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Performance Analysis of a Multi-user MIMO-OFDM System Based on a Hybrid Genetic Algorithm

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Abstract

Conventional Multi-User Detection (MUD) algorithms for the Multi-Input, Multi-Output-Orthogonal Frequency Division Multiplexing (MIMO-OFDM) system fail to consider the detection performance and algorithm complexity simultaneously. To address this problem, a new Joint Intelligent MUD (JI-MUD) algorithm that aims to improve the MUD performance of the MIMO-OFDM system and to reduce the complexity of the algorithm was proposed. First, a new MUD method based on the genetic algorithm (GA) for the MIMO-OFDM system was introduced. Utilizing the results of the Minimum Mean Square Error (MMSE) algorithm as the initial population and the criterion of the Maximum Likelihood (ML) algorithm as the fitness function, the proposed algorithm performs genetic operations through the roulette wheel selection operator, two-point crossover operator, and adjacent bit reverse mutation operator, which generate a new population. Second, a Hybrid GA (HGA) was presented by combining the simulated annealing and particle swarm optimization algorithms. The extended study on the HGA complexity and performance was conducted from a mathematical perspective. Finally, a quantitative analysis on the complexity and convergence of the HGA, as well as the correlation of the fitness function, was implemented. Research results demonstrated that the convergence measurement function value of the proposed HGA is 0. Furthermore, its signal-to-noise ratio is approximately 1 dB lower than that of the MMSE-MUD algorithm and approximately 1 dB higher than that of the ML-MUD algorithm when the error rate is 5×10^{-2}. This finding indicates that the proposed algorithm perform better than the MMSE algorithm and approach the ML algorithm at the cost of appropriate complexity. These research results can better balance complexity and performance and guide the follow-up on the MUD development in the MIMO-OFDM system.

Keywords: MIMO-OFDM, Multi-User Detection, Hybrid Genetic Algorithm, PSO, ML-MUD

1. Introduction

Multi-User Detection (MUD) technology deals with the demodulation of mutually interfering digital streams of information that occur in areas of 3G mobile communication systems such as wireless communications; this technology is widely utilized as the industry standard [1]. Multi-user detection technology is the solution from the receiver side of an effective Multi-User (MU) interference. Along with the study of B3G/4G, MUD based on Multi-Input, Multi-Output-Orthogonal Frequency Division Multiplexing (MIMO-OFDM) technology in Code Division Multiple Access systems has become a popular research topic in communications [2][3]. MIMO technology can increase system bandwidth even without additional bandwidth to improve spectrum efficiency and exponentially increase system capacity. OFDM technology has shown several advantages and attracted substantial interest as it can address frequency selective fading and Inter-Symbol-Interference. The combination of MIMO and OFDM is considered as a major trend and basis for the development of the next generation mobile communication systems. Many MUD methods for the MIMO-OFDM system exist. However, existing MUD methods such as the Minimum Mean Square Error (MMSE) and Maximum Likelihood (ML) algorithms remain unsatisfactory. The MMSE algorithm has low computational complexity and can be realized easily, but it has limited detection performance. The ML algorithm can achieve enhanced detection performance, but the computational complexity increases with the exponential rise in the number of users, leading to extreme difficulty in hardware implementation [3][4].

Given the low performance of the MMSE algorithm and the high complexity of the ML algorithm, a new algorithm for the MIMO-OFDM system called the Joint Intelligent MUD (JI-MUD) based on the hybrid genetic algorithm (HGA) was proposed. The proposed method combines the Genetic Algorithm (GA), Simulated Annealing (SA) and Particle Swarm Optimization (PSO) algorithms to construct a new HGA on the one hand. On the other hand, the complexity and performance of the proposed algorithm were further explored from a mathematical perspective. Moreover, a quantitative analysis on the complexity and convergence of the proposed algorithm and the correlation of the fitness function were implemented.

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2. State of the art

MUD technology has become a hotspot in communications research with the increased user population of mobile communication systems. This technology was proposed by Schneider, who first combined the codon information and timing of multiple users to detect each user [5]. Verdu presented an optimal MU detector based on ML that can theoretically analyze the optimal performance of MU detectors [6]. However, the complexity of this MU detector increased exponentially as user population rose, making it inapplicable in practice. Therefore, many scholars shifted their attention to suboptimum MU detectors. A suboptimum MU detector decreases the algorithm complexity to the level of actual engineering while maintaining system performance. Lupas presented a decorrelation MU detector that can suppress Multiple Access Interference (MAI) to its maximum extent and amplify the noise effect on communication quality [7]. Hence, Madhow proposed an MMSE detector [8]. This MMSE detector is superior to the decorrelation detector under the same signal-to-noise ratio (SNR) and can suppress noise effectively; however, it cannot eliminate MAI completely. With the increasing number of theoretical studies and actual applications of MUD technology, applying intelligent optimization algorithms (e.g., GA, SA, and PSO algorithms) into MUD technology has become the development trend of the future [9]. Juntti et al. proposed a GA-based MUD for the first time that can enhance system reliability and attain approximate optimal performance [10].

Given the development of the mobile communications technology, MUD technology can combine with OFDM and MIMO technologies. As a multi-carrier modulation technology, OFDM can effectively overcome the inter-symbol interference caused by fading channels. Therefore, the combination of MUD and OFDM technologies can enhance the anti-interference of a system. In MIMO systems, simultaneously sent signals to different antennas serve as the different user information. Such information overlaps on each receiving antenna and mutually forms interference. This scenario is largely similar with the MU Spatial-Division Multiple Access. Therefore, MUD can combine with MIMO. Jiang [11] reviewed a range of classic MU detectors designed for MIMO-OFDM systems and characterized their attainable performance and broadly applicable principles of various GA-assisted optimization techniques, which were recently proposed for use in MU MIMO-OFDM. The study further demonstrated that a family of GA-aided MUDs can accomplish a near-optimum performance at the cost of a significantly lower computational complexity than that imposed by their optimum ML MU-aided counterparts.

The aforementioned studies illustrate that these methods are unsatisfactory with limited detection performance. Balancing system performance and computational complexity for traditional MUD algorithms is difficult. The MUD algorithm based on HGA in the MIMO-OFDM system, which has better MUD performance than the MMSE algorithm and approximate performance to the ML algorithm, was investigated in the current study. This algorithm aims to solve the shortcomings of the MUD algorithm in traditional MIMO-OFDM systems by simultaneously considering detection performance and algorithm complexity.

The remainder of this paper is organized as follows. Section 3 establishes the flowchart of the proposed JI-MUD algorithm. Section 4 analyzes the proposed JI algorithm as applied to MUD in the MIMO-OFDM system. Finally, Section 5 summarizes the conclusions.

3. Methodology

3.1 MIMO-OFDM system

The block diagram of the MIMO-OFDM MUD system is shown in Fig. 1 [12]. Assume that the L users at the transmitter and the signal, $s_l(l=1,\ldots,L)$, of each user by OFDM modulation is transmitted through the MIMO channel to the P element antenna array at the base station. The OFDM demodulated output, $x_p(p=1,\ldots,P)$, is then divided into different user signals, $y_l(l=1,\ldots,L)$, by the MUD. Finally, the output signals are independently decoded.

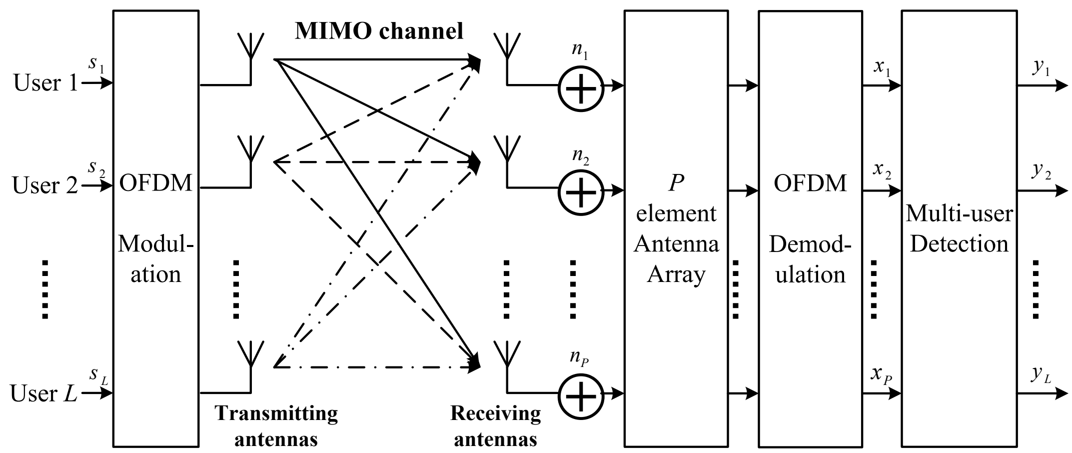

Fig. 1. The block diagram of MIMO-OFDM multi-user detection system

Fig. 1 shows that the P element antenna array in the MIMO-OFDM system receives the nth OFDM symbols in the kth way carrier transmission of a complex signal vector, $x[n,k]$ (i.e., $[n,k]$ is omitted in the following equation for simplicity, similar to other instances):

$$x_{P\times1} = H_{P\times L} \cdot s_{L\times1} + n_{P\times1} \tag{1}$$

where x is the received signal of the antenna at the receiver, s is the input signal, and n is the channel noise, which can be expressed as Eq. (2).

$$\begin{cases} x_{P\times 1}=\left[x_1,x_2,\cdots,x_P\right]^T \\ s_{L\times 1}=\left[s_1,s_2,\cdots,s_L\right]^T \\ n_{P\times 1}=\left[n_1,n_2,\cdots,n_P\right]^T \end{cases} \tag{2}$$

The complex signal s_l transmitted by the lth user has a zero-mean and variance σ_l^2. The Additive White Gaussian Noise signal n_p also has a zero-mean and variance σ_n^2. H is the frequency domain channel transfer function in Eq. (1), which is given in Eq. (3) as follows:

$$H_{P\times L}=\begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1L} \\ H_{21} & H_{22} & \cdots & H_{2L} \\ & & \ddots & \\ \vdots & \vdots & H_{pl} & \vdots \\ & & \ddots & \\ H_{P1} & H_{P2} & \cdots & H_{PL} \end{bmatrix} \tag{3}$$

where H_{pl} is the transmitting coefficient from the lth user's transmitting antenna to the pth receiving antenna in a P-element antenna array. The transmitting coefficients differ from various p values. These values are assumed as independent and identically distributed Gaussian distribution with a zero-mean and a variance of 1.

3.2 JI-MUD algorithm

A flowchart of the proposed JI-MUD algorithm is shown in Fig. 2.

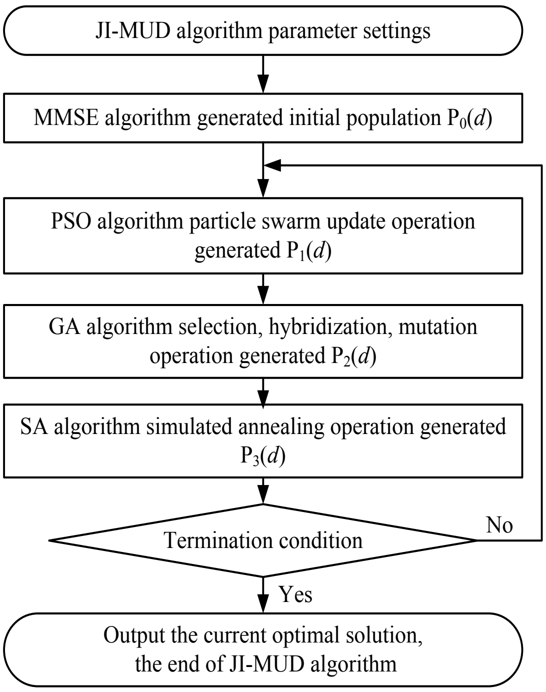

Fig. 2. Flowchart of the proposed joint intelligent multi-user detection algorithm

The initial population selection, PSO algorithm, GA (including the fitness function, selection operation, cross-over operation, and mutation operation), SA algorithm, and optimal solution conditions are all key parts of the JI-MUD algorithms. These concepts will be discussed in detail in the following sections.

3.2.1 Initial population selection

The MMSE algorithm results are set to the initial group P_0 of the JI-MUD algorithm. The P-element antenna array assisted by the MMSE algorithm weight matrix receives a P number of different antenna signals. The MMSE algorithm detection signal vector can be obtained using linear combination as expressed in Eq. (4).

$$\bar{s}_M=W_M x \tag{4}$$

where W_M is the weight matrix of the MMSE algorithm defined as Eq. (5).

$$W_M=\left(HH^H+\sigma_n^2 I\right)^{-1}H \tag{5}$$

The L user vector detected by the MMSE algorithm is set to the first generation of the JI-MUD algorithm which can be expressed as a group that contains a population of M individuals. The mth (m = 1, 2, ... M) individual can be expressed as Eq. (6).

$$\tilde{s}_{(d,m)}=\left[\tilde{s}^1_{(d,m)},\tilde{s}^2_{(d,m)},\cdots,\tilde{s}^L_{(d,m)}\right] \tag{6}$$

where $d\in[1,D]$ is the iteration number, D is the maximum iteration number, and $\tilde{s}^l_{(d,m)}\in M_c$ is the complex-valued symbol of individuals [13].

3.2.2 PSO algorithm

Iteration particles update the velocity and position according to Eq. (7).

$$\begin{cases} v_{mn}^{d+1}=wv_{mn}^d+c_1r_1\left(p_{mn}-z_{mn}^d\right)+c_2r_2\left(p_{gn}-z_{mn}^d\right) \\ z_{mn}^{d+1}=z_{mn}^d+v_{mn}^{d+1} \end{cases} \tag{7}$$

where w and d are the inertia weight and iteration number, respectively, both r_1 and r_2 are the random variables on [0, 1] utilized to maintain group diversity, and c_1 and c_2 are learning factors that provide the particles with the ability of a groups' summary and learning from outstanding individuals. Thus, each particle moves to its own historical and global best positions. $c_1r_1\left(p_{mn}-z_{mn}^d\right)$ and $c_2r_2\left(p_{gn}-z_{mn}^d\right)$ are the cognitive and social parts, respectively, which represent the particles' learning and mutual cooperating abilities.

The particles update their speed according to the last iteration of the velocity, current position of each particle, distance between their own best experience, and groups' best experience as expressed in Eq. (7); afterwards, the particles fly to a new location [14]. Each individual corresponds to a particle. The new group P_1 is generated after the operation updates the speed and location utilizing the PSO algorithm.

3.2.3 GA
The proposed PSO-based network-clustering algorithm works as follows:

(1) Fitness function
The optimal decision criterion is applied based on the ML algorithm, and the transmitted symbols vector $\overline{s}_G$ is detected. The signal vector in the *p*th receiving antennas based on *L* users can be expressed as Eq. (8).

$$\overline{s}_G^p = \arg\left\{\min_{\overline{s}}\left[G_p\left(\overline{s}\right)\right]\right\} \tag{8}$$

The symbol vector $\overline{s}$ that sets the objective function $G_p\left(\overline{s}\right)$ as the smallest value is $\overline{s}_G$ in Eq. 8, and the total objective functions of all *P*-receiving antennas are expressed as Eq. (9).

$$G\left(\overline{s}\right) = \sum_{p=1}^{P} G_p\left(\overline{s}\right) = \left\|x - H\overline{s}\right\|^2 \tag{9}$$

The decision rules of the JI-MUD algorithm determine the vector $\overline{s}_G$ that minimizes $G\left(\overline{s}\right)$.

$$f_{dm} = G_{dT} - G\left(\tilde{s}_{(d,m)}\right) + C_{\min} \tag{10}$$

where $C_{\min}$ is the minimum constant that ensures a positive fitness function value f_{dm} , and G_{dT} is the maximum objective function that corresponds to *T* individuals in the *d*th generation hybrid group as expressed in Eq. (11).

$$G_{dT} = \max_{t\in\left[1,T\right]}\left\{G\left(\tilde{s}_{(d,m)}\right)\right\} \tag{11}$$

(2) Selection operation
First, *T* individuals with a higher fitness in group P_1 were selected to create a hybrid set. $T = M/2$ at this point; in particular, the individuals with higher fitness value is half of the group. $T/2$ pairs of individuals from the hybrid set are then selected as hybrid parents. The survival probability of the *t*th individual in the *d*th generation hybrid set is expressed as Eq. (12).

$$p_t = f_{dt} \Big/ \sum f_{dt} \tag{12}$$

where f_{dt} is the fitness function of the *t*th individual in the *d*th generation hybrid set, and $\sum f_{dt}$ is the sum of the fitness functions of the *T* individuals in the *d*th generation hybrid set.

The cumulative probability from the first individual to the current *t*th individual can thus be obtained by Eq. (13).

$$p_d\left(t\right) = p_1 + p_2 + \cdots + p_t \tag{13}$$

A random number distributed in the interval [0, 1] is produced based on the roulette wheel selection method. If this number satisfies the condition in Eq. 14, then the *t*th individual in the hybrid set is placed in the paired library.

$$p_d\left(t\text{-}1\right) < r < p_d\left(t\right) \tag{14}$$

(3) Cross-over operation
The two-point cross-over method is adopted in the cross-over operation. The front location of the two genes is selected randomly as the intersection, and then the two middle portions of the intersection from each of the hybrid parents are interchanged. A binary-coded string based on the two-point cross-over method diagram is shown in Fig. 3. The cross-over probability P_c determines whether hybridization occurs. The $T/2$ pairs of the hybrid parents' cross-over to generate *T* new individuals ready for mutation operation.

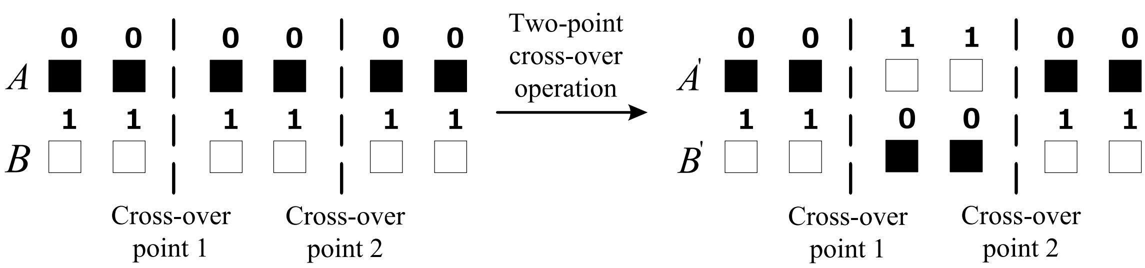

Fig. 3. Diagram of the two-point cross-over method

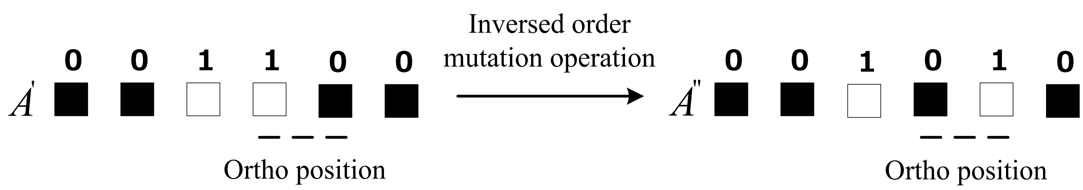

Fig. 4. Diagram of inversed order mutation method based on adjacent position

(4) Mutation operation
An inverse order method based on the adjacent position is employed in the mutation operation. Two adjacent coding positions of individuals are selected randomly, and then their genetic value conversion is obtained. The binary string "A" in Fig. 4 is taken as an example. The corresponding adjacent

position inversed order mutation method diagram is shown in Fig. 4. The aforementioned mutation method also depends on the mutation probability PM to determine whether mutation operation occurs. The T individuals generate T new individuals after mutation.

The T new individuals are generated after the genetic operation. They combine with T individuals in the hybrid set together to form the new group P_2 .

3.2.4 SA algorithm

The system in the SA algorithm encounters a type of disturbance that can change the state of x. The energy functions of the system $E(x)$ correspondingly changes. The acceptance probability of the process wherein the original state of x_{old} turns into a new state of x_{new} in the system is determined by the Meteopolis rules as shown in Eq. (15).

$$p=\begin{cases} 1 & ,\Delta E<0 \\ \exp\left(-\Delta E/C\right) & ,\Delta E\geq 0 \end{cases} \tag{15}$$

where $\Delta E=E(x_{new})-E(x_{old})$, and C is the current temperature. The meaning of the Meteopolis rules is as follows: when the new state decreases the system energy function value, then the system accepts the new state with the probability p = 1; when the new state increases the system energy function value, then the system accepts the new state with the probability $p=\exp(-\Delta E/C)$.

Each individual corresponds to a state of the SA algorithm. The new group P_3 is generated by the judgment operation of the acceptance probability.

3.2.5 Optimal solution

The aforementioned analysis shows that the OFDM subcarriers with the highest fitness values can be detected by the L users' transmission symbol vector. When the algorithm attains the maximum iteration times D or the average fitness of M/10 and the individuals with the highest fitness value in every generation does not change for five consecutive generations, then the optimal solution has been determined [15].

3.3 Computational complexity and convergence analysis of the proposed JI algorithm

3.3.1 JI algorithm complexity

The following section details the algorithm complexity analysis of the HGA in the MIMO-OFDM system based on MUD. Time complexity is considered in this study. The complexities of the MMSE and ML algorithms increase linearly and exponentially, respectively, with increasing number of users. The multiplication and addition computational complexity of the MMSE algorithm are $MMSE_\times$ and $MMSE_+$, respectively. The MMSE result is the initial population of the GA. Given Eqs. (4) to (6), the computational complexity is expressed as Eq. (16).

$$\begin{cases} \text{Multiplication:} MMSE_\times=2L^2\cdot P\cdot M \\ \text{Addition:} MMSE_+=L^2\cdot\left(2P+1\right)\cdot M \end{cases} \tag{16}$$

(1) Individual evaluation

The individual evaluation process complexity in every generation is expressed as Eq. (17).

$$\begin{cases} \text{Multiplication:} & \left(L+1\right)\cdot P\cdot M \\ \text{Addition:} & \left(2L+\frac{5}{2}\right)\cdot M \end{cases} \tag{17}$$

(2) Genetic operation

The genetic operation complexity in each generation is shown as Eq. (18) according to the selection operation.

$$\begin{cases} \text{Multiplication:} & \frac{1}{2}M+2 \\ \text{Addition:} & \frac{1}{2}M^2+\frac{3}{4}M \end{cases} \tag{18}$$

Given Eqs. (16) to (18), the algorithm complexity of the GA based on the results of the MMSE algorithm after the D generation genetic operations is expressed as Eq. (19).

$$\begin{cases} \text{Multiplication:} MMSE_\times+D\cdot\left[\left(L+1\right)\cdot P\cdot M+\left(\frac{1}{2}M+2\right)\right] \\ \text{Addition:} MMSE_++D\cdot\left[\left(\frac{1}{2}M^2+\frac{3}{4}M\right)+\left(2L+\frac{5}{2}\right)\cdot M\right] \end{cases} \tag{19}$$

Thus, the multiplication and addition computational complexity of the GA are expressed as Eq. (20).

$$\begin{cases} GA_\times=\left[2L^2\cdot P+\left(L+1\right)\cdot P\cdot D+\frac{1}{2}\cdot D\right]\cdot M \\ GA_+=\frac{1}{2}\cdot D\cdot M^2+\left[L^2\cdot\left(2P+1\right)+\left(2L+\frac{13}{4}\right)\cdot D\right]\cdot M \end{cases} \tag{20}$$

The aforementioned analysis of the GA process shows that the multiplication and addition complexity of GA is slightly higher than that of the MMSE algorithm. With the assistance of GA, the operation complexity of the SA operation and PS update operation are analyzed.

(3) SA operation

Given Eqs. (15) and (20), the multiplication and addition operations complexity of the Genetic Simulated Annealing Algorithm (GSAA) are expressed as Eq. (21).

$$\begin{cases} GSAA_\times=\left[2L^2\cdot P+\left(L+1\right)\cdot P\cdot D+p_{gs}\cdot D+\frac{1}{2}\cdot D\right]\cdot M \\ GSAA_+=\frac{1}{2}\cdot D\cdot M^2+\left[L^2\cdot\left(2P+1\right)+\left(2L+\frac{17}{4}\right)\cdot D\right]\cdot M \end{cases} \tag{21}$$

SA operation can improve the local convergence ability of GA, which can lessen genetic iterations. We denote ΔD as the lowered genetic iterations. The complexity of GSAA is lower than that of GA when $\Delta D>3$.

(4) PS update operation
Given Eqs. (7) and (20), the multiplication and addition operations complexity of the Genetic Particle Swarm Algorithm (GPSA) are expressed as Eq. 22.

$$\begin{cases} GPSA_{\times} = \left[2L^2 \cdot P + (L+1) \cdot P \cdot D + \frac{11}{2} \cdot D \right] \cdot M \\ GPSA_{+} = \frac{1}{2} \cdot D \cdot M^2 + \left[L^2 \cdot (2P+1) + \left(2L + \frac{33}{4} \right) \cdot D \right] \cdot M \end{cases} \tag{22}$$

The PS update operation can improve the ability of the GA population convergence, which can lessen genetic iterations. We denote ΔD as the reduced genetic iterations. The complexity of GPSA is lower than that of GA when $\Delta D > 5$.

The aforementioned analyses show that the complexity levels of the two types of HGAs (i.e., GSAA and GPSA) are between those of the GA and MMSE algorithms when $\Delta D > 5$. Without loss of generality, the HGA complexity is slightly higher than that of the MMSE algorithm and far lower than that of the ML algorithm.

3.3.2 JI algorithm convergence

Every generation population in the HGA can be regarded as a type of state. If the algorithm process is random, then the Markov chain can be utilized to analyze this theory [16]. Basic GA can be described as a homogeneous Markov chain, $P_t = \{P(t), t \geq 0\}$, where P_t denotes the probability of a transferred state being independent on the starting time. The selection, cross-over, and mutation operations in basic GA are independent and random. New groups are only dependent on their parents' groups and genetic operator parameters. These groups are unrelated to the generation of groups generated before their parents' groups. GA observes the following theorems: (1) the probability of the basic GA converging to the optimal solution is less than 1; (2) the probability of the GA with the scheme that retains the best individual converging to the optimal solution is equal to 1. Both conclusions ensure the optimal solution searched process in the GA theoretical analysis and practical application. Further conclusions can be obtained as follows based on the probabilistic convergence theorems of GAs: the probability of an individual strongly converging to the optimal solution set in the GSAA when $T \to 0$ can be expressed as $\{\vec{X}(n)\}$.

$$\lim_{n\to\infty} P\{\vec{X}(n) \subset M\} = 1 \tag{23}$$

The HGA convergence is analyzed according to the GSA algorithm and combined with the conclusion of the aforementioned basic GA. The HGA has numerous factors and parameters. The best individual fitness in each generation or average fitness of groups is applied to evaluate the algorithm performance.

(1) De Jong [17] proposed an evaluation criterion that contains a quantitative analysis of the on-line and off-line performance of GA.

The on-line performance evaluation criterion is as follows: suppose $F_1(s)$ is the on-line performance of scheme s. $\overline{f}(d)$ is the average fitness value of the dth generation. The on-line performance can then be represented as the average value from the first generation to the current generation of the optimization process, i.e.

$$F_1(s) = \frac{1}{D}\sum_{d=1}^{D}\overline{f}(d) \tag{24}$$

The off-line performance evaluation criterion is as follows: suppose $F_2(s)$ is the off-line performance of scheme s. It can be expressed as the cumulative average value of the best performance in a particular generation, i.e.

$$F_2(s) = \frac{1}{D}\sum_{d=1}^{D}\tilde{f}(d) \tag{25}$$

where $\tilde{f}(d) = \max\{\overline{f}(1), \overline{f}(2), \cdots, \overline{f}(d)\}$.

The on-line performance evaluation criterion is utilized to evaluate the dynamic algorithm performance, whereas the off-line performance evaluation criterion is utilized to evaluate the algorithm convergence. The evaluation process aims to determine the best fitness or best average fitness in the population from the beginning to the current generation, as well as the average number of evolution calculation iterations. The average values of the fitness functions in GA and HGA increase, so the performance difference between the two aforementioned criteria is minimal and the natures they reflect are basically the same.

(2) Himmeblau proposed the termination criterion of the optimization method, which can be expressed as Eq. (26).

$$\frac{|f(x_{i+1}) - f(x_i)|}{|f(x_i)|} \leq \varepsilon \text{ or } |f(x_{i+1}) - f(x_i)| < \varepsilon \tag{26}$$

where ε is an appropriate less positive number.

The termination criterion of the optimization method is introduced into GA, such that the convergence criterion GA is proposed. This criterion is also applied to the HGA.

The convergence evaluation criterion is as follows: suppose $F_3(s)$ is the convergence measurement function of scheme s; this can be expressed as the mean difference of the fitness function in each generation, i.e.

$$F_3(s) = \frac{1}{D}\sum_{d=1}^{D}\left[\overline{f}(d+1) - \overline{f}(d)\right] \tag{27}$$

4 Result analysis and discussion

The proposed JI algorithm is applied to the MUD in a MIMO-OFDM system. In the MIMO-OFDM system, the user number is set as $L = 2$, the number of receiving antennas is $P = 2$, the SNR is from 0 to 9 dB, and the subcarrier number is K = 1024. Binary coding is utilized for the JI-MUD algorithm. The other parameters of the JI algorithm are listed in Table 1.

Table 1. The simulation parameters used in MIMO-OFDM system joint intelligent multi-user detection algorithm

Intelligent algorithm	Parameters	Value

PSO	Learning factors c_1=c_2	2
	Inertia weight w	1
	Maximum speed V_{max}	4
GA	Population size M	10000
	Cross-over probability p_c	0.8
	Mutation probability p_m	0.02
	Number of genetic iterations D	10
SA	Initial temperature T	10

The performance results of the JI-MUD, MMSE, and ML algorithms are shown in Fig. 5, as well as performance of the MUD based on the JI-MUD algorithm in the MIMO-OFDM system between those of the MMSE-MUD and ML-MUD algorithms. The SNR of the JI-MUD algorithm is 1 dB less than that of the MMSE-MUD algorithm and 1 dB more than that of the ML-MUD algorithm when $BER = 5\times10^{-2}$. Given the MMSE-MUD algorithm, the PS update, genetic, and SA operations are added to the JI-MUD algorithm, which can increase the acceptable algorithm complexity. Thus, the JI-MUD algorithm outperforms the MMSE-MUD algorithm and approaches the ML-MUD algorithm performance at the cost of slightly higher complexity.

Eqs. (24) and (25) show the simulations on the on-line and off-line performance of GA and HGA (Fig. 6). Fig. 6 shows that the on-line and off-line performance curves of the HGA completely overlap. Therefore, this result indicates that the HGA has satisfactory stability and rapid convergence. The on-line and off-line performance curves of GA did not completely overlap; however, the difference is insignificant and gradually converges with increasing hereditary generation.

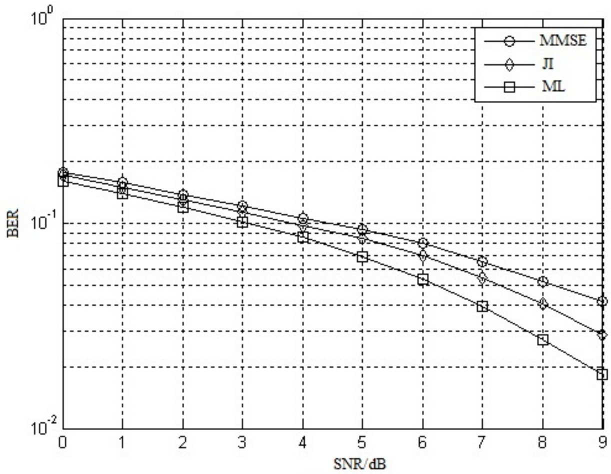

Fig. 5. The performance of multi-user detection in MIMO-OFDM system based on joint intelligent optimization algorithm

HGA convergence measurement function is shown in Fig. 7. This figure shows the convergence measurement function values of HGA at completely zero. This result indicates the excellent convergence of the HGA. The convergence measurement function values of GA vary in a small range and are slightly larger than 0, which can be considered as an approximate convergence. Therefore, the convergence of HGA is superior to that of the GA.

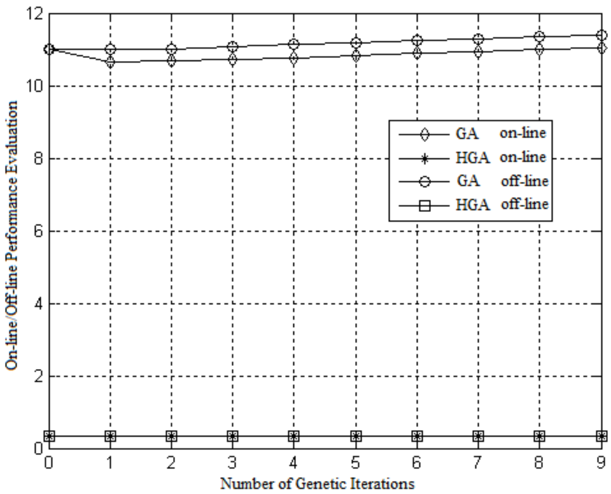

Fig. 6. Simulation of performance evaluation

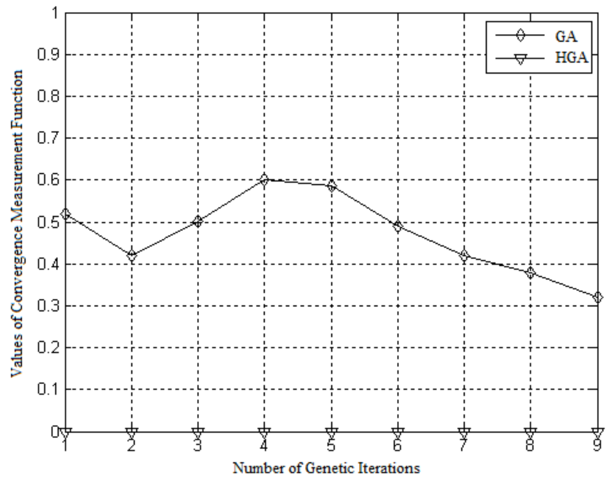

Fig. 7. Simulation of convergence evaluation

Given Eqs. (26) and (27), the simulation of the GA and

5. Conclusions

Conventional MUD, MMSE, and ML algorithms in a MIMO-OFDM system failed to consider the detection performance and algorithm complexity simultaneously. This study proposed a new JI-MUD MIMO-OFDM algorithm based on HGA, which can effectively solve the aforementioned problem. The MUD algorithm model in the MIMO-OFDM system is theoretically constructed utilizing a hybrid strategy with the GA, SA, and PSO algorithms. Furthermore, a quantitative analysis on the HGA complexity and convergence, as well as the correlation of the fitness function, is performed from a mathematical perspective. The following conclusions are derived:

(1) The performance of GA is between those of the MMSE and ML algorithms. The SNR of the GA-MUD algorithm is approximately 1 dB lower than that of the MMSE-MUD algorithm and approximately 1 dB higher than that of the ML-MUD algorithm when BER = 5 × 10^{-2}. Therefore, the GA-MUD algorithm in the MIMO-OFDM system showed better MUD performance than the MMSE-MUD algorithm and approximated the ML-MUD algorithm performance. The GA-MUD algorithm optimized based on the MMSE-MUD algorithm only has a slightly higher

complexity than the MMSE-MUD algorithm, which can easily be attained in practical engineering.

(2) The complexities of the MMSE and ML algorithms increase linearly and exponentially, respectively as user population increased. The HGA complexity is slightly higher than that of the MMSE algorithm, but is significantly lower than that of the ML algorithm. The on-line and off-line performance curves of the HGA overlap completely, which indicates its proper stability. The convergence measurement function values of HGA are 0, which indicates that it can attain rapid convergence.

(3) The correlation coefficient of the fitness function decreases gradually as SNR rises. When the SNR is sufficiently high, then HGA has suitable randomness and high solving quality.

This study proposed a new HGA-MUD algorithm in the MIMO-OFDM system by combining the GA, SA, and PSO algorithms. The proposed algorithm not only balances the detection performance and complexity properly, it also approaches actual engineering applications. Thus, it provides a novel trade-off between the computational complexity and detection performance. The proposed algorithm is also significant in demonstrating and promoting the follow-up development of MUD in MIMO-OFDM systems. Theory is currently verified by analogue simulation because of the lack of MU actual data. Future research can combine the mobile user monitoring data and proposed algorithm model, as well as correct them to obtain a more accurate understanding of the laws of the MU MIMO-OFDM system.

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