

QPSO-based Beamforming in Dual RIS-assisted Uplink Anti-jamming Communication System

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Abstract—Considering a dual reconfigurable intelligent surface (RIS) assisted uplink cellular communication system under a malicious jamming user with known positions, we propose a joint active and passive anti-jamming beamforming scheme to maximize the system signal-to-interference-plus-noise ratio (SINR) and enhance the system achievable rate in this paper. To obtain the optimal solution, the quantum particle swarm optimization (QPSO) algorithm is utilized, which also mitigates the risk of falling into the local optimum and achieves better reliable global optimization. The simulation results illustrate that the proposed beamforming design in the dual RIS-assisted uplink cellular system exhibits superior anti-jamming performance compared with the other typical optimized beamforming schemes.

Index Terms—anti-jamming, RIS, QPSO, beamforming, SINR

I. INTRODUCTION

RECENTLY, reconfigurable intelligence surface (RIS) becomes a critical technology for 6G networks, offering flexible and cost-effective options to alter the wireless environment. The phases of RIS units can be designed to enable directional reflection of incident signals, leading to an improved channel propagation environment [1]. The change of the RIS reflection phase by controlling the reflection pattern is called the passive beamforming (PB), as compared to the active beamforming (AB) at the base station (BS) [2].

Specifically, [3] studied the RIS-assisted multi-cell wireless network, where the AB and the PB were designed to maximize the minimum achievable rate of the edge users. Furthermore, considering the non-ideal channel state information (CSI), robust beamforming optimization algorithms were proposed in [4] for RIS-assisted multi-user multiple input single output (MU-MISO) system. In response to potential eavesdropping attacks, [5] employed RIS to enhance the secrecy rate of the wireless communication system, simultaneously achieving

lower transmission power. Furthermore, in [6], the transmission power was minimized by RIS deployment under the secrecy rate constraints. AB and PB of RIS were designed to enhance the secrecy rate in the anti-jamming scenarios for the multi-user multiple input multiple output (MU-MIMO) system [7].

Previous anti-jamming communication methods mainly utilize single RIS to improve the system performance. However, recent research has investigated the utilization of dual RIS-assisted wireless communication systems, which can enhance the system performance compared to single RIS cases, due to increased diversity and better beamforming vector design. Joint optimization of the reflection phase-shift matrices and the AB was studied in [8]. Moreover, the dual RIS in wireless secure transmission and an alternating optimization (AO) algorithm were proposed based on the product Riemannian manifold to jointly optimize the AB vector at the transmitter and the PB vector at the RIS for maximizing the system secure rate [9]. However, as the number of RISs increases, more inter-RIS links are formed, resulting in deep coupling of the reflected phase-shifts and increasing complexity in the joint optimization of the phase-shift matrix of each RIS. Therefore, researchers have focused on the beamforming design in multiple RIS-assisted wireless systems and intelligent algorithms to analyze the balance between performance benefits and complexity.

Inspired by the above research, we propose the quantum particle swarm optimization (QPSO) based joint AB and PB design for a dual RIS-assisted anti-jamming MISO wireless system in this paper. The QPSO algorithm is taken to iteratively optimize the beamforming in the cellular communication system, leveraging the strong global convergence properties of QPSO to improve algorithm efficiency and accuracy. We also present a beamforming design that optimizes the PB of both RISs, leading to more comprehensive optimization and better anti-jamming performance. Through simulation results, we demonstrate the effectiveness of our approach in reducing the jamming levels and improving the system signal-to-interference-plus-noise ratio (SINR) compared to conventional joint AB and PB optimization algorithms.

The paper is organized as follows. Section II briefly presents

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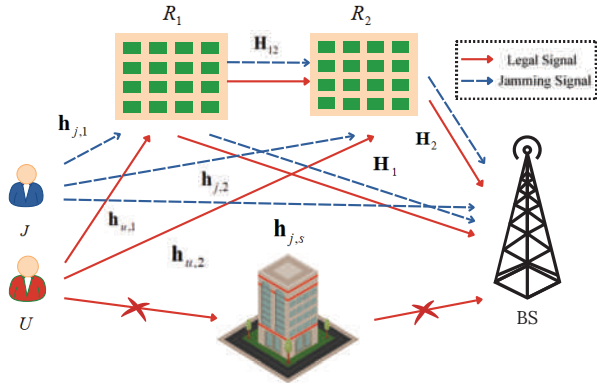


Fig. 1. Dual RIS-assisted uplink anti-jamming cellular system model.

the system model and the objective problem. Section III proposes the optimization of joint AB and PB design and the solution to maximize the system SINR and the achievable rate. Section IV contains the simulation results and analyses. Finally, Section V concludes the contents of the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

The dual RIS-assisted anti-jamming cellular system consists of one BS with N_t antenna, two RISs (R_1 and R_2), a legal user U , and a malicious jamming user J , as shown in Fig. 1. R_1 is near U with M_1 reflection elements, whereas R_2 is close to the BS with M_2 reflection elements. U and J have single transmit antenna. Due to the obstacles, such as building, there is no direct link between U and the BS. The signal from U should be transmitted to the BS by R_1 and R_2 . We assume that $\mathbf{H}_{12} \in \mathbb{C}^{M_2 \times M_1}$, $\mathbf{H}_1 \in \mathbb{C}^{N_t \times M_1}$, and $\mathbf{H}_2 \in \mathbb{C}^{N_t \times M_2}$ denote the channel matrix from R_1 to R_2 , from R_1 to the BS, and from R_2 to the BS, respectively. In a real urban environment, long-distance transmission tends to cause severe path loss. Therefore, we only assume the direct and the first-reflection links from U to the BS. The other signal transmissions, including scattered, diffracted, and multi-reflected signals through the RIS, are ignored.

The two RISs reflect the received signals from the BS to users through the RIS plane array, resulting in a multiplicative channel model. We define the diagonal PB matrices for R_1 and R_2 as $\Theta_1 = \text{diag}(\theta_1) \in \mathbb{C}^{M_1 \times M_1}$ and $\Theta_2 = \text{diag}(\theta_2) \in \mathbb{C}^{M_2 \times M_2}$, respectively. Here, θ_1 and θ_2 are reflection coefficient, where $|\theta_{1,m_1}| = 1, \forall m_1 \in \{1, 2, \dots, M_1\}$ and $|\theta_{2,m_2}| = 1, \forall m_2 \in \{1, 2, \dots, M_2\}$ are the m_1 -th element of θ_1 and the m_2 -th element of θ_2 , respectively.

B. Problem Formulation

The transmission of the legal signal and the jamming signal is shown in Fig. 1. The composite channel from U to the BS can be expressed as

$$\mathbf{H}_u = \mathbf{H}_2 \Theta_2 \mathbf{H}_{12} \Theta_1 \mathbf{h}_{u,1} + \mathbf{H}_1 \Theta_1 \mathbf{h}_{u,1} + \mathbf{H}_2 \Theta_2 \mathbf{h}_{u,2}, \quad (1)$$

where $\mathbf{h}_{u,1} \in \mathbb{C}^{M_1 \times 1}$ and $\mathbf{h}_{u,2} \in \mathbb{C}^{M_2 \times 1}$ are the channel matrices of the U - R_1 link and the U - R_2 link, respectively. The channel between J and the BS is $\mathbf{h}_{j,s} \in \mathbb{C}^{N_t \times 1}$. We can also write the composite channel from J to BS as

$$\mathbf{H}_j = \mathbf{H}_2 \Theta_2 \mathbf{H}_{12} \Theta_1 \mathbf{h}_{j,1} + \mathbf{H}_1 \Theta_1 \mathbf{h}_{j,1} + \mathbf{H}_2 \Theta_2 \mathbf{h}_{j,2} + \mathbf{h}_{j,s}, \quad (2)$$

where the channel matrices of the J - R_1 link and the J - R_2 link are $\mathbf{h}_{j,1} \in \mathbb{C}^{M_1 \times 1}$ and $\mathbf{h}_{j,2} \in \mathbb{C}^{M_2 \times 1}$, respectively. We assume that, in the uplink transmission, the transmit signals of the legal user U and the jamming user J are x_u and x_j , respectively. Let $\mathbf{w}$ denote as the AB vector at the BS. The transmit power of U and J are respectively set to be P_u and P_j , and the received signal at the BS is given by

$$y = \mathbf{w}^H \left(\sqrt{P_u} \mathbf{H}_u x_u + \sqrt{P_j} \mathbf{H}_j x_j + \mathbf{n} \right) \quad (3)$$

where $\mathbf{w}^H \in \mathbb{C}^{1 \times N_t}$, $\mathbf{w} \mathbf{w}^H = 1$. $(\cdot)^H$ indicates the conjugate transpose operation of the vector and $\mathbf{n} \in \mathbb{C}^{N_t \times 1}$ represents the complex Gaussian noise with mean 0 and variance σ^2 . By combining the equations (1)-(3), the system SINR can be calculated as

$$\text{SINR} = \gamma(\mathbf{w}, \theta_1, \theta_2) = \frac{P_u |\mathbf{w}^H (\mathbf{H}_u)|^2}{P_j |\mathbf{w}^H (\mathbf{H}_j)|^2 + \sigma^2}. \quad (4)$$

According to the Shannon channel capacity theorem, the system achievable rate is given by

$$R_a = \log_2 \left[1 + \frac{P_u |\mathbf{w}^H (\mathbf{H}_u)|^2}{P_j |\mathbf{w}^H (\mathbf{H}_j)|^2 + \sigma^2} \right]. \quad (5)$$

To improve the system anti-jamming capability and achieve higher system achievable rates, the joint optimization of AB and PB is formulated by maximizing the system SINR as

$$\begin{aligned} \max_{\mathbf{w}, \theta_1, \theta_2} & \gamma(\mathbf{w}, \theta_1, \theta_2) \\ \text{s.t. } & C_1: \mathbf{w} \mathbf{w}^H = 1 \\ & C_2: |\theta_{1,m_1}| = 1, \forall m_1 \in \{1, 2, \dots, M_1\} \\ & C_3: |\theta_{2,m_2}| = 1, \forall m_2 \in \{1, 2, \dots, M_2\}, \end{aligned} \quad (6)$$

where C_1 is the energy normalization constraint for the BS, C_2 , and C_3 are the unit modulus constraints for the PB at these two RISs. Obviously, obtaining the optimum solution to the above optimization problem is challenging due to the coupled optimization variables and the non-convex objective function. Simultaneously optimizing the variables of the objective function with $\mathbf{w}$, θ_1 , and θ_2 is difficult. To overcome these problems, we use the QPSO algorithm to obtain the global optimum solution.

III. ALGORITHM DESIGN

A. Algorithm Basics

The QPSO algorithm was first proposed as an intelligent optimization algorithm. In contrast to the standard particle swarm optimization (PSO) algorithm, the QPSO algorithm has faster search speeds and fewer parameters for convergence [10]. Let $\mathbf{X}_i$ and $\mathbf{pbest}_i$ be the vector position and the individual optimum position of the particle i , respectively.

The optimization formula to update the individual optimum position of the particle i is given by

$$\mathbf{pbest}_i = \begin{cases} \mathbf{pbest}_i, & \text{if } (f[\mathbf{X}_i] \leq f[\mathbf{pbest}_i]) \\ \mathbf{X}_i, & \text{if } (f[\mathbf{X}_i] > f[\mathbf{pbest}_i]) \end{cases} \quad (7)$$

Meanwhile, the updated formula of the global optimum position is

$$\mathbf{gbest} = \begin{cases} s = \arg \max_{1 \leq i \leq N} \{f[\mathbf{pbest}_i]\} \\ \mathbf{gbest}(t) = \mathbf{pbest}_s \end{cases} \quad (8)$$

where $\mathbf{gbest}$ is the global optimum position and N is the size of the particle population [10].

The individual attractor update equation is written as

$$\mathbf{art}_i = r_1 \cdot \mathbf{pbest}_i + (1 - r_1)\mathbf{gbest}, \quad (9)$$

where $\mathbf{art}_i$ denotes the individual attractor of the particle i , and r_1 is a random factor, with uniform distribution $r_1 \sim U(0, 1)$.

In the process of the QPSO algorithm, the attractors integrate the individual optimum position and the global optimum position to represent the directive effect on the particle motion and ensure algorithm convergence. The particle position is

$$\mathbf{X}_i(t) = \mathbf{atr}_i \pm \frac{\mathbf{L}_i}{2} \ln\left(\frac{1}{r_2}\right), \quad (10)$$

where r_2 is a random factor, with uniform distribution $r_2 \sim U(0, 1)$.

We insert the average of the individual best position $\mathbf{mbest}$ to calculate the next iteration of the particle i of the feature-length $\mathbf{L}_i$ and to control the feature-length. We have

$$\mathbf{mbest} = \frac{1}{N} \sum_{i=1}^N \mathbf{pbest}_i. \quad (11)$$

According to [10], the feature-length is calculated as

$$\mathbf{L}_i = 2\alpha \cdot |\mathbf{mbest} - \mathbf{X}_i(t)|. \quad (12)$$

Moreover, the evolution function of the particle i is

$$\mathbf{X}_i(t+1) = \mathbf{art}_i \pm \alpha \cdot |\mathbf{mbest}(t) - \mathbf{X}_i(t)| \cdot \ln\left(\frac{1}{r_3}\right), \quad (13)$$

where r_3 is a random factor, with uniform distribution $r_3 \sim U(0, 1)$ and α is the contraction-expansion coefficient and controls the activity range from particles to attractors.

By modifying the value of the contraction-expansion coefficient, which affects the search range of the particles, we can control the algorithm convergence rate. A larger contraction-expansion coefficient may increase the search range and enhance the global search ability. We set the value of α by the linear decreasing strategy as [1.0, 0.5] for improving algorithm performance.

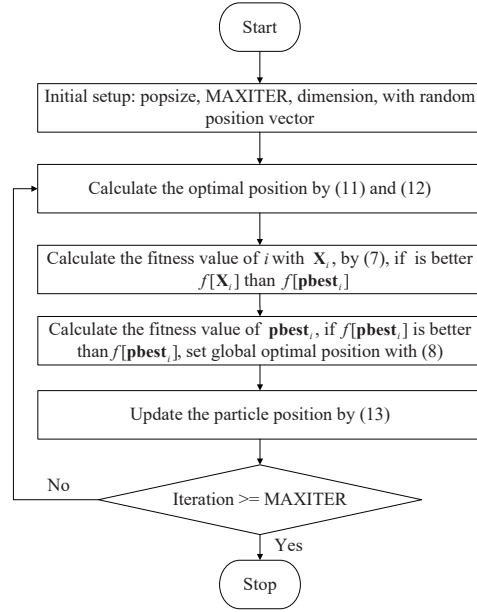


Fig. 2. QPSO-based beamforming process.

B. Algorithm Process

We denote the position vectors of particles as $\mathbf{w}$, θ_1 , and θ_2 . The QPSO-based joint AB and PB optimization flowchart is shown in Fig. 2 and its procedure is provided in the following.

step 1: Initialize the algorithm parameters, including the population size (popsize), dimension, and the maximum number of iterations (MAXITER).

step 2: Calculate the fitness values by mapping particles from the complex domain to the real domain.

step 3: Iterate to update the particle positions, including individual and global optimum positions, and attractor positions.

step 4: Set the maximum iteration limit. If the iteration meets the maximum iteration limit, output the optimum particle position. Otherwise, repeat steps 2 to 4.

step 5: According to the optimum particle position, calculate the optimization result.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, simulation results are provided to validate the effectiveness of the proposed algorithm. We assume that the receive antenna number of BS is 5. The system setup scenario is designed as follows, U and J are positioned at (1, 50, 0)m and (5, 40, 0)m, respectively. The BS is situated at (1, 0, 2)m. R_1 is placed close to U and R_2 is near the BS, with coordinates (0, 49, 1)m and (0, 1, 1)m, respectively. All channels within the system are modeled as Rayleigh fading distribution, and the path loss is $\varepsilon = \frac{\varepsilon_0}{d^\alpha}$, where d is the transmission distance, ε_0 is set as -30dB at the reference distance $d_0 = 1$, and α is the path loss coefficient. Also, the path loss coefficient of the U - R_1 link and J - R_1 link are both set to be 2.2, while to be 3 for the other links [11]. We compare the performance of the proposed QPSO algorithm with the

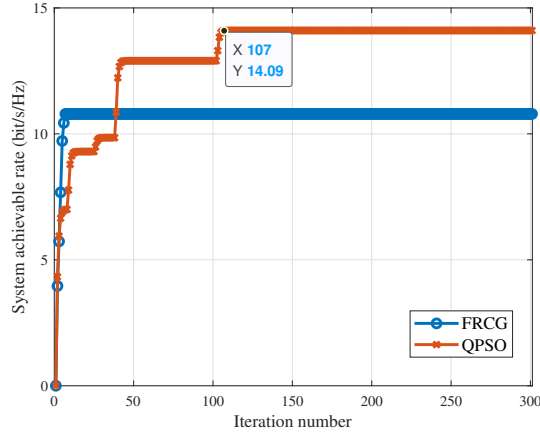


Fig. 3. Convergence performance of FRCG and QPSO.

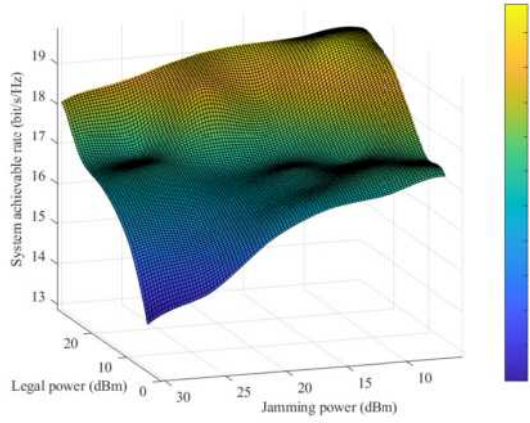


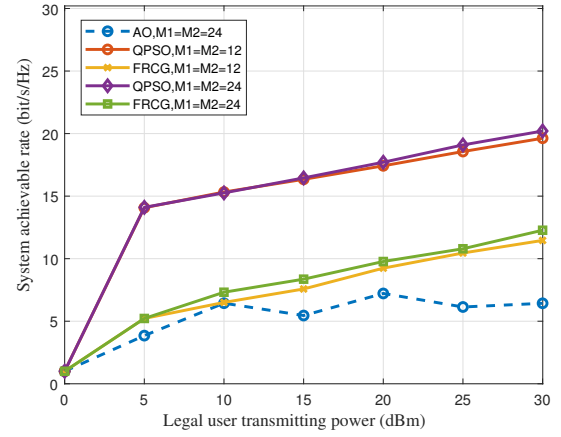
Fig. 4. Anti-jamming performance of the QPSO scheme vs. legal power and jamming power.

following benchmark algorithms, such as the Fletcher-Reeves conjugate gradient (FRCG) algorithm and the AO algorithm.

A. Performance comparison

The convergence performance of the FRCG and QPSO algorithms is evaluated in Fig. 3. We assume the same number of reflection elements for R_1 and R_2 as $M_1 = M_2 = 24$. The FRCG algorithm gets the system achievable rate converged to the fixed value with 11bit/s/Hz. As the iteration number increases above 107, the QPSO algorithm obtains the optimum achievable rate, which is 14bit/s/Hz. Although the FRCG algorithm has fewer iterations to converge than the QPSO algorithm, the system achievable rate of the QPSO algorithm is about 30% higher than that obtained by the FRCG algorithm.

In Fig. 4, the relationship between QPSO-based anti-jamming beamforming optimization performance and the legal power, as well as jamming power is plotted. The system achievable rate increases almost linearly with the power of the legal user. In contrast, when the jamming power rises, the increase in the system achievable rate plateaus. This is

Fig. 5. Relationship between R_a and P_u for typical beamforming schemes.

because the RIS consistently enhances the radio environment with phase-shift adjustment.

Fig. 5 illustrates the relationship between the transmit power P_u of the legal user and the system achievable rate. The proposed joint AB and PB design in the uplink anti-jamming cellular system enhances signal transmission and anti-jamming ability through diverse links and reduces channel correlation. Furthermore, the QPSO-based beamforming design achieves higher achievable rates compared to traditional AO and FRCG algorithms, highlighting its superior anti-jamming capability. We also simulate the case of $M_1 = M_2 = 12$, which shows that reducing the number of RIS elements is detrimental to the system anti-jamming performance.

In Fig. 6, the system achievable rate is plotted against the transmit power of the jamming user P_j . As P_j increases, the system achievable rate decreases, demonstrating the effectiveness of the optimization of PB at the two RISs in the suppression of jamming. Moreover, our proposed algorithm outperforms the other schemes and shows its advantages in improving the jamming immunity performance.

The relationship between the number of RIS elements and the system achievable rate is shown in Fig. 7 with legal user power $P_u = 15$ dBm and jamming user power $P_j = 15$ dBm. In Fig. 7(a), the system achievable rate rises with the element number of R_1 under the condition of $M_1 + M_2 = 48$. The proposed QPSO algorithm outperforms the FRCG algorithm in achieving higher transmit rates at the same M_1 , demonstrating its superior anti-jamming capability. Fig. 7(b) depicts that the system achievable rate increases as the total element number of the two RISs increases, indicating that the dual RIS-assisted approach can effectively enhance system anti-jamming capability. Regardless of the value of $M_1 + M_2$, our proposed QPSO-based scheme outperforms the other methods. Overall, the results have shown that the RIS can improve the system anti-jamming performance significantly when it is located near the BS.

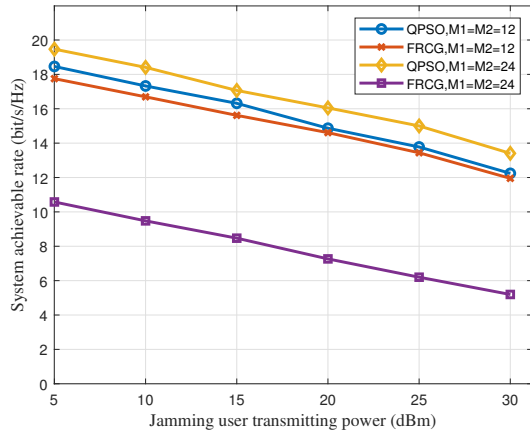


Fig. 6. Relationship between R_a and P_j for typical beamforming schemes.

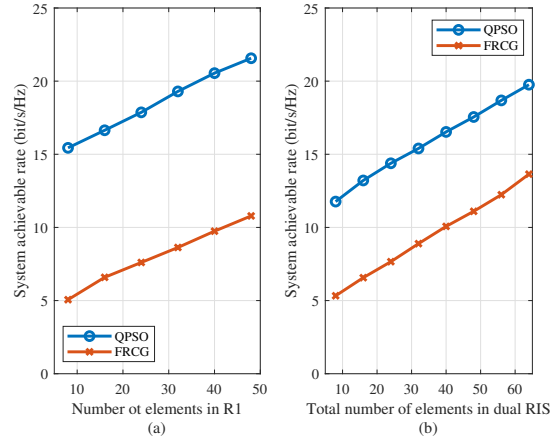


Fig. 7. System achievable rate of QPSO and FRCG schemes. (a) Different element number of R_1 . (b) Different element number of dual RIS.

B. Complexity comparison

To perform a comprehensive comparison based on profiling the anti-jamming performance of the proposed algorithm, we also analyze the balance of the performance and the computational complexity. Firstly, the QPSO algorithm convergence is affected by the number of iterations and the number of particles. The QPSO-based scheme requires more iterations and particles to avoid the local optimum and improve the performance of the global search for non-convex problems [10]. Thus, the number of maximum iterations and the number of particles for QPSO are set as $Q_i = 500$ and $N_p = 50$, respectively.

Meanwhile, the FRCG algorithm is faster in convergence and suitable for some low-dimensional problems but may be limited to locally optimum for non-convex problems. Its convergence performance is affected by the iteration number and the iteration step size, which may converge to the local optimum within relatively small number of iterations [12]. Therefore, for the FRCG algorithm, the maximum number

of iterations is $F_i = 500$ and the step size of iterations is $S_i = 0.06$.

Particularly, the computational complexities of the QPSO and FRCG algorithms, which achieve the best outputs in terms of the system achievable rate and convergence behavior, are calculated as $\mathcal{O}(Q_i N_p)$ and $\mathcal{O}(F_i S_i)$, respectively. The QPSO algorithm can achieve the stable condition after 107 iterations, while the FRCG algorithm requires 16 iterations, as shown in Fig. 3. Although the complexity of the FRCG algorithm is lower than that of the QPSO algorithm, its anti-jamming performance is obviously poor. Overall, the QPSO algorithm is more suitable for solving the high-dimension non-convex optimization problem in this paper.

V. CONCLUSION

In this paper, we propose a QPSO-based joint AB and PB design for dual RIS-assisted uplink anti-jamming cellular communication to achieve enhanced global convergence and system performance. We formulate the joint AB and PB optimization problem to maximize the system SINR, utilizing the QPSO algorithm to optimize the global solution within beamforming vector constraints. Simulation results reveal that the proposed QPSO-based beamforming outperforms the standard AO and the FRCG algorithms in anti-jamming performance with respect to the system achievable rate.

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