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Mmwave massive MIMO: one joint beam selection combining cuckoo search and ant colony optimization

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Abstract

In order to degrade the inter-user interference caused by the same beam selected for different users in mmWave massive MIMO systems, this paper proposes a joint beam selection combining cuckoo search (CS) and ant colony optimization (ACO) (referred to as CSACO). Differently from the existing interference-aware beam selection, a candidate beam set (CBS) for all users is created according to the power distribution of the beamspace channel, thereby all users can be classified into non-interfering users (NIUs) and interfering users (IUs), and NIUs will be assigned the beams with large power directly, while for IUs, the beams are selected by the CSACO; in the proposed CSACO, all beams for IUs are regarded as an optimizable individual, which is continuously evolved towards the direction of sum-rate maximization. Simulation results verify that the proposed beam selection can obtain the higher sum-rate and energy efficiency compared with the existing ones.

Keywords: Millimeter wave MIMO, Beam selection, Inter-user interference

1 Introduction

In millimeter-wave (mmWave) massive multi-input multi-output (MIMO) systems [1, 2], each beam corresponds to a single radio-frequency (RF) chain. For reducing hardware cost and energy consumption, beam selection has become one of the key techniques to reduce the number of RF chains [3–5]. The traditional magnitude maximization (MM) beam selection [6] assigns the beam with the largest power for each user directly, which may cause one beam to be selected for multiple users simultaneously, resulting in the inter-user interference. To overcome this problem, the authors in [7] proposed an interference-aware (IA) beam selection. It first adopts the criterion of MM to select one beam for each user, then removes the shared beams and reselects them under the criterion of sum-rate maximization. Although its performance is greatly improved over the MM beam selection, it only focuses on the strongest beam of each user when grouping users, which does not fully consider the potential inter-user interference. To jointly select beams for all users, the beam selection is expressed as a traveling problem, and the idea of ant colony optimization (ACO) is utilized to obtain a near-optimal solution

[8], whereas the convergence speed of ACO algorithm is slow and the solutions are easy to fall into the local optimum. In [9], the signal-to-interference plus noise ratio (SINR) maximization beam selection is presented, which consists of two stages: in the first stage, each user is assigned a non-overlapping beam determined by the Kuhn–Munkres assignment algorithm; in the second stage, several dominant beams are selected for all users under the sum-rate maximization criterion. Although the SINR maximization beam selection has higher sum-rate performance, the number of selected beams is larger than the number of users; thus, it requires more RF chains and hardware consumption. To satisfy with the rapidly changing channel scenarios, the problem of beam selection in time-varying channels from user mobility and user orientation changes has been considered in [10]. Furthermore, in order to improve the spectral efficiency of traditional beam selection, a joint beam selection and precoding method based on differential evolution are proposed in [11], which can provide higher spectral efficiency and sum-rate; however, in the proposed method, the joint optimization of beam selection and precoding is required; it will bring more computational complexity. [12] presents a joint optimization scheme based on beam selection and interference cancellation for non-orthogonal multiple access (NOMA) systems; this scheme considers the interference between users, and design one beam selection algorithm based on K-means and the digital precoding, so as to reduce inter-cluster interference and improve the sum-rate. Reviewing the current research, the beam selection is one optimization problem maximizing the sum-rate, and the interference between users has a noticeable impact on system performance. Besides, in actual mmWave massive MIMO system, the level of interference between users is significantly different; thereby, the optimal beam selection should be assigned by interference levels between users.

As mentioned above, inter-user interference and beam selection should be considered jointly for all users. In our studies, a joint beam selection consisting of two stages is proposed: In the first stage, one candidate beam set (CBS) for all users is created according to the power distribution of the beamspace channel, which can classify all users into non-interfering users (NIUs) and interfering users (IUs); in the second stage, different beam selection schemes are introduced for different types of users. For NIUs, the beam with the largest power is selected, while for IUs, a joint beam selection combining cuckoo search (CS) and ant colony optimization (ACO) (referred to as CSACO) is proposed, aiming to optimize selected beams under the criterion of sum-rate maximization. In the proposed CSACO, all beams for IUs are combined and regarded as an optimizable individual, which is continuously evolved toward the direction of sum-rate maximization. Compared with the ACO beam selection in [8], the CSACO beam selection has faster convergence speed and higher global searching ability, which allows the evolutionable population consisting of many individuals to obtain a better global solution with fewer iterations.

2 System model

A downlink mmWave massive MIMO system is shown in Fig. 1, where the base station (BS) employs a lens antenna array with N antennas and N_{RF} RF chains to serve K single-antenna users.

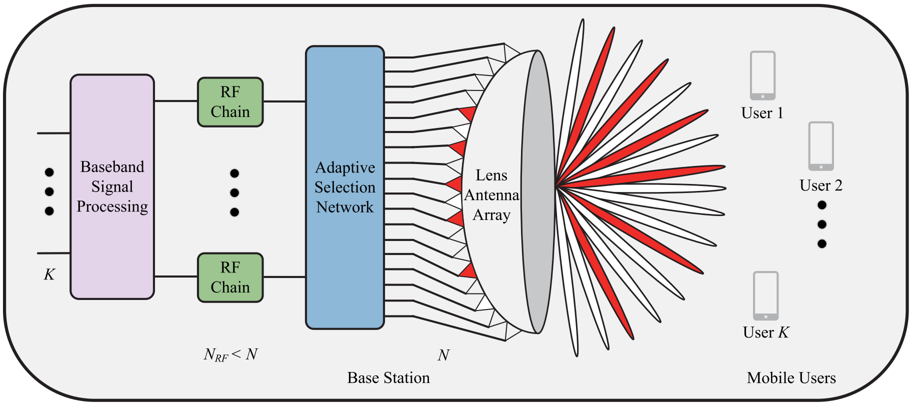

Fig. 1 Architecture of mmWave massive MIMO system relying on lens antenna array

To characterize the dispersive mmWave MIMO channel, the Saleh–Valenzuela multipath channel model is adopted [13–15]. The channel vector $\mathbf{h_k}$ of size $N \times 1$ between the kth user and the antenna can be presented by:

$$\mathrm{h}_k = \sqrt{\frac{N}{L}} \sum_{l=1}^{L} A_{k,l} e^{-j2\pi \tau_{k,l} f} \boldsymbol{\gamma}(\psi_{k,l}) \tag{1}$$

where L is the number of paths, $A_{k,l}$ and $\tau_{k,l}$ are the complex gain and the time delay of the lth path, respectively, f is the carrier frequency and $\boldsymbol{\gamma}(\psi_{k,l}) = \frac{1}{\sqrt{N}}[e^{-j2\pi b \psi_{k,l}}]_{b\in\mathcal{J}(N)}$ denotes the array steering vector, where $\mathcal{J}(N) = \left\{j - \frac{N+1}{2}, j = 1, 2, \ldots, N\right\}$ [16].$\psi_{k,l} = \frac{d \sin(\theta_{k,l})}{\lambda}$ denotes the spatial direction, where λ is wavelength, d is antenna spacing given as $\frac{\lambda}{2}$ and $\theta_{k,l}$ is the spatial angle of arrival [17].

The mmWave massive MIMO system, as shown in Fig. 1, employs a lens antenna array to convert spatial channel into beamspace channel; thereby, this mmWave system is also often referred to as the beamspace MIMO system. The role of lens antenna array can be simulated by a spatial discrete Fourier transform matrix $\mathrm{U} \in \mathbb{C}^{N\times N}$. Specifically, U can be expressed as $\mathrm{U} = [\boldsymbol{\gamma}(\bar{\psi}_1), \boldsymbol{\gamma}(\bar{\psi}_2), \ldots, \boldsymbol{\gamma}(\bar{\psi}_N)]^H$, where $\bar{\boldsymbol{\psi}}_n = \frac{1}{N}(n - \frac{N+1}{2})$, $n = 1, 2, \ldots, N$ are the spatial directions predefined by the lens antenna array [18]. Then, in the beamspace MIMO system, the received signal $\mathrm{y} \in \mathbb{C}^{K\times 1}$ can be expressed as:

$$\mathrm{y} = \mathrm{H}^H \mathrm{U}^H \mathbf{S} \mathrm{F} \mathrm{x} + \mathrm{n} = \tilde{\mathbf{H}}^H \mathbf{S} \mathrm{F} \mathrm{x} + \mathrm{n} \tag{2}$$

where $\mathrm{H} = [\mathrm{h}_1, \mathrm{h}_2, \ldots, \mathrm{h}_K] \in \mathbb{C}^{N\times K}$ is the conventional spatial channel, $\mathbf{S} \in \mathbb{Z}^{N\times N_{\mathrm{RF}}}$ is the beam selection matrix, $\mathrm{F} \in \mathbb{Z}^{N_{\mathrm{RF}}\times K}$ is the precoding matrix in the baseband signal processing with ρ satisfying $\mathrm{tr}(\mathrm{F}\mathrm{F}^H) \leq \rho$, where ρ denotes the total transmit power, $\mathrm{x} \in \mathbb{C}^{K\times 1}$ is the data transmitted by K users with $\mathbb{E}(\mathrm{x}\mathrm{x}^H) = \mathrm{I}_k$, $\mathrm{n} \sim \mathbb{CN}(0, \sigma^2 \mathrm{I}_k)$ of size $K \times 1$ represents the additive white Gaussian noise vector, and $\tilde{\mathbf{H}} = \mathrm{U}\mathrm{H} = [\tilde{\mathbf{H}}_1, \tilde{\mathbf{H}}_2, \ldots, \tilde{\mathbf{H}}_k, \ldots, \tilde{\mathbf{H}}_K]$ is the beamspace channel, where $\tilde{\mathbf{H}}_k = \mathrm{U}\mathrm{h}_k$ is the beamspace channel of the kth user. Here H^H indicates conjugate transpose of H.

According to the widely used zero-forcing (ZF) method [19, 20], the precoding matrix can be designed as $\mathrm{F} = (\mathbf{S}^H \tilde{\mathbf{H}})[(\mathbf{S}^H \tilde{\mathbf{H}})^H (\mathbf{S}^H \tilde{\mathbf{H}})]^{-1}$. Then, the multi-objective optimization problem under the criterion of sum-rate maximization can be presented as:

$$\mathbf{S}^{opt} = \arg\max_{\mathbf{S}} \mathcal{R} = \arg\max_{\mathbf{S}} K\log_2(1 + \frac{\rho}{\sigma^2 \mathrm{tr}[(\mathbf{S}^H\tilde{\mathbf{H}})^H(\mathbf{S}^H\tilde{\mathbf{H}})]^{-1})} \tag{3}$$

where the beam selection matrix $\mathbf{S}$ needs to satisfy $||\mathbf{S}(:,r)||_0 \leq 1$, $||\mathbf{S}(n,:)||_0 = 1$ and $\sum \mathbf{S}(:,r) = 1$ for $n = 1, 2, \ldots, N$ and $r = 1, 2, \ldots, N_{\mathrm{RF}}$ in order to ensure that K users match N_{RF} different RF chains. From the perspective of effective channel, (3) can be converted into

$$\mathcal{B}^{opt} = \arg\max_{\mathcal{B}} \mathcal{R} = \arg\max_{\mathcal{B}} K\log_2(1 + \frac{\rho}{\sigma^2 \mathrm{tr}(\tilde{\mathbf{H}}_r^H\tilde{\mathbf{H}}_r)^{-1})}) \tag{4}$$

where $\tilde{\mathbf{H}}_{\mathbf{r}} = \mathbf{S}^H\tilde{\mathbf{H}} = \tilde{\mathbf{H}}(b,:)_{b\in\mathcal{B}} \in \mathbb{C}^{N_{\mathrm{RF}}\times K}$ is the reduced-dimension effective channel after beam selection, mathematical set $\mathcal{B}$ contains all selected beams for K users, which needs to satisfy $\mathcal{B} \in \{1, 2, \ldots, N\}$ and the number of unequal elements of $\mathcal{B}$ is N_{RF}. The beam selection matrix $\mathbf{S}^{opt}$ can be constructed by assigning the corresponding position in $\mathbf{S}^{opt}$ to 1 through the beam in $\mathcal{B}^{opt}$. Then, the adaptive selection network in Fig. 1 can be implemented in hardware through $\mathcal{B}^{opt}$. As to energy efficiency η, it can be defined as $\eta = \frac{\mathcal{R}}{\rho + N_{\mathrm{RF}}P_{\mathrm{RF}}}$(bps/Hz/W), where P_{RF} is the energy consumed by one RF chain. Notely, when designing the number of the required RF chains, the hardware consumption and the spatial multiplexing gain of K users are considered with a trade-off; therefore, let $N_{\mathrm{RF}} = K$ in this paper. Therefore, the optimization problem of η in this paper is to maximize $\mathcal{R}$ under the fixed ρ, N_{RF} and P_{RF}.

3 Methods

To solve (4), the idea of simultaneous beam selection for multi-users and the discrepancy of inter-user interference are considered. This paper proposes a joint beam selection consisting of two stages: 1) creating the CBS and then classifying all users into NIUs and IUs; 2) for NIUs, the beams with large power are selected, while for IUs, the CSACO is proposed to optimize selected beams under the criterion of sum-rate maximization.

3.1 Feasibility analysis

Figure 2 shows an example of the power distribution of beamspace channel $\tilde{\mathbf{H}}$. Specifically, there are $N = 256$ optimal beams for $K = 32$ users, but the number of dominant beams (i.e., the beams with large power) is much smaller than N due to beamspace channel sparsity. Furthermore, for a certain user k, Fig. 3 shows an example of the channel power of each beam. One can observe from Fig. 3 that a few dominant beams have occupied most of the energy of the beamspace channel. Therefore, these dominant beams can be selected in advance as the candidate beams to narrow the range of beam search.

Due to the sparse scattering of millimeter waves, only a few beams with large energy (dominant beams) can reach the target user. Generally, the goal of beam selection is to maximize the achievable sum-rate, and these beams with larger power will be selected for each user according to the channel state information (i.e., the channel transmission matrix $\tilde{\mathbf{H}}$ in (2)).

Since the dominant beams of each user may overlap, if the beam with the largest power is directly assigned to each user, it will cause serious inter-user interference; besides, the beam selection criteria by exhaustive search can assign optimal beams for

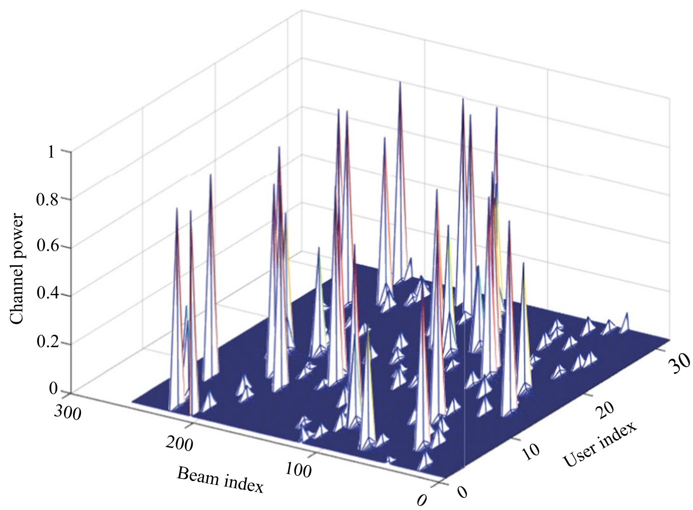

Fig. 2 An example of the power distribution of the beamspace channel for each user

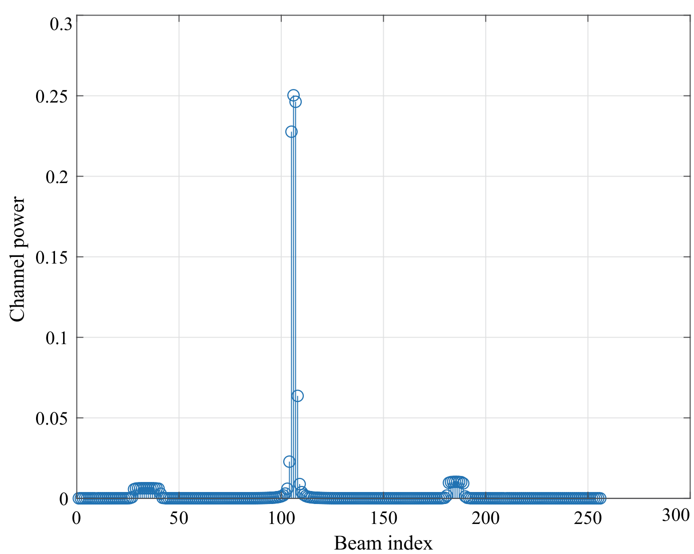

Fig. 3 An example of the channel power of each beam of the user *k*

all users; however, the high complexity will be involved. The ACO has a strong local searching ability for the characteristic of positive feedback, that is, the ants can leave more pheromones on the optimal solution, and more pheromones can attract more ants. This positive feedback mechanism will help to quickly search the optimal solution within the local range. Comparatively, the solutions generated by the CS have a certain degree of randomness in the global scope, which may cause the CS to oscillate near the optimal solution. Thereby introducing the ACO to the CS can make the CS converge quickly to the optimal solution, called as the CSACO.

In the proposed CSACO beam selection, firstly, this paper assumes that the perfect channel $\tilde{\mathbf{H}}$ has been obtained through channel estimation, and the $\tilde{\mathbf{H}}$ contains the channel power distribution information of each user, so several dominant beams with large power can be obtained for each user; secondly, according to whether the dominant beams of each user overlap with other users, all users can be classified into NIUs and IUs, and for NIUs, one beam with the largest power can be selected directly, which not only contains more power of the beamspace channel, but also causes less interference to others. For IUs, the beam selection can be considered as a traveling problem, where the IUs are regarded as the cities and all dominant beams are taken as optional paths for each interfering user. Our goal is to travel all the cities (i.e., IUs) once with K_{IU} paths (i.e., K_{IU} beams, and K_{IU} is the number of IUs) under the criteria of sum-rate maximization.

3.2 Beam selection

3.2.1 Stage1: Create the CBS and identify the user groups

Instead of assigning the strongest beam directly to each user in MM beam selection [6], this paper aims to select N_{RF} optimal unshared beams from N beams to maximize the system sum-rate. Note that the optimal method to solve this problem is the exhaustive search; however, it involves high complexity. For a typical mmWave massive MIMO system with $N = 256$ and $K = 32$, the total number of searches can reach up to 6×10^{40}. Therefore, a beam selection scheme with low complexity and without obvious performance loss is required.

Algorithm 1 The method of generating CBS.

Input: $\tilde{\mathbf{H}}$, K, C_a.
Output: The CBS $\mathcal{B}_a$.
Initialize: $\mathcal{B}_a = \mathrm{zeros}(K, C_a) \in \mathbb{Z}^{K \times C_a}$.
1: **for** each user k **do**
2: Calculate the energy $\bar{\mathbf{h}} = \left\| \tilde{\mathbf{H}}(:, k) \right\|^2$.
3: Sort the elements of $\bar{\mathbf{h}}$ in descending order of magnitude and let vector $\bar{\mathbf{h}}_s$ denotes the sorted $\bar{\mathbf{h}}$.
4: Let $\bar{\mathbf{h}}_p$ denotes the position index of the elements of $\bar{\mathbf{h}}_s$ in $\bar{\mathbf{h}}$.
5: $\mathcal{B}_a(k, :) = \bar{\mathbf{h}}_p(1 : C_a)$.
6: **end for**

Notely, the number of dominant beams of the user k is much smaller than N owing to the channel sparsity. Thereby, the $C_k (C_k \ll N)$ dominant beams can be used as the candidate beams[1] of the user k, and the C_k dominant beams can be obtained by Algorithm 1. The dominant beams mainly depend on the channel power distribution of each user, and the beams with large channel power will be selected as the dominant beams. The criterion for determining C_k is that the C_k dominant beams selected for user k must be able to contain most of the channel energy of user k. Specifically, when generating CBS, a threshold P need be set, and the ratio of the channel power contained in the C_k dominant beams selected by user k to the total channel power of user k is required to be greater than P. Due to the different power distribution characteristics of each user's channel, the number of dominant beams selected by each user will also vary, and then, each user will set a different C_k. The value of C_k with different users is analyzed as Fig. 4. However, this paper considers assigning only

[1] The value C_k, $\forall k$, could be predefined as a fixed constant or be obtained by setting thresholds on the magnitudes of beams. This paper assumes $C_1 = C_2 = \cdots = C_k = \cdots = C_K$ in the proposed beam selection.

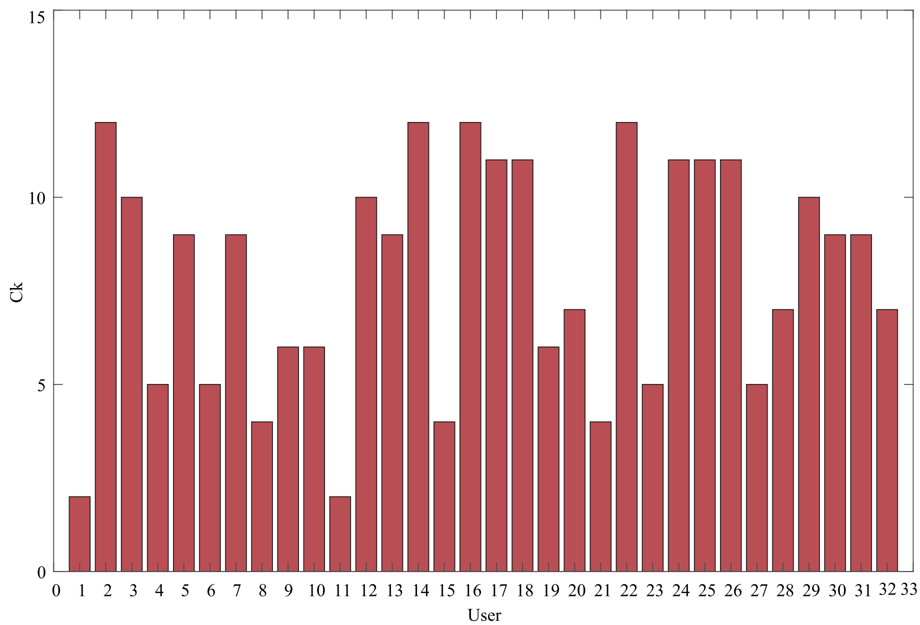

Fig. 4 An example of the value of C_k

one beam to each user, and a large C_k will result in a longer search time. Without loss of generality, this paper introduces the C_a and set $C_k = C_a, k = 1, 2, \ldots, K$.

In Algorithm 1, $\mathcal{B}_a$ is the CBS (i.e., dominant beams for all users), zeros() means generating a matrix where all elements are 0, and constant C_a is the number of dominant beams for each user (i.e., $C_a = C_1 = C_2 = \cdots = C_k = \cdots = C_K$). So, the first column of $\mathcal{B}_a$ is the strongest beam index of all users, and let b_k^1 denotes the first column element of the kth row of $\mathcal{B}_a$, i.e., $b_k^1 = \mathcal{B}_a(k, 1)$. Note that the K strongest beams $\left\{b_k^1\right\}_{k=1}^K$ contain most of the beamspace channel power. Therefore, if $b_1^1 \neq b_2^1 \neq \cdots \neq b_K^1$, the beam set $\mathcal{B} = \left\{b_1^1, b_2^1, \ldots, b_K^1\right\}$ can achieve the near-optimal performance; however, if there are same beams in $\mathcal{B}$, the corresponding users will suffer from serious inter-user interference. Therefore, this paper classifies all K users into two groups according to whether the beams in CBS overlap, i.e., NIUs and IUs, as follows:

(1) This paper defines the CBS of the user k is $\mathcal{S} \in \mathbb{Z}^{1 \times C_a} = \mathcal{B}_a(k, :)$, and define the user k is non-interfering user if each beam in the $\mathcal{S}_k$ is different from the beams in $\mathcal{S}_i$, $i = 1, 2, \ldots, K$ and $i \neq k$, i.e., $\mathcal{S}_k \cap \left\{\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_{k-1}, \mathcal{S}_{k+1}, \ldots, \mathcal{S}_K\right\} = \varnothing$. Therefore, the group $\mathcal{G}_{\mathrm{NIU}}$ consisting of all NIUs can be obtained.

(2) This paper defines $\mathcal{G}_{\mathrm{IU}} = \{1, 2, \ldots, K\} \backslash \mathcal{G}_{\mathrm{NIU}}$. Obviously, the $\mathcal{G}_{\mathrm{NIU}}$ and $\mathcal{G}_{\mathrm{IU}}$ satisfy $\mathcal{G}_{\mathrm{NIU}} \cup \mathcal{G}_{\mathrm{IU}} = \{1, 2, \ldots, K\}$ and $\mathcal{G}_{\mathrm{NIU}} \cap \mathcal{G}_{\mathrm{IU}} = \varnothing$. For user $k \in \mathcal{G}_{\mathrm{IU}}$, this paper will jointly search the appropriate beams from the set $\mathcal{S}^{\mathrm{IU}} = \left\{\mathcal{S}_k | k = 1, 2, \ldots, K\right\} \backslash \left\{\mathcal{S}_k | k \in \mathcal{G}_{\mathrm{NIU}}\right\}$ by the CSACO algorithm. Here $\mathcal{A}_1 \backslash \mathcal{A}_2$ denotes the elements in set $\mathcal{A}_2$ are eliminated from set $\mathcal{A}_1$ and $\mathcal{S}^{\mathrm{IU}} \in \mathbb{Z}^{K_{\mathrm{IU}} \times C_a}$ denotes the CBS of $\mathcal{G}_{\mathrm{IU}}$ with K_{IU} is the number of users in $\mathcal{G}_{\mathrm{IU}}$.

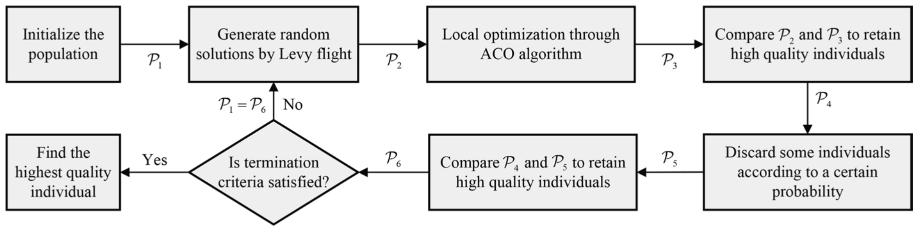

Fig. 5 The flow diagram of the proposed CSACO algorithm

3.2.2 Stage2: Search the beams for NIUs and IUs

For user $k \in \mathcal{G}_{\text{NIU}}$, the strongest beam $b_k^1 = \mathcal{B}_a(k,1)$ will be assigned directly, because the strongest beam contains most of the beamspace channel power and causes less inter-user interference. Therefore, the beams $\mathcal{B}_{\text{NIU}} = \left\{b_k^1\right\}_{k \in \mathcal{G}_{\text{NIU}}}$ for $\mathcal{G}_{\text{NIU}}$ can be obtained. Therefore, the problem (4) can be further simplified as

$$\mathcal{F}^{opt} = \arg\max_{\mathcal{F}} \mathcal{R} = \arg\max_{\mathcal{F}} K\log_2(1 + \frac{\rho}{\sigma^2 \text{tr}(\tilde{\mathbf{H}}_r^H \tilde{\mathbf{H}}_r)^{-1})}) \tag{5}$$

where $\mathcal{F}$ is a possible beam set without same elements selected from $\mathcal{S}^{\text{IU}}$ and $\tilde{\mathbf{H}}_r = \tilde{\mathbf{H}}(b,:)_{b \in \{\mathcal{F} \cup \mathcal{B}_{\text{NIU}}\}}$. It is worth noting that the dimension of the solution in (5) is smaller than that of (4) (i.e., the dimension of $\mathcal{F}$ is smaller than the dimension of $\mathcal{B}$), which can effectively reduce the search complexity compared with solving (4) directly. In order to solve (5), this paper proposes a CSACO algorithm to select beams simultaneously for all IUs. For user $k \in \mathcal{G}_{\text{IU}}$, the key idea is to select the $\text{Card}(\mathcal{B}_{\text{IU}}) = K - \text{Card}(\mathcal{B}_{\text{NIU}})$ beams by the proposed CSACO algorithm. The remaining task is to jointly search another $\text{Card}(\mathcal{B}_{\text{IU}})$ beams for the $\mathcal{S}^{\text{IU}}$ to maximize the achievable sum-rate $\mathcal{R}$. Here $\text{Card}(\mathcal{A})$ denotes the cardinality of set $\mathcal{A}$.

In order to ensure that the beams in $\mathcal{F}$ are all elements in $\mathcal{S}^{\text{IU}}$, this paper defines $\mathcal{I} \in \mathbb{Z}^{K_{\text{IU}} \times 1}$ to represent the index of $\mathcal{F} \in \mathbb{Z}^{K_{\text{IU}} \times 1}$ in $\mathcal{S}^{\text{IU}}$. For example, for a possible case with $K_{\text{IU}} = 2$, $C_a = 3$, $\mathcal{S}^{\text{IU}} = \{56, 23, 155; 80, 56, 35\} \in \mathbb{Z}^{2 \times 3}$ and $\mathcal{I} = \{1, 3\}^T \in \mathbb{Z}^{2 \times 1}$, then the selected beams set for $\mathcal{G}_{\text{IU}}$ is $\mathcal{F} = \{56, 35\}^T \in \mathbb{Z}^{2 \times 1}$. Here $\{\cdot\}^T$ indicates transpose of $\{\cdot\}$.

Assume that there are Q optimizable individuals in the CSACO algorithm. Since the first column of $\mathcal{S}^{\text{IU}}$ is the strongest beam of each user in $\mathcal{G}_{\text{IU}}$, the each optimizable individual can be initialized as $\mathcal{I}_{1,q} = \{1, 1, \ldots, 1\}^T \in \mathbb{Z}^{K_{\text{IU}} \times 1}$, $q = 1, 2, \ldots, Q$ and the whole population can be given as $\mathcal{P}_1 = \left\{\mathcal{I}_{1,1}, \mathcal{I}_{1,2}, \ldots, \mathcal{I}_{1,Q}\right\}$. In the proposed CSACO algorithm, the key idea is to find a suitable $\mathcal{I}_{\text{best}}$ by updating $\mathcal{P}$ to solve (5). The flow diagram of the proposed CSACO algorithm is shown as Fig. 5, and the tth iteration includes mainly the following steps:

(1): Initializing $\mathcal{P}_1 = \left\{\mathcal{I}_{1,1}, \mathcal{I}_{1,2}, \ldots, \mathcal{I}_{1,Q}\right\}$ with $\mathcal{I}_{1,q} = \{1, 1, \ldots, 1\}^T$, $\forall q$ and $\mathcal{I}_{\text{best}}^0 = \mathcal{I}_{1,q}$.

(2): Generating random population $\mathcal{P}_2 = \left\{\mathcal{I}_{2,1}, \mathcal{I}_{2,2}, \ldots, \mathcal{I}_{2,Q}\right\}$ by Levy flight for $\mathcal{P}_1$. The Levy flight strategy satisfies $\mathcal{I}_{2,q} = \mathcal{I}_{1,q} + \alpha \otimes \mathcal{L}(\beta)$, $q = 1, 2, \ldots, Q$, where α denotes the step factor, $\otimes$ denotes dot product, β is the parameter skewness and

Table 1 Simulation parameters

Parameter	Description	value
C_a	The number of dominant beams for each user	3
Q	The number of optimizable individuals in CS	20
P_a	The probability of discarding individuals	0.25
M	The number of optimizable individuals selected for ACO	2
$T_{\max}$	The maximum number of iterations	200
V	The number of times that the $\mathcal{I}_{\text{best}}$ does not update continuously	15
α	The step factor in Levy flight	1
β	The parameter skewness in Levy flight	1.5

$\mathcal{L}(\beta) = \mu/|\nu|^{1/\beta}$ is the random optimization route of Levy flight, here μ and ν are random numbers that following the normal distribution.

(3): Performing local optimization for $\mathcal{P}_2$ by ACO algorithm [8] and generating $\mathcal{P}_3$. Considering an attractive trade-off between the computational complexity and system performance, this paper only randomly selects M individuals from $\mathcal{P}_2$ for local optimization.

(4): Sequentially comparing individuals in $\mathcal{P}_2$ and $\mathcal{P}_3$ to retain high-quality individuals, which can constitute $\mathcal{P}_4$. Here the high-quality individual denotes that it can solve (5) better, e.g., if the $\mathcal{F}$ corresponding to $\mathcal{I}_{2,1}$ has a higher $\mathcal{R}$ in (5) than $\mathcal{I}_{3,1}$, then discard $\mathcal{I}_{3,1}$, retain $\mathcal{I}_{2,1}$ and let $\mathcal{I}_{4,1} = \mathcal{I}_{2,1}$.

(5): Discarding some individuals in $\mathcal{P}_4$ according to the probability P_a and replacing them with the best individual from the previous generation. For example, if $\mathcal{I}_{4,1}$ is selected to be discarded, then let $\mathcal{I}_{5,1} = \mathcal{I}^{t-1}_{\text{best}}$, if $\mathcal{I}_{4,2}$ is not selected to be discarded, then let $\mathcal{I}_{5,2} = \mathcal{I}_{4,2}$. Then, the population $\mathcal{P}_5$ can be obtained.

(6): Sequentially comparing individuals in $\mathcal{P}_4$ and $\mathcal{P}_5$ to retain high-quality individuals, which can constitute $\mathcal{P}_6$.

(7): Finding the highest quality individual in $\mathcal{P}_6$ and assigning it to $\mathcal{P}^t_{\text{best}}$. Then, it is determined whether the predetermined terminated condition has been satisfied. if so, go to step 8), if not, let $\mathcal{P}_1 = \mathcal{P}_6$ and return to step 2). The traditional terminated condition is to determine whether t is equal to the maximum number of iterations $T_{\max}$, which may cause some inefficient iterations. In order to improve the effectiveness of the CSACO algorithm, this paper introduces a new terminated condition, that is $\mathcal{I}_{\text{best}}$ do not update for consecutive $V(V \le T_{\max})$ times, i.e., $\mathcal{I}^t_{\text{best}} = \mathcal{I}^{t-1}_{\text{best}} = \cdots = \mathcal{I}^{t-V+1}_{\text{best}}$, $t \ge V$ or $t = T_{\max}$, which can judge in time whether the algorithm has converged before reaching the maximum number of iterations.

(8): Assigning $\mathcal{I}^t_{\text{best}}$ to $\mathcal{F}^{opt}$, which is the beam set jointly searched by CSACO algorithm for the $\mathcal{G}_{\text{IU}}$. Thereby, all selected beams $\mathcal{B}^{opt} = \mathcal{F}^{opt} \cup \mathcal{B}_{\text{NIU}}$ can be obtained.

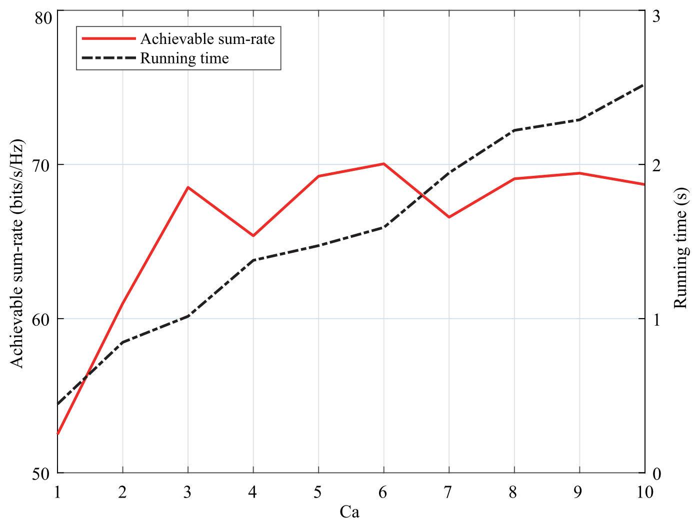

Fig. 6 The achieve sum-rate and running time versus different values of C_a with SNR = 25 dB

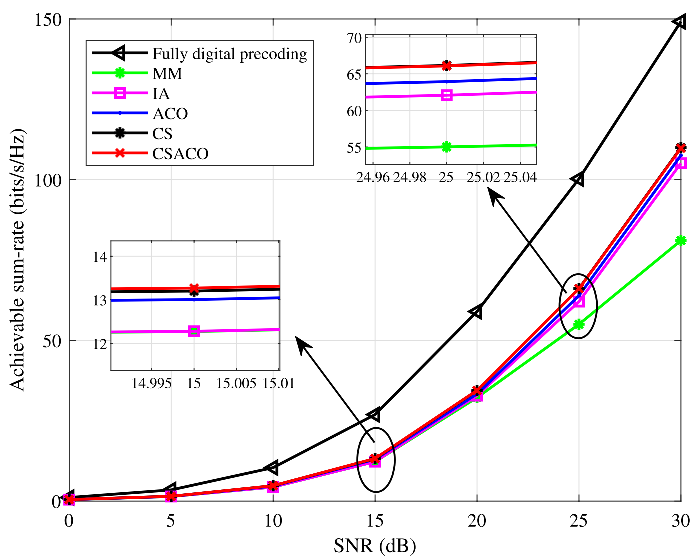

Fig. 7 Achievable sum-rate comparison versus different SNRs with $K = 32$

4 Results and discussion

4.1 Results

In our simulations, a lens antenna array with $N = 256$ and $N_{\mathrm{RF}} = 32$ is used. The channel parameters are set as follows [21–23]: $L = 3$, $A_{k,l} \sim \mathbb{CN}(0,1)$, $\theta_{k,l} \sim \mathcal{U}(-\frac{\pi}{2}, \frac{\pi}{2})$ for $l = 1, 2, \ldots, L$ and $k = 1, 2, \ldots, K$. Other simulation parameters are shown in Table 1.

To further determine C_a, Fig. 6 shows the achievable sum-rate and running time of the proposed beam selection under different C_a. It is worth noting that with the increase of C_a, more beams will be stored in the CBS, resulting in longer search times. The determination of the value of C_a should simultaneously satisfy the achievable

Table 2 The values of achievable sum-rate versus different SNRs with $K = 32$

Model	SNR						
	0 dB	**5 dB**	**10 dB**	**15 dB**	**20 dB**	**25 dB**	**30 dB**
FDP	1.1145	3.4815	10.4161	26.9202	58.9917	100.2865	149.1983
MM	0.4511	1.4281	4.3603	12.2690	32.2121	55.0155	81.0764
IA	0.4585	1.4332	4.3663	12.2748	32.8215	62.0742	105.1163
ACO	0.4715	1.4673	4.6501	13.0028	33.3328	63.9350	107.5671
CS	0.4881	1.4964	4.7879	13.1988	34.3881	66.0802	109.8138
Proposed	0.4886	1.5028	4.7886	13.2674	34.4597	66.1418	109.9584

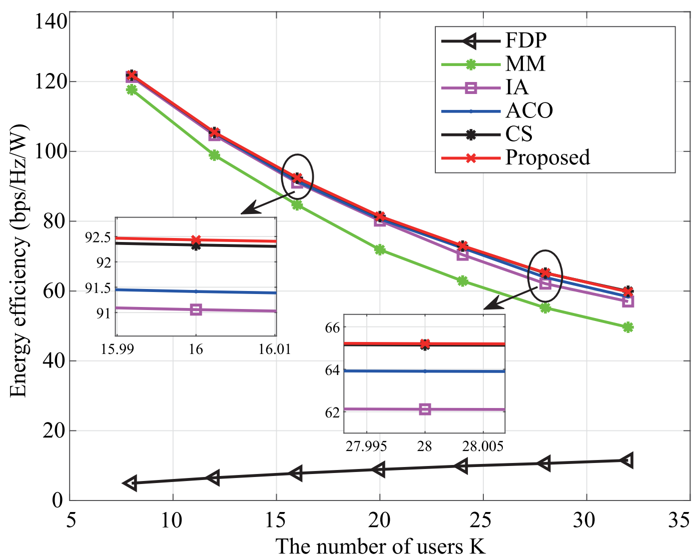

Fig. 8 Energy efficiency comparison versus different number of users with SNR = 25 dB

sum-rate as high as possible, and the running time as short as possible. Taking into account the above two indicators, this paper sets $C_a = 3$.

Figure 7 shows the sum-rate performance comparison between the proposed CSACO beam selection, MM beam selection [6], IA beam selection [7], ACO beam selection [8] and CS beam selection versus different signal-to-noise ratios (SNR). This paper also tests the performance of the fully digital precoding (FDP) using all beams as the benchmark for comparison. From Fig. 7, it can be observed that the proposed CSACO beam selection achieves better sum-rate performance than the other ones. This is because the proposed beam selection can separate potential interfering users through the CBS and jointly select beams for all IUs, which fully considers the inter-user interference and then improves the achievable sum-rate. Table 2 shows the numerical values of achievable sum-rate comparison versus different SNR with $K = 32$. With respect to SNR = 25 dB in Table 2, the sum-rate of the proposed CSACO beam selection is improved by 3.45% and 6.55% compared with the existing ACO beam selection and IA beam selection, respectively.

Figure 8 compares the energy efficiency η versus the number of users K. This paper adopts the values $P_{\mathrm{RF}} = 34.4$ mW, $\rho = 32$ mW (15 dBm) [24] and $N_{\mathrm{RF}} = K$. It can be

Table 3 The values of energy efficiency versus different number of users with SNR = 25 dB

Model	K						
	$K=8$	$K=12$	$K=16$	$K=20$	$K=24$	$K=28$	$K=32$
FDP	4.9560	6.5201	7.8019	8.8946	9.8886	10.6326	11.5168
MM	117.6803	98.9128	84.6865	71.8480	62.8732	55.1938	49.6338
IA	121.3344	104.6632	91.0581	80.1747	70.3892	62.1172	57.0092
ACO	121.7620	105.2785	91.4151	80.6606	72.3296	63.9057	58.3835
CS	121.8202	105.4177	92.3325	81.3254	72.8750	65.1404	59.7739
Proposed	121.8684	105.4777	92.4332	81.4188	72.9632	65.2068	59.9484

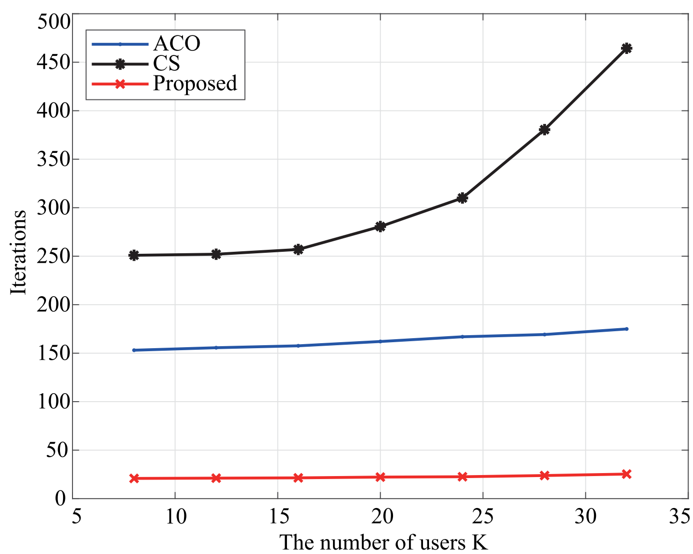

Fig. 9 Iterations comparison versus different number of users with SNR = 25 dB

seen that the CSACO beam selection achieves higher energy efficiency than the other ones. Notely, although full digital precoding has a high sum-rate, it employs the overall RF chains equal to the number of antennas (i.e., $N_{\mathrm{RF}} = N$ for full digital precoding and $N_{\mathrm{RF}} = K$ for other beam selection methods), resulting in low energy efficiency. Table 3 shows the numerical values of energy efficiency comparison versus different number of users with SNR = 25 dB. With respect to $K = 32$ in Table 3, the energy efficiency of the proposed CSACO is improved by 2.68% and 5.16% compared with the existing ACO and IA, respectively.

To evaluate the convergence speed compared to the ACO beam selection, CS beam selection and CSACO beam selection, Fig. 9 shows the number of iterations to achieve convergence under the condition of different number of users. It can be seen that the iterations of the CSACO sharply decrease compared to the ACO beam selection and CS beam selection, owning to the proposed CSACO combining the advantages of global search and local search. In addition, the running time of the CSACO is lower than that of the ACO and CS, as shown in Fig. 10.

It is worth noting that although the CS has almost the same sum-rate and energy efficiency performance as the CSACO, CS is prone to generate oscillation solutions near the optimal solution, resulting in more iterations and a longer searching time, as

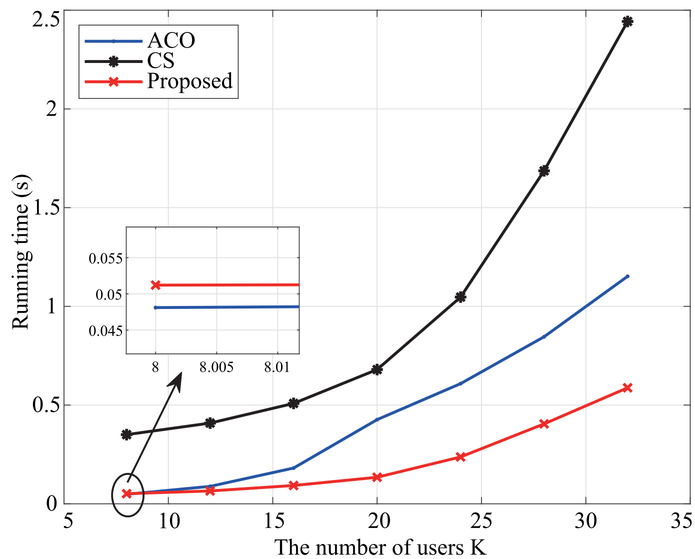

Fig. 10 Running time comparison versus different number of users with SNR = 25 dB

shown in Figs. 9 and 10, respectively. Introducing the ACO to the CS can make the CS converge quickly to the optimal solution.

4.2 Discussion

Simulation results show that the proposed beam selection can achieve better sum-rate, energy efficiency and iterations. Notely, the number of RF chains is also significantly reduced by 8 times than that of fully digital precoding. In beam selection, all users classified into NIUs and IUs can customize effective beam selection criteria for different users. However, in IA beam selection [7], although the users are also classified, the principle of assigning beams to IUs belongs to the greedy algorithm, which is difficult to achieve the global optimum. Comparatively, the proposed CSACO algorithm can combine all IUs to perform beam selection simultaneously, and each evolving individual will select beams for all IUs after each iteration, which can consider all IUs simultaneously instead of only one user as in the greedy algorithm.

In the ACO beam selection [8], although it regards beam selection as a traveling problem, it selects beams from the dominant beams for each user sequentially, which is also a greedy idea. Besides, the convergence speed of ACO algorithm is slow, and the solutions are easy to fall into the local optimum. In the proposed CSACO beam selection, all users perform beam selection simultaneously instead of one by one, which can better consider inter-user interference. Furthermore, the combination of CS algorithm with strong global search ability and ACO algorithm with strong local optimization ability can make the proposed CSACO to find an approximate global optimal solution.

The advantages of the proposed beam selection method with respect to other schemes can be summarized as follows:

(1) Utilizing the power distribution characteristics of the beamspace channel, the proposed method can preselect the dominant beams of all users to form a CBS.
(2) Grouping users by determining whether the beams in CBS overlap, rather than just considering the strongest beam of each user, can more accurately identify inter-user interference.
(3) The proposed method can narrow the search range without significant performance loss by using CBS, which can improve beam search efficiency.
(4) The proposed CSACO can search beams for multiple users simultaneously, rather than using greedy algorithms to search beams for users one by one, and can obtain a better solution in the global range.
(5) Compared with the ant colony optimization and cuckoo search algorithms, the proposed CSACO can achieve the better convergence quickly and can find the beams with more contribute to the sum-rate.

5 Conclusions

This paper proposes a joint beam selection to degrade the potential inter-user interference, which mainly involves the following work: 1) creating the candidate beam set and selecting the beams for different user groups, respectively, which can decrease the computation complexity; 2) for NIUs, the beams with large power are selected, while for IUs, the CSACO is proposed to optimize selected beams under the criterion of sum-rate maximization. Simulation results validate the proposed CSACO beam selection can select the optimal beams for multi-users simultaneously with few iterations, which can improve the sum-rate performance close to the fully digital system, and obtain the higher energy efficiency than MM, IA, ACO and CS beam selection. Besides, the idea of creating the CBS can distinguish users and narrow the search range with the fewer iterations and the shorter search time, which can be expanded to other communication scenarios or for the more complicated classification of interference users.

Abbreviations

mmWave	Millimeter-wave
MIMO	Multi-input multi-output
MM	Magnitude maximization
IA	Interference-aware
ACO	Ant colony optimization
SINR	Signal-to-interference plus noise ratio
NOMA	Non-orthogonal multiple access
CBS	Candidate beam set
NIUs	Non-interfering users
IUs	Interfering users
CS	Cuckoo search
CSACO	Combining CS and ACO
BS	Base station
ZF	Zero-forcing
SNR	Signal-to-noise ratio
FDP	Fully digital precoding

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Author contributions
QWJ designed the algorithm, performed the simulation results and drafted the manuscript under the supervision of CHZ, XYG and JKZ. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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