_R	Number of antennas at the receiver
$\boldsymbol{H}_{corr}$	Matrix of correlation channel
N	Additive Gaussian white noise
K	Number of subcarriers
W_{MMSE}	Weighted matrix using MMSE
H	Channel matrix
σ_z^2	Noise variance
I	Unit matrix
$SINR$	Signal-to-interference-noise ratio
E_x	Energy of the transmitted signal
$\hbar_i$	Column i of channel matrix
r	Received signal
s	All symbol sequences at the transmitter
C	Spatial domain
Y_i	Received signal for i-th detection
$P(r/s)$	Likelihood function estimation
x_i	The i-th symbol to be detected after sorting
σ_n^2	Statistical information of interference
$\widehat{x_i}$	Slice value of the i-th symbol to be detected after sorting

3. MMSE-OSIC detection method

The MMSE-OSIC method entails the use of one of the OSIC detection algorithms. It uses the MMSE as a criterion to extract the signal containing noise and reduce the influence of noise.

The OSIC algorithm is a nonlinear signal detection algorithm, which itself is an improvement on linear detection algorithms MMSE and ZF. OSIC achieves better detection performance with minimal increase in complexity [36]. The OSIC algorithm can be roughly divided into several steps, such as sorting, zeroization and interference elimination. The whole process can be described as follows:

- Use the receiving end of the system to sort the sent signals in a certain order after receiving them;
- Test in sequence according to the order;
- Subtract the signal detected through quantitative feedback each time from the original received signal to avoid the influence of the first detected signal on the subsequent detected signal.

In turn, the OSIC signal detection process for detecting the signal in its entirety is shown in Figure 2.

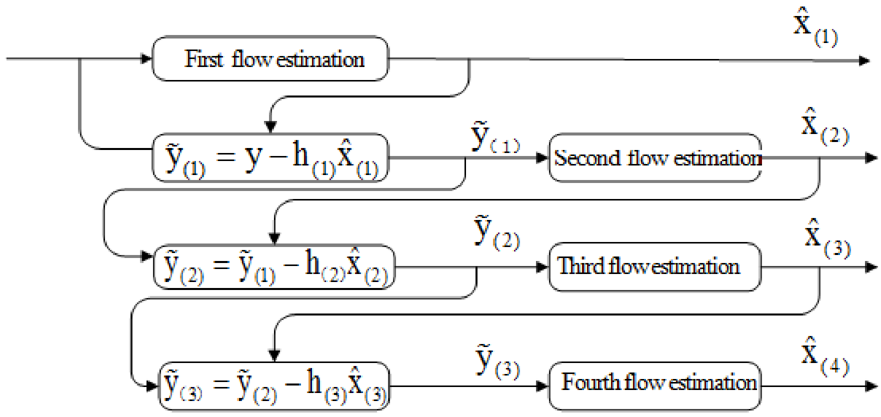

Figure 2. The flowchart of the OSIC signal detection process.

In Figure 2, x_i represents the i-th symbol to be detected after sorting, $\hat{x}_i$ is the slice value of x_i and h_i is the i-th column of the channel matrix. Here, the first line of the weighted matrix of the MMSE or ZF is used to estimate and slice the first data stream to obtain $\hat{x}_i$, and then $\hat{x}_i$ is subtracted from the signal received by the receiver to obtain the remaining signal. The whole process is shown in formula (2).

$$\overline{y}_{(1)} = y - h_{(1)}\hat{x}_{(1)} = h_{(1)}\left(x_{(1)} - \hat{x}_{(1)}\right) + h_{(2)}x_{(2)} + \cdots + h_{(N_T)}h_{(N_R)} + n \tag{2}$$

In formula (2), only when $\hat{x}_{(1)}$ is completely equal to $x_{(1)}$ can the interference of the previous symbol $x_{(1)}$ be eliminated when the next symbol $x_{(2)}$ is estimated, so as to avoid error propagation. Therefore, the selection of the estimation sequence and zero-trap criterion is crucial for signal detection.

The MMSE is one of the commonly used zero-trap criteria. In the MMSE-OSIC algorithm, the first line W_{MMSE} of the MMSE weighting matrix is used to estimate and slice the received data, and the corresponding $\hat{x}_i$ is obtained. The calculation formula for W_{MMSE} is shown in formula (3).

$$W_{MMSE} = (H^H H + \sigma_Z^2 I)^{-1} H^H \tag{3}$$

where H represents the channel matrix, σ_Z^2 represents the noise variance and I represents the identity matrix of $n_t \times n_t$.

It can be ascertained from the formula that the influence of noise on signal detection is considered in the W_{MMSE} matrix.

The MMSE criterion is used to detect signals sorted based on the signal-to-jamming and noise ratio (SINR); the posterior SINR can be expressed as

$$SINR_i = \frac{E_x|w_{i,MMSE}h_i|^2}{E_x\sum_{l\neq i}|w_{i,MMSE}h_l| + \sigma_n^2\|W_{i,MMSE}\|^2}, i = 1,2,3 \ldots, N_T \tag{4}$$

where E_x is the energy of the transmitted signal, h is the i-th column of the channel matrix, σ_n^2 is the statistics of interference and $W_{i,MMSE}$ is the i-th row of the weighted matrix. As can be understood from the formula, the SINR changes with the mean square error, When the mean square error is the minimum, the SINR can achieve the maximum. When the SINR of all received signals is obtained, the layer corresponding to the maximum SINR can be found through comparison and detected. Before the next detection, the interference generated by the previous signal needs to be eliminated. Assuming that the i-th element of the transmitting signal is detected, the specific steps are as follows. First, delete the last detected signal and its column in the channel matrix to eliminate its channel gain and obtain a new channel matrix:

$$H^i = \left[h_1, h_2, \dots, h_{i-1}, h_{i+1}, \dots, h_{N_T}\right] \tag{5}$$

Replace the original matrix with the new channel matrix to obtain the new MMSE weighted matrix W_{MMSE}, and repeat the above operations until all components are detected. Calculation in the MMSE-OISC algorithm requires $N_T\ (N_T + 1)/2$ times in total.

Above all, the MMSE-OISC detection algorithm can be applied to scenes with large interference, such as mines, because it takes into account noise factors and has the advantage of low algorithm complexity. However, low algorithm complexity also leads to poor signal detection performance. In the mine scene, it is of great significance that a mine communication system be able to detect the signal accurately and effectively, so this paper focuses on an improved MMSE-OSIC detection algorithm, which can adapt to the influence of mine-specific environmental factors to ensure the performance of signal detection.

4. Improved MMSE-OSIC detection algorithm

4.1. ML detection algorithm

The ML detection algorithm is recognized as the optimal detection algorithm. When a signal is received, the algorithm conducts a global search in all possible transmitting signal domains and looks for the transmitting symbol with the shortest distance from the received signal as the original transmitting symbol. According to the probability theory, if the system inputs are all sequences of information with equal probability, then, by comparing the conditional probability of these information sequences and selecting the information sequence with the largest conditional probability, the error probability of the decoder can be minimized. If the following formula is satisfied, the decoder will select s, namely,

$$s_{ML} = \arg\max_{all\ s} P(r/s) \tag{6}$$

For all information sequences, formula (9) is the expression for making the decision. If the likelihood function $P(r/s)$ of a sequence s reaches the maximum, the decoder selects the transmitted sequence s.

Generally, the Bayesian maximum posterior probability criterion is the detection basis of ML estimation. When the estimated quantity s is a random unknown parameter, the ML function $P(r/s)$ corresponding to s needs to be taken as the estimator, i.e.,

$$\frac{\partial \ln P(r/s)}{\partial s}\Big|_{s=\hat{s}\mathrm{MAP}(x)} \tag{7}$$

Therefore, the ML detection criterion for MIMO-OFDM systems is expressed as

$$\hat{s} = \underset{s\in\Omega}{\mathrm{argmax}} \|r - Hs\| \tag{8}$$

where r is the received signal, H is the channel's fading sparsity and s denotes all possible symbol sequences sent by the sender.

According to formula (1), the signal vector expression of a MIMO-OFDM system in a mine is established. The optimal ML detection algorithm vector expression can be expressed as

$$\hat{x}_{ML} = \underset{x\in\Omega^{N_T}}{argmin} p(y|H_{corr}, X) = \underset{x\in\Omega^{N_T}}{argmin} \parallel Y - H_{corr}x \parallel^2 \tag{9}$$

It can be concluded from formula (9) that signal detection with the ML algorithm requires searching each lattice point one by one over the whole spatial domain C, and $|C|^{N_T}$ ML metric values in total need to be calculated.

4.2. MMSE-OSIC detection algorithm

According to the above analysis, the core part of the MMSE-OSIC algorithm can be described as the following process:

Initialization: $G = ({H_{corr}}^H H_{corr} + \sigma^2 I_M)^{-1} {H_{corr}}^{H_{corr}}$.

Iterative process:

$$\begin{aligned} k_i &= argmin\left\|(\mathrm{G}_i)_j\right\|^2 \\ y_{k_i} &= (\mathrm{G}_i)_{k_i}\mathrm{Y}_i \\ \hat{x}_{k_i} &= Q\left(y_{k_i}\right) \\ \mathrm{Y}_{i+1} &= \mathrm{Y}_i - \mathrm{H}_{\mathrm{corr}_{k_i}}\hat{x}_{k_i} \\ \mathrm{G}_{i+1} &= (\mathrm{H}_{\mathrm{corr}_{k_i}}^{H}\mathrm{H}_{corr_{k_i}} + \sigma^2\mathrm{I}_{N-i+1})^{-1}\mathrm{H}_{corr_{k_i}}^{H} \\ i &= i+1 \end{aligned} \tag{10}$$

where represents the *j*-the row of weighted matrix G_i based on the MMSE zero-notch criterion; k_i represents the detected signal layer i, Y_i represents the received signal detected for the *i*-th time, $\hat{x}_{k_i}$ represents the transmitted signal of the transmitting antenna k_i of the quantitative judgment, I is the unit matrix and H_{corr} is the k_i-th column of the spatial correlation matrix $\boldsymbol{H}$. When $i = N + 1$, all signals are detected.

4.3. Improved signal detection algorithm

According to formula (9), the ML algorithm is the optimal detection algorithm among all signal detection algorithms, but, with the increase of modulation order and the number of antennas, the amount of computation increases exponentially [37]. ML is often used for low-order simulations to compare the performance of other detection algorithms. Because the MMSE-OSIC algorithm considers the noise factor, it is suitable for underground mines. The MMSE algorithm has an advantage over ML in terms of computational complexity, but its detection performance is still much worse. However, note that, the signal can be accurately and effectively detected in mines, which is of great significance for a mine communication system. In this work, an improved MMSE-OSIC signal detection algorithm is obtained by combining the high performance of the ML algorithm and low complexity of the MMSE-OSIC algorithm.

The SNR formula after detection by the improved MMSE-OSIC algorithm is

$$\rho_i = \frac{\sigma_s^2}{\|\mathrm{G}_i\|^2\sigma_n^2} \sim \frac{1}{\|\mathrm{G}_i\|^2} \tag{11}$$

where σ_s^2 is the transmitted signal energy; σ_n^2 is noise energy. $\|G_i\|$ is the norm of a weighted matrix based on the MMSE zero-notch criterion. It can be understood from formula (11) that the SNR ρ_i is inversely proportional to the norm of G_i. It can be seen from the algorithm flow formula for MMSE-OSIC that the sorting criterion is to sort the SNR, which is achieved by detecting the strongest SNR first so as to reduce the signal interference of this layer to other layers. However, the signal with the lowest SNR is of poor quality and has a high possibility of error. If the signal at this layer can be accurately detected, the performance of the system will be improved. Therefore, the influence brought by the weakest layer should be eliminated first, and the calculation expression is as follows:

$$k_i = argmax\left\|(\mathrm{G}_i)_j\right\|^2 \tag{12}$$

where k_i is the weakest signal layer.

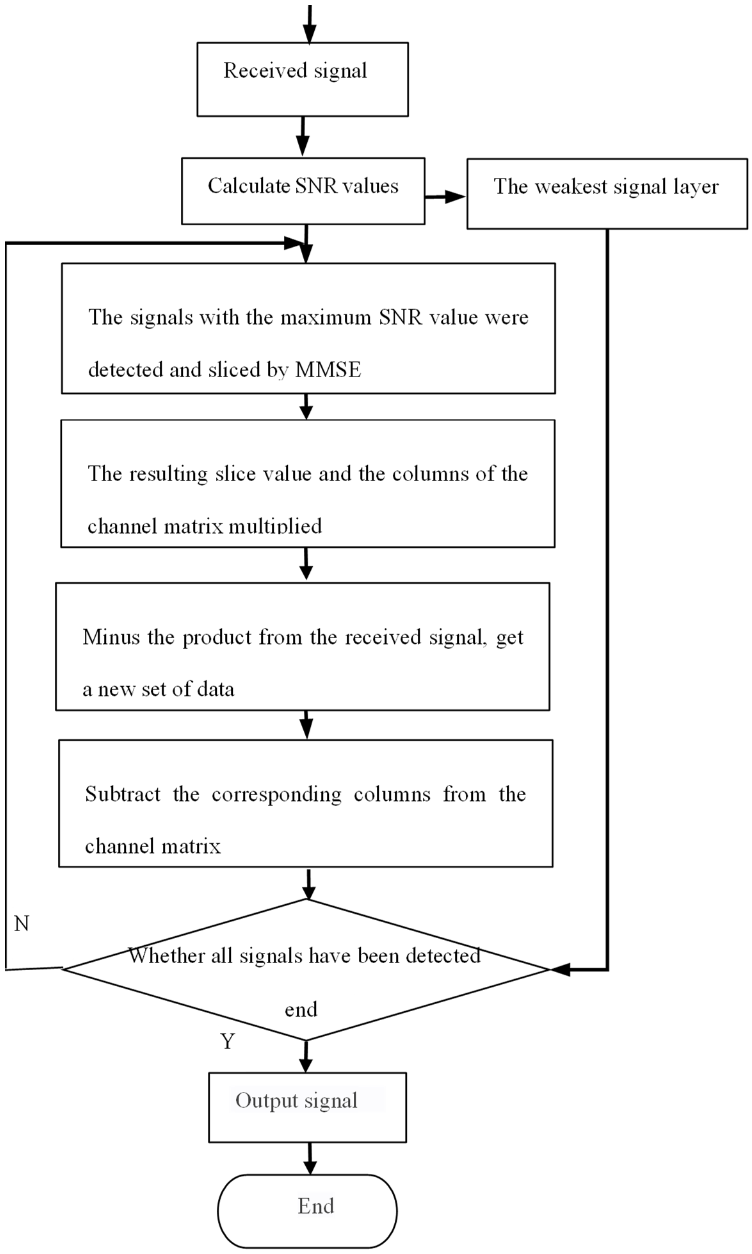

Figure 3. Flowchart of MMSE-OSIC signal detection algorithm.

After the weakest signal layer is detected by formula (12), the global search and detection of the weakest layer is accurately carried out in combination with the best detection performance of ML, so as to weaken the interference of the worst signal of this layer in other signals. The remaining signals will be detected by applying OSIC according to the MMSE's zero-trap criterion, and all signals will be detected eventually.

It should be noted here that the determination of which value is the correct value of the detected signal is made by comparing the error metric ζ obtained by traversing the search for various signal values, calculated as

$$\zeta = \|r - Hs\|^2 \tag{13}$$

The detection flow of the improved MMSE-OSIC detection algorithm is shown in Figure 3. The whole process can be divided into the following four steps:

1) The receiver receives the signal and calculates the SNR value of each received signal. According to the calculated value, the SNR is sorted from small to large. The minimum value (the weakest signal layer) is selected for ML detection, various values are traversed and the remaining layers are sorted from large to small.
2) MMSE detection and the sectioning of signals with the maximum SNR value are performed.
3) The obtained slice value $\hat{x}_i$ is multiplied by column h_i of the channel matrix.
4) To eliminate the influence of the detected signal of the previous layer, the product of $\hat{x}_i$ and h_i should be subtracted from the signal to obtain the signal that eliminates the interference of the detected signal layer, and column h_i of the channel matrix used for detection of the upper layer should also be removed.

Repeat Steps 2 to 4 until all signals are detected.

4.4. Complexity analysis

The MMSE-OSIC detection algorithm with low complexity is improved by an ML traversal search, which reduces the influence of a wrong decision caused by poor signal quality on subsequent signals.

From the perspective of the complexity of the algorithm, when ML detection of signals is carried out, it is necessary to conduct a global search for the ownership point of the modulation constellation; while the transmitting antenna is N_T, B paths need to be searched.

When the signal is detected via the MMSE-OSIC technique, the algorithm needs $N_T\ (N_T + 1)/2$ operations on the signal. In the improved MMSE-OSIC algorithm, the worst signals are detected via a global ML search, all possible values of the modulation lattice points are determined and the remaining signals are detected by applying the MMSE-OSIC technique. Because the improved MMSE-OSIC algorithm adds the ML global search detection of the worst signal layer, the complexity of the improved MMSE-OSIC algorithm is $N_T\ (N_T + 1)/2 + L$, which only increases the traversal of L values compared with MMSE-OSIC detection.

5. Simulation and results analysis

5.1. Performance analysis of OSIC algorithm based on different zero-trap criteria

The ZF, ZF-OSIC, MMSE and MMSE-OSIC algorithms with different zero-trap criteria were simulated and compared by using MATLAB simulation software. Considering that most of the non-line-of-sight path transmission exists in the mine passageway, the Nakagami spatial correlation channel model with m = 1 is adopted in order to conform to the characteristics of an underground mine channel, which is similar to a Rayleigh channel. In the simulation, we chose the quadrature phase shift keying (QPSK) and binary quadrature amplitude modulation (4QAM) methods. QPSK is the most commonly used orthogonal phase-shift keying modulation method; it has high spectral efficiency, strong anti-interference ability and is relatively simple to implement in the circuit. QAM is a type of orthogonal amplitude modulation method in which the amplitude and phase of the carrier signal are used to represent different digital bit encodings during the modulation process. It combines multi-band and orthogonal carrier technology to further improve frequency band utilization. 4QAM represents the use of four signal points to transmit two bits of information. Generally, the higher the number of sampling points, the better the transmission efficiency. However, considering its practicality in underground mines, the 4QAM modulation method is chosen here. The system parameters were set as shown in Table 3; other simulation parameters can be found in [38–40].

Table 3. Simulation parameters.

Parameter	Value
Modulation method	QPSK, 4QAM
Subframe length/ms	1
Antenna configuration	4 × 4
Noise type	Gaussian white noise with mean 0 and variance 1

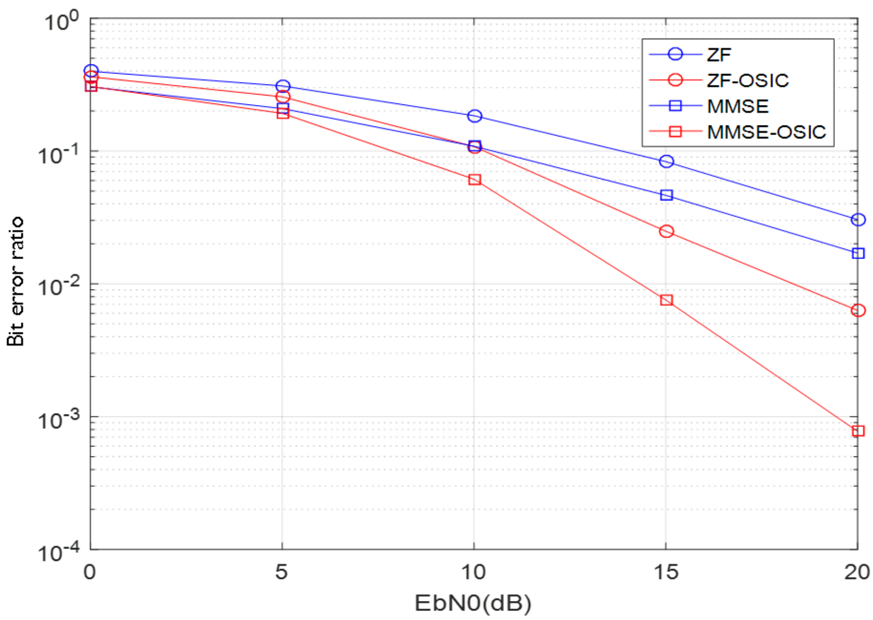

Figure 4. Comparison of OSIC algorithms with different zero-dip criteria under 4 × 4 antenna QPSK modulation.

Simulation results are shown in Figures 4 and 5. As we can see in Figures 4 and 5, when the SNR value is within the range of 0–5 dBm, the BERs obtained by the four detection algorithms do not differ significantly. When the SNR is greater than 5 dB, the BERs of the ZF-OSIC and MMSE-OSIC algorithms are significantly lower than those of the ZF and MMSE detection algorithms. Among them, under the conditions of the QPSK and 4QAM modulation methods, the maximum difference in BERs between the MMSE-OSIC and MMSE algorithms is about 4.2×10^{-2} and 3.7×10^{-3}, respectively. Therefore, the OSIC algorithm based on sorting criteria can significantly improve the detection performance of the linear detection algorithm, and the performance of 4QAM modulation is also better than that of QPSK modulation. Compared with the linear detection algorithm, the OSIC BER decreases more with the increase of the SNR (E_b/N_0). The detection performance of the OSIC algorithm using the MMSE zero-notch criterion is better than that based on the ZF zero-notch criterion; this is because the influence factor of noise is considered in the MMSE-OSIC algorithm.

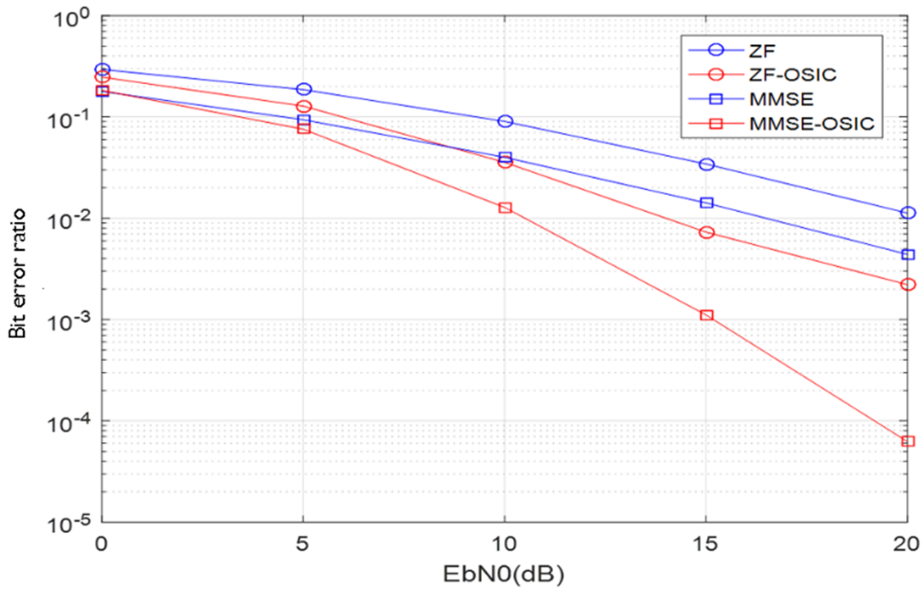

Figure 5. Comparison of OSIC algorithms with different estimation criteria under 4 × 4 antenna 4QAM modulation.

5.2. Performance analysis of MMSE-OSIC detection algorithm based on different modulation methods

MATLAB simulation software was used to simulate the MMSE-OSIC algorithm, the improved MMSE-OSIC algorithm and ML detection algorithm in the mining-purposed MIMO-OFDM system. In this simulation, we used two modulation methods: binary phase shift keying (BPSK) and QPSK. These two methods belong to the phase-shift keying digital modulation method. BPSK has stronger noise resistance than QPSK, but the transmission efficiency is worse. BPSK is a two-phase-shift keying method, while QPSK is a four-phase-shift keying method, and QPSK modulation ensures both signal transmission efficiency and BER performance. The system parameter settings are shown in Table 4.

Table 4. Simulation parameters.

Parameter	Value
Modulation method	BPSK, QPSK
Subframe length/ms	1
Antenna configuration	4 × 4
Noise type	Gaussian white noise with mean 0 and variance 1

The simulation results are shown in Figures 6 and 7.

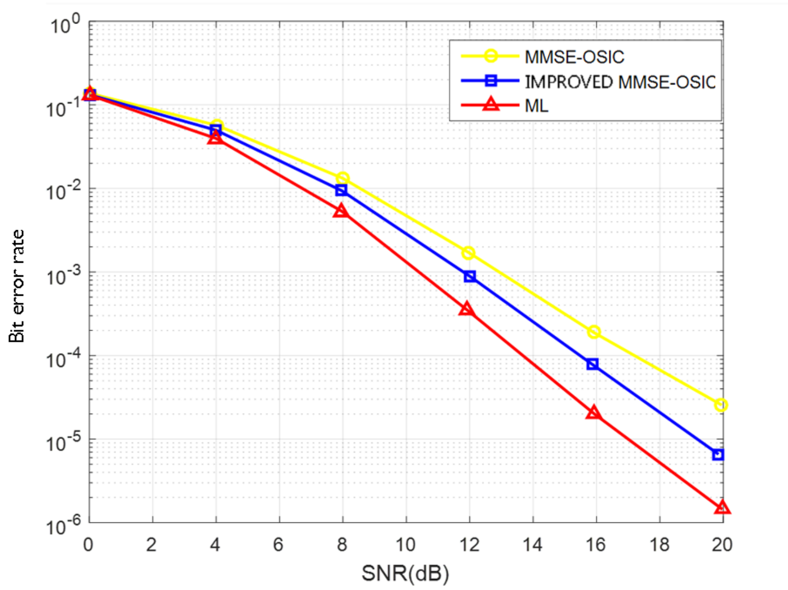

Figure 6. Performance comparison of MMSE-OSIC, improved MMSE-OSIC and ML detection algorithms (BPSK modulation).

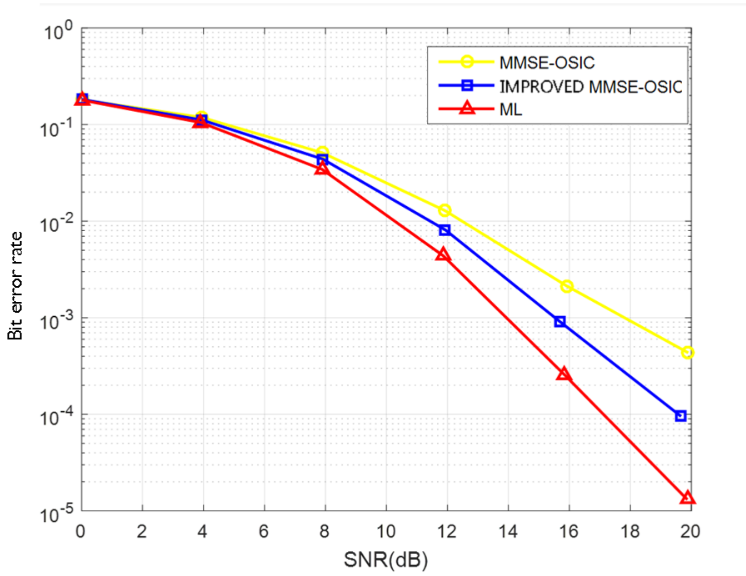

Figure 7. Performance comparison of MMSE-OSIC, improved MMSE-OSIC and ML detection algorithms (QPSK modulation).

Figure 6 shows a comparison of the BERs of the MMSE-OSIC algorithm, improved MMSE-OSIC algorithm and ML detection algorithm using BPSK modulation. Figure 7 shows a comparison of the BERs of the MMSE-OSIC, improved MMSE-OSIC and ML detection algorithms using QPSK modulation. Comparing Figures 6 and 7, it can be seen that, when the SNR is in the range of 0–4 dB, the decrease in BER for each of the three algorithms is relatively smooth. When the SNR is greater than 4 dB, the magnitude of the decrease in BER for each of the three algorithms is significantly improved. In addition, the improved MMSE-OSIC algorithm has the lowest BER of approximately 10^{-5}

under BPSK modulation, while the lowest BER under QPSK modulation is approximately 10^{-4}. Therefore, BPSK modulation is superior to QPSK modulation. As can be seen in Figure 6, the performance of the improved MMSE-OSIC algorithm is better than that of the MMSE-OSIC algorithm, but it has a slightly higher BER than the ML algorithm, which was shown to be the best performance algorithm. From the analysis of algorithm complexity, because the improved MMSE-OSIC pair only uses the ML algorithm to traverse search and detect the weakest signal layer, the remaining layers are detected by the MMSE-OSIC algorithm. Compared with all of the layers detected by the MMSE-OSIC algorithm, the complexity is slightly increased, but the detection performance is significantly improved.

5.3. Performance analysis of the improved MMSE-OSIC signal detection algorithm based on channel multipath number

MATLAB simulation software was used to conduct a performance simulation of the channel multipath at the receiving end of the MIMO-OFDM system based on the improved MMSE-OSIC signal detection algorithm. The system parameter settings are shown in Table 5.

Table 5. Simulation parameters.

Parameter	Value
Bandwidth/MHz	1
Subcarrier number	256
Bits/symbol	2
Maximum time delay/ms	7
Space-time coding	STBC
Cyclic prefix/μs	40
Modulation method	BPSK
Antenna configuration	2 × 2
Channel multipath number	2, 4, 6

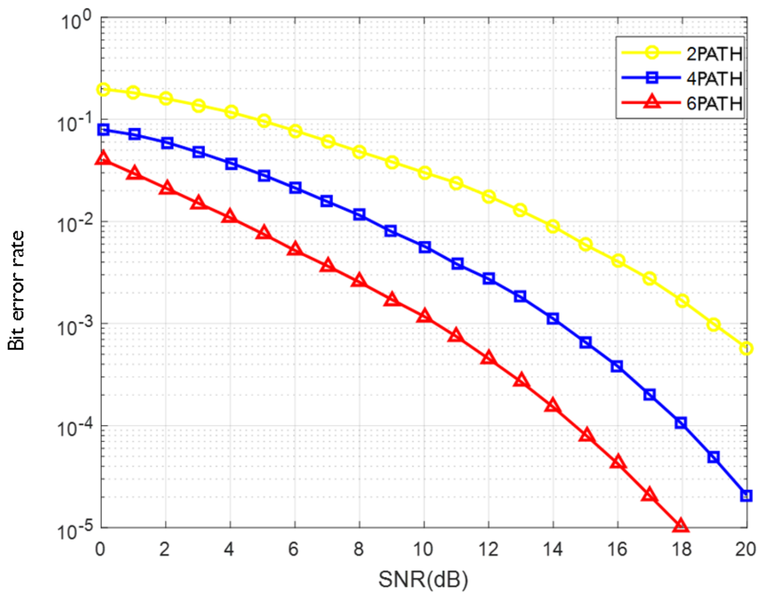

Figure 8. BER of MIMO-OFDM system under different multipath number conditions.

Figure 8 is a simulation diagram showing the influence of channel multipath number on the performance of the MIMO-OFDM communication system.

As can be seen in Figure 8, with the increase of the SNR, the BER significantly decreases for different multipath numbers, with a multipath number of 6 yielding the lowest BER, almost reaching 10^{-5}. This indicates that, as the number of multipath channels increases, the performance of the communication system improves. This also proves that the MIMO-OFDM communication system has the advantage of resisting multipath fading. Coupled with the superior detection algorithm, the performance of the whole communication system is improved, and it is of great significance for the development of the whole underground mine communication system in the future.

6. Conclusions

MIMO technology utilizes spatial multipath effects to enhance the capacity of wireless channels, thereby improving the transmission rate and reliability. OFDM technology can achieve parallel transmission of multiple subcarriers by dividing a given channel into multiple orthogonal subchannels in the frequency domain. Therefore, it is of great significance to study the wireless communication system based on MIMO and OFDM in mines. In order to solve the multipath fading problem in IoT communication systems for coal mines, a MIMO-OFDM-based coal mine-specific IoT system was constructed by combining MIMO and OFDM technologies. Due to the complex environment and serious noise interference under the mine, an improved MMSE-OSIC signal detection algorithm has been proposed. First, the SINR of the received signal is calculated and sorted. An ML algorithm is used to find the weakest layer of the received signal and search for the nearest sending symbol as the original sending signal. Then, MMSE-OSIC algorithm is used to extract all signals without the weakest layer of the signal. Finally, the improved MMSE-OSIC algorithm was simulated and verified on the MIMO-OFDM system. Through extensive simulations, we can draw the following conclusions. On the one hand, the OSIC algorithm with the MMSE as the zero-trap criterion and SINR as the sorting criterion is the optimal signal detection algorithm. On the other hand, due to the complexity of underground mine environments and serious noise interference, the MMSE zero-trap criterion and OSIC algorithms for sorting the SNR are suitable algorithms for underground mine signal detection algorithms. Moreover, the BER of the improved MMSE-OSIC algorithm has been demonstrated to be lower than that of the traditional MMSE-OSIC algorithm when the algorithm complexity is not increased significantly. The results are of great significance for improving the communication performance of IoT systems for mines. However, in order to simplify the analysis, the impact of other environmental parameters on the signal transmission process was not considered in this study. In the future, further research will be conducted on the characteristics of signal transmission processes in actual mine environments, and more widely applicable signal detection algorithms will be proposed.

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Conflict of interest

The authors declare no conflict of interest.

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